

Graeber, Thomas; Roth, Christopher; Schesch, Constantin

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Working Paper No. 490

Explanations

Thomas Graeber, Christopher Roth and Constantin Schesch

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EXPLANATIONS*

Thomas Graeber

Christopher Roth

Constantin Schesch

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Abstract

When people exchange knowledge, both truths and falsehoods can proliferate. We study the role of explanations for the spread of truths and falsehoods in 15 financial decision tasks. Participants record the reasoning behind each of their answers with incentives for accuracy of their listeners' responses, providing over 6,900 unique verbal explanations in total. A separate group of participants either only observe one orator's choice or additionally listen to the corresponding explanation before making their own choice. While listening to explanations somewhat improves average accuracy, there is substantial heterogeneity: explanations enable the spread of truths, but do not curb the contagion of falsehoods. To study mechanisms, we extract every single argument provided in the explanations, alongside a large collection of speech features, revealing the nature of financial reasoning on each topic. Explanations for truths are richer and contain higher argument quality than explanations for falsehoods. These content differences in the supply of explanations for truths versus falsehoods account for 60% of their asymmetric benefit, whereas orator and receiver characteristics play a minor role.

Keywords: Explanations, Social Learning, Speech Data, Financial Knowledge

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1 Introduction

We obtain most ideas, news, and knowledge from listening to others (Hirshleifer, 2020; Schotter, 2023). Some of the information we receive is accurate, while some of it is flawed. Whether learning from others improves or impairs our decisions therefore critically depends on our ability to discern what is right and what is wrong. The epitome of a welfare-improving social aggregation of information is the *marketplace of ideas*: the truth will emerge and prevail in an environment where thoughts, insights and knowledge are freely exchanged.¹ Yet, misbeliefs can spread rapidly, too, whenever individuals systematically fail to identify falsehoods (Lazer et al., 2018). Indeed, some argue that recent technological advances catalyze the spread of falsehoods, marking the onset of a “post-truth era.”

At the center of any knowledge exchange are explanations: people share justifications for and reasoning behind their beliefs and choices, often conveyed by word of mouth from peer to peer (Shiller, 2017). Unlike in canonical economic models of social learning, people do not only learn from observing *what* someone else does or believes, but also from *why* they do so. To examine how explanations affect the contagion of truths and falsehoods, we conduct large-scale experiments in which respondents solve canonical financial decision tasks, receive one of over 6,900 explanations recorded by other respondents and are then allowed to update their answer. We focus on financial decisions because they are known to be shaped by information that circulates through social networks (Duflo and Saez, 2003) and include topics where false narratives are widespread, such as cryptocurrencies or stock-picking.

We run a series of pre-registered experiments using a design comprising two separate stages. We start with an Orator experiment that characterizes the *supply of explanations*. Respondents complete 15 canonical financial decision problems with an objectively correct answer, allowing us to characterize mistakes. These include questions on nominal illusion, the net returns of active and passive investing, the relationship between interest rates and bond prices, compounding of interest and other topics. In each task, respondents first indicate their choice, with incentives for accuracy. Then, they record a voice message in which they provide an explanation for their answer to randomly matched participants in a separate study. Orators’ incentives induce aligned interests with the listeners of their recording: an orator’s likelihood of receiving a bonus payment

¹The marketplace of ideas is a foundational rationale for freedom of speech and open discourse, frequently attributed to U.S. Supreme Court Justice Oliver Wendell Holmes Jr.

increases with the accuracy of the listener’s subsequent response to the question.² The faithful exchange of knowledge pervades real-world interactions in education (e.g., classroom teaching), business (e.g., collaboration across business functions), healthcare (e.g., patient-doctor consultations, public health campaigns), the legal system (e.g., advice on contracts) and finance, including peer-to-peer information sharing.

To study the *interpretation of explanations* and its consequences for social learning, we then conduct a Receiver experiment with 1,103 respondents, in which respondents face the same 15 tasks. They first make their own incentivized choice. For each task, we randomly assign respondents to the *Choice Only* or the *Explanation* condition. In *Choice Only*, they learn about the choice of a randomly chosen respondent in the Orator experiment. In the *Explanation* treatment arm, participants additionally listen to the respondent’s explanation. In both conditions, respondents then again select their own best choice, which may now differ from their initial choice, yielding a dataset with more than 30,000 incentivized choices. The comparison between *Explanation* and *Choice Only* allows us to identify the specific effect of listening to a verbal explanation on imitation, above and beyond the mere observation of another respondent’s choice. The *Choice Only* condition provides a natural benchmark that captures learning in the absence of an explanation, and further allows us to control for the direct effects of the respondents’ confidence in their prior answers, measurement error in priors and other factors, such as experimenter demand.

Do explanations matter? We begin by analyzing how explanations shape average optimality rates. The prior optimality rate across tasks is 55.3%, meaning participants perform far better than the 33.3% rate implied by choosing randomly in a three-option task. In *Choice Only*, just observing someone else’s answer increases the frequency of optimal choices to 59.5% ($p < 0.01$). Explanations somewhat increase the aggregate improvement from social learning: across all tasks, the *Explanation* treatment raises the accuracy rate to 62.7% ($p < 0.01$). This modest aggregate treatment effect, however, conceals that a large fraction of receivers encounter confirmatory advice (58.5%), in which case little or no improvement should be expected. We decompose the aggregate effects by separately analyzing different combinations of prior receiver and orator accuracy. First, in “learning situations,” a receiver with an incorrect prior receives information from a correct orator. Second, in “unlearning situations,” a receiver with a correct prior receives information from an incorrect orator. Third, we study receivers who are either correct or incorrect and receive a confirmatory signal.

²Our *explanations* thus differ from *persuasive messages*, which can reflect misaligned incentives.

We find that the aggregate benefit of explanations over merely observing someone’s answer is predominantly driven by learning opportunities: in those cases, the imitation rate is only 42.8% in *Choice Only* but 55.8% in *Explanation*. This corresponds to a 13.0 p.p. ($p < 0.01$) increase in seizing learning opportunities. The *Explanation* treatment does not, however, decrease the frequency with which receivers switch to a wrong answer in unlearning opportunities. Receivers switch from accurate to inaccurate answers in 23.1% and 22.9% of unlearning situations in *Choice Only* and *Explanation*, respectively ($p = 0.87$). Finally, we turn to receivers that receive confirmatory signals and, perhaps unsurprisingly, document muted effects of explanations. In situations where the orator and receiver are both correct, the posterior optimality rate is 99.1% and 99.2% in both treatment groups ($p = 0.77$). When both the receiver and the orator begin with an incorrect answer, the *Explanation* condition yields a slightly higher optimality rate (3.8%) than *Choice Only* (2.0%; $p < 0.01$) that contributes only 12% to the aggregate treatment effect.

Average effects of explanations also shroud heterogeneity at the task level. Explanations have a positive effect in 14 out of 15 tasks, though it is only statistically significant for 6 tasks. At the same time, asymmetric effects of explanations for learning and unlearning situations emerge in 14 out of 15 tasks, though only in a statistically significant manner for 7 of these.³

As a starting point for understanding these findings, we turn to the role of confidence. Prior work indicates that confidence in one’s choice can shape both the supply of explanations and the likelihood that others choose to imitate. We first analyze heterogeneous treatment effects by orators’ confidence levels. We show that imitation in learning situations is significantly higher when respondents are exposed to confident orators in the *Explanation* condition, suggesting that confident orators supply more credible explanations. We then examine the heterogeneous treatment effects by receiver confidence. Our data show that receivers with high prior confidence—who typically do not change their response based on the orator’s choice alone—become more likely to change their mind when in the *Explanation* condition. This evidence hints at an important role of confidence and motivates the following more systematic unpacking of our findings.

Why do explanations help? We develop a simple model to interpret and decompose how explanations affect social learning. Receivers observe another person’s answer but are uncertain about its reliability. Without explanations, all answers are treated as equally informative. With explanations, however, receivers obtain an imprecise signal about the underlying strength of

³Our experiments were not designed with sufficient statistical power for task-level analyses. We cannot reject the null hypothesis that the variation across tasks reflects pure sampling variation.

the signal. The agent’s optimal response to this imprecision creates a *pivot* in belief movements, leading to overinference from weak and underinference from strong signals, as in Augenblick et al. (2025). In our model, explanations may also uniformly *shift* beliefs—making correct answers more persuasive regardless of confidence—or change how strongly receivers rely on their *priors*.

Taking the model to the data to decompose the treatment effect into these three components, we estimate regressions leveraging elicited confidence (Grether, 1980). First, the belief data corroborate the patterns found in the choice data. Second, the decomposition of the average treatment effect reveals that only a modest share of it reflects greater sensitivity to orator beliefs (*pivot*) with explanations than without, while explanations in fact reduce reliance on informative priors. The dominant force is a sizable shift effect: correct explanations receive a uniform credibility boost, which drives the entirety of aggregate gains. These asymmetric gains point to additional informational content embedded in correct explanations.

This model-guided evidence raises the question of what information explanations transmit. Is the impact of explanations akin to observing the orator’s numerically expressed confidence, which is, on average, higher in learning than in unlearning opportunities? To test this hypothesis directly, we conduct an additional Receiver experiment, in which respondents observe both the orator’s choice and their stated confidence. Compared to only observing the orator’s choice, additionally learning about their confidence does not significantly shift imitation in learning and unlearning opportunities on average. Therefore, an explanation is a signal of accuracy that is distinct from the orator’s numerical confidence.

Which features of oral explanations convey the additional information? Both the content—*what* is said—and its delivery through the speaker’s voice—*how* it is said—may shape the receivers’ behavior. To distinguish between these two channels, we design an additional Receiver experiment, in which respondents read the transcript of the orator’s explanation instead of listening to the corresponding recording. This preserves the exact verbal content of the explanation while eliminating the role of the speaker’s delivery and voice, effectively reducing the dimensionality of the message space. A strongly asymmetric effect on learning and unlearning persists in the *Transcript* treatment, suggesting the effect of explanations is primarily driven by the supply and interpretation of their *content*. While we exactly replicate the average null effect of explanations in unlearning situations of the *Transcript* treatment, there is an 8.1 p.p. increase of the imitation rate in learning opportunities (relative to *Choice Only*), which equals approximately two thirds of the effect size induced by *Explanation*. The effect size difference across *Transcript*

and *Explanation* is statistically significant ($p = 0.03$). This difference points to the possibility that the effectiveness of explanations depends on the dimensionality of the message space.⁴

Having established that the impact of explanations is distinct from confidence statements and primarily operates through content, the question remains as to why the asymmetric effect of explanations emerges. To address this, we conduct a mechanism analysis that systematically examines content differences in the supply of explanations.

Mechanisms: The content of explanations. In the first step of our mechanisms analysis, we characterize the content of the more than 6,900 explanations and study its effects on imitation. Analyzing the content of speech recordings is non-trivial due to the high-dimensional nature of language data: each sentence has innumerable features and interpretations. We pursue a two-pronged approach based on the following distinction. On the one hand, explanations are characterized by their substantive content: they provide *arguments*, which tend to be domain-specific and directly relate to a specific question and answer. We identify and code every argument provided across the universe of our explanations, delivering the first dataset of its kind for studying their effect on social learning and unlearning in a controlled setting. On the other hand, explanations are characterized by a large number of text features: they exhibit various classes of expressions (e.g., certainty phrases, hedges or questions), many linguistic and rhetorical attributes, and can be described by speech and text metrics, among others. We code a broad set of text features from the existing literature. These domain-general features apply across explanations for different questions and answers. To analyze transcripts, we combine human coding, a large language model, and machine learning methods, ensuring robustness and replicability.

Our argument annotation yields, for each of the 15 tasks, the full set of arguments, their frequency in correct versus incorrect explanations, and estimates of their effects on imitation. To illustrate, consider the task on whether actively managed funds outperform passive ones. The dominant argument—that active funds can quickly adapt to market changes—appears in 57.2% of incorrect explanations but only 4.0% of correct ones. By contrast, the claim that active funds charge higher fees occurs in 22.7% of correct explanations but just 3.2% of incorrect ones. In total, we identify 11 distinct arguments. Some are particularly influential: for instance, “active

⁴One interpretation of this lower treatment effect might be that people are less attentive in the *Transcript* treatment than the *Explanation* treatment. Yet, our decomposition exercise displayed in Table E10 shows that 74% of the differential effect of explanations in the *Transcript* treatment is explained away by our content-based measure of explanation richness. This, in turn, suggests that respondents are highly attentive to differences in the content of the scripts.

funds can react to the market” (in unlearning situations) and “passive funds target long-term growth” (in learning situations) both raise imitation by more than 20 p.p. relative to *Choice Only*. Across tasks, we document heterogeneity in the number of arguments, the degree of consensus, and the strength of their marginal effects on imitation. This perspective provides a useful lens on how individuals reason and how their reasoning persuades others. It does not, however, isolate the mechanisms underlying the asymmetric treatment effect, because argument content is not directly comparable across choices and tasks.

To compare explanations for correct and incorrect choices across tasks, we classify arguments into four categories of increasing quality: (i) no argument, (ii) irrelevant (off-topic) arguments, (iii) fallacious arguments with false premises or invalid reasoning, and (iv) sound arguments with true premises and valid conclusions. This classification matters since respondents can sometimes arrive at the right answer even with irrelevant or fallacious arguments. We find striking differences across contexts: in unlearning situations, respondents more often face no argument (21.8% vs. 16.0% in learning), irrelevant arguments (22.6% vs. 17.7%), or fallacious ones (51.0% vs. 10.5%), whereas in learning situations they are much more likely to encounter sound arguments (55.8% vs. 4.7%).

Are argument classes linked to different imitation effects? Indeed, higher-quality arguments yield stronger effects. The absence of an argument or the presence of an irrelevant one tends to reduce imitation, while even fallacious arguments raise it. Yet, conditional on argument class, imitation remains far higher in learning than in unlearning. In fact, the argument gap explains at most 25% of the asymmetry.

What content features beyond argument quality distinguish explanations for correct and incorrect answers? An analysis of domain-general speech and text markers (e.g., certainty) shows that explanations for correct answers are substantially *richer*: they include more of most features, even controlling for length. In fact, 24 of 31 features appear more often in correct explanations. A pre-registered LLM-based measure confirms this pattern: richness scores are on average 0.77 SD higher for correct than for incorrect explanations.

Can differences in explanation features account for the asymmetric treatment effect? We first test which features predict imitation and find that richness is by far the strongest predictor: a one-standard deviation increase in richness is associated with a 13.0 p.p. increase in imitation ($p < 0.01$), even after controlling for length and other features. This benefit diverges from *Occam’s Razor*: rather than preferring simplicity, listeners are more persuaded by comprehensive,

detailed explanations, perhaps because they are taken as signaling credibility. Next, we show that the richness gap explains about 60% of the differential effect between learning and unlearning opportunities. We investigate the key drivers of the richness effect and find that linguistic richness—the complexity, variety, and uniqueness of vocabulary—plays a pivotal role. Finally, we systematically test and rule out differences in participant characteristics (both as orators and receivers) as the source of the asymmetry.

Motivated by this correlational evidence, we conduct an additional receiver experiment to isolate the causal effect of linguistic richness. We exogenously vary linguistic richness while holding factual content and arguments constant, by instructing a large language model to generate two versions of each transcript: a rich version with structured, coherent language, and a sparse version with fragmented sentences. Participants were randomly assigned to one version at the task level. Richness significantly increases imitation: from 40% to 58% in learning scenarios and from 15% to 26% in unlearning. These effects remain when restricting to transcripts where both versions contain exactly the same arguments, highlighting the importance of linguistic richness.

Taken together, our mechanism evidence suggests that content differences are the key determinant of imitation decisions in our setting. We leverage novel methods that were unavailable to the earlier literature on advice and social learning (see, e.g., Schotter, 2023), providing direct access to *what* people communicate in unconstrained natural language and how it affects imitation. Our data allow us to compare and emphasize the role of content over that of the identity of speakers on imitation, the focus in much of the previous literature (Cialdini, 2001). The overall beneficial effect of explanations on optimality directly hinges on the positive association between richness and truth. This relationship may be specific to settings that have, like ours, aligned incentives between speakers and listeners to identify the truth in the exchange of knowledge rather than opinions.

Finally, we note that our main financial decision-making tasks involve high-dimensional signals that combine arguments, reasoning, and knowledge. To further benchmark the effects in this rich setting, we leverage a more abstract, self-contained task in which communicable information is plausibly lower-dimensional: the classic balls-and-urns problem (Edwards, 1968). In contrast to our financial tasks, explanations have more muted effects on imitation and posterior accuracy. Together, these results suggest that explanations may be more effective in environments in which communicable information is high-dimensional.

Literature. Our paper contributes to an emerging literature on learning from qualitative information, e.g., in the form of stories and narratives (e.g., Graeber et al., 2024; Andre et al., 2025; Kendall and Charles, 2022; Hüning et al., 2022; Schwartzstein and Sunderam, 2021; Eliaz and Spiegler, 2020; Bursztyn et al., 2023). Barron and Fries (2024) study strategic communication of model parameters as a persuasive tool when financial advisors hold incentives that differ from those of the individuals they are advising. Thaler et al. (2025) provide evidence that senders with incentives to directionally persuade are more likely to communicate using language rather than numbers. Graeber et al. (2025) examine how verbal transmission distorts the supply of qualitative economic information and show that information about signal reliability gets lost in transmission more than information about signal values because it fails to come to mind. We differ from existing work in our focus on characterizing the supply and interpretation of explanations for people’s choices in canonical financial decision problems.

We relate to an interdisciplinary literature on explanations (Lombrozo, 2006; Langer et al., 1978) and arguments (Sloman et al., 1998). Our contribution lies in providing a characterization of the supply of qualitative explanations and in estimating their consequences for economic decisions in a controlled setting. Our experimental manipulations of explanations highlight that linguistic richness shapes social learning, above and beyond arguments and facts.

We further contribute to a literature that studies how social learning among non-experts—labeled “naive advisors” by Schotter (2003)—affects the prevalence of biases and misinformation.⁵ In a setting that—unlike ours—features incentives for deception, Serra-Garcia and Gneezy (2021) show that individuals fail to detect others’ lies when they are shown a video message of another respondent paid to invent a news story. A series of papers has examined social learning in the context of motivated beliefs (Oprea and Yuksel, 2022; Thaler, 2025). Grunewald et al. (2024) study whether biases are contagious in a setting with motivated beliefs. They find that communication of personal opinions via a written text message amplifies belief biases relative to a setting of observational learning. Conlon et al. (2025) show that in the context of a balls-and-urns updating task, people are less sensitive to information others discover than to equally relevant information they receive themselves.

⁵The literature on social learning (typically defined as observational learning from others’ actions, our control condition) is vast (Jackson and Yariv, 2007; Galeotti et al., 2010), especially in the context of financial decisions (Ambuehl et al., 2022; Bursztyn et al., 2014; Akçay and Hirshleifer, 2021; Hirshleifer et al., 2023). The present paper builds on an earlier literature on advice-giving (Schotter and Sopher, 2003; Çelen et al., 2010; Schotter, 2023), which has focused on pre-structured messages and not yet studied the nature and causal effect of explanations in natural language.

Finally, by characterizing the spread of truths versus falsehoods through social learning, we contribute to a long-standing literature on whether individual-level biases matter for aggregate market-level outcomes (e.g., Fehr and Tyran, 2005). Enke et al. (2023) show that awareness about biases reduces the impact of individual-level biases on aggregate outcomes through institutions that rely on self-selection, while Amelio (2024) studies how meta-cognition shapes social learning. Unlike those findings, ours cannot, by design, be explained by meta-cognition. Instead, we examine how explanations affect perceptions of others’ accuracy and thereby the proliferation of truths and falsehoods.

2 Experimental Design

2.1 Overview

Our experimental design studies 15 canonical financial decision problems and consists of two stages. In the *Orator* experiment, respondents record an explanation for their answer for each of the tasks. In the subsequent *Receiver* experiment, respondents first provide their choice. Then, they either only see another respondent’s choice (from the *Orator* experiment) or additionally listen to that respondent’s explanation, before providing their answer to the same task again.

2.2 Financial Decision Problems

We select 15 financial decision tasks based on three criteria. First, we aim for a collection that is broadly representative of the reasoning and decision biases studied in the finance literature. This spans behavioral phenomena like exponential growth bias and nominal illusion, but also more specific knowledge about different asset classes and investment decisions, for example expected returns under active versus passive investing. Many of the problems we study are tightly linked to common high-stakes financial decisions, such as whether to invest in active or passive funds. Second, we restrict our attention to questions with an objectively correct answer or ones where a broad consensus exists in the financial economics literature, excluding those that rely on tastes. Moreover, participants in our studies are made aware that a “correct” solution exists.⁶ Third, the questions should be reasonably short. Some tasks have a logically correct answer, for example the following question about the concept of inflation, with the correct answer underlined:

⁶This is motivated both by our focus on the exchange of knowledge—rather than opinions—and a precondition for incentivizing answers. The effect of explanations on imitation choices might be different in settings where people think that no correct answer exists.

Imagine that the interest rate on your savings account was 2.5% per year and inflation was 3% per year. After 1 year, how much would you be able to buy with the money in this account?

1. *More than today*
2. *Exactly the same as today*
3. *Less than today*

Other questions relate to a broad consensus in financial economics, like the following:

Do actively managed investment funds systematically outperform passively managed investment funds in terms of expected net returns, i.e., after accounting for investment fees?

1. *Actively managed funds outperform passively managed ones.*
2. *Actively managed funds do not outperform passively managed ones.*

We embrace that differences across these tasks will likely evoke structurally different explanations. A participant might give a wrong answer because they have not heard of the concept of a call option—in a sense, they may not really know what the question is about—or they fully understand the question but still do not know its answer. This difference captures two separate important features of bias in practice and may be reflected in explanations as we discuss in the following sections. Appendix Table E6 outlines the motivation and origin of the tasks, as well as the exact wording of all questions. Three tasks have two options, while the others all have three. In most analyses, we are only interested in whether the correct option is chosen.⁷

2.3 Part 1: Orator Experiment

The main objective of the Orator experiment is to obtain recordings of people’s verbal explanations for each of the financial decision tasks.⁸ In the beginning, participants are told that we are interested in how they would give advice in an informal conversation. They are informed that they should share an explanation behind their response and that their recording will be played to other participants who will have to answer the same question. We ask respondents not to search for answers on the internet.⁹

⁷Due to these differences, one could expect different frequencies of correct responses, because randomizing would create an optimality rate of 50% in a two-option and 33% in a three-option task. However, this is constant across conditions and thus cannot affect treatment comparisons. Appendix C.2 shows treatment effects of explanations are very similar for tasks with two and three response options.

⁸The full set of instructions is reproduced in Online Appendix L.

⁹We ask participants at the end of the study whether they searched for any answers, stressing there is no penalty for indicating that they did. As pre-registered, we exclude the 7.0% of participants indicating that they searched for answers from our data.

People typically have some time to think about explanations they give. Correspondingly, rather than forcing respondents to talk immediately upon reading the question, we show them the question first and they decide when to start their recording. An example screen is shown in Online Appendix Figure K19. After recording their explanation, respondents first select their preferred answer and then state their confidence in its accuracy by answering “*How certain are you that your above answer is correct?*” on a scale from 0 “*Not at all certain*” to 100 “*Fully certain*”.

Incentives. With a 10% chance, a respondent is eligible for a bonus payment of \$10. Whether a selected respondent receives a bonus is based on one randomly drawn task. The orator is matched with another randomly selected participant in the Receiver experiment, who either only sees that orator’s answer or additionally listens to their voice recording. The bonus is paid if the matched receiver gives the correct answer after exposure to the orator’s answer. Our experiment thus creates aligned incentives between the orator and the receiver: the orator is incentivized not to be imitated *per se*, but to induce the receiver to make the right choice. The orators’ instructions emphasize that their incentives will be known to listeners (“Participants listening to your recordings will be informed that you will receive a bonus if they select the correct answer.”). We confirm that orators understand the aligned incentives scheme using a control question.

Speech recordings. The Orator experiment relies on speech recordings of people’s explanations. Relative to written text, speech recordings have a series of advantages for our purposes. A voluminous literature outside of economics has characterized the differences between written and spoken text production (e.g., Akinnaso, 1982). Written text tends to be more formal, structured and cognitively taxing to produce (e.g., Bourdin and Fayol, 2002). Because writing text is typically more exhausting than speaking, the transcripts of orally provided explanations are often substantially longer. Much of social learning follows from oral conversations, making speech recordings an ideal testing ground to study the effects of explanations. Second, speech data include features of natural language that plausibly affect social learning but are mostly absent from written texts, including tone, emphasis, and disfluencies such as pauses, repetitions, revisions, hesitations, or filler words. Third, writing text as opposed to spontaneously talking about one’s thoughts adds another filter that may distort measured explanations compared to explanations people give spontaneously in the real world.

2.4 Part 2: Receiver Experiment

To characterize the effect of explanations on social learning, we conduct a Receiver experiment that leverages the choices and recordings from the Orator experiment.¹⁰

As in the Orator experiment, respondents complete the 15 decision tasks. To measure imitation rates at the individual level, we use a within-design with five steps in each round. First, respondents read the financial decision task and are incentivized to indicate their preferred choice, which provides our measure of their prior belief. Second, they indicate their confidence in the accuracy of their response in the same format as respondents in the Orator experiment. Third, they either only learn about the choice of another randomly selected respondent in the Orator experiment (*Choice Only* condition) or additionally listen to the recording of their explanation (*Explanation* condition). Fourth, the receiver again has an opportunity to select their preferred choice with incentives for accuracy. Fifth, they indicate their confidence in their posterior answer.

Treatments. In the *Choice Only* treatment, receivers may infer and adjust their belief about the optimal answer from learning what someone else chose, even absent an explanation. This same source of learning is present in the *Explanation* treatment, but the explanation provides an additional source of information. We randomize treatments between participants, at the task level. For each task, 80% of receivers are sampled into the *Explanation* condition, while the remaining 20% are assigned to *Choice Only*.¹¹

The comparison between *Explanation* and *Choice Only* allows us to identify the specific effect of listening to a recorded explanation on learning and unlearning, above and beyond the mere observation of another respondent's choice. The *Choice Only* condition is critical to control for (i) the effects of prior confidence, (ii) measurement error in priors, and (iii) other confounders, such as experimenter demand effects. At the same time, this comparison captures various potential channels of learning which we disentangle through additional treatments.

Incentives. Receivers have a 10% chance of being eligible for an additional \$10 bonus payment. Whether they receive the bonus is determined by the accuracy of their answer in a randomly selected reasoning task. For every task, we randomly select whether their first answer or their second answer is the decision that counts for the bonus.

¹⁰We provide the full set of instructions in Online Appendix M.

¹¹We oversample the *Explanation* condition to obtain the statistical power needed to examine heterogeneous effects by features of the explanations.

2.5 Logistics

Respondents in both studies received a base reward of \$6 for completing the study. Median completion times were 25 minutes in the Orator experiment and 26 minutes in the Receiver experiment. All experiments were conducted on the online platform Prolific, which is widely used for experiments in the social sciences. The Orator experiment was run for a total of 505 U.S. respondents in December 2023, of whom 466 provided valid responses.¹² Participants were required to have a working microphone to record their voice message. The Orator experiment yields a total of 6,910 valid recordings obtained by integrating speech recordings with Phonic into Qualtrics surveys. We use an Amazon Web Services backend to stratify and distribute recordings into our Receiver experiment. The Receiver experiment was run with 1,235 U.S. respondents in December 2023, of whom 1,103 provided valid responses. Appendix Table E7 provides an overview of all data collections and corresponding pre-registrations.

3 Explanations and Social Learning

We start by providing basic descriptives about our respondents' explanations. We then turn to the effects of explanations on imitation and optimality. We conclude with additional results on heterogeneity and robustness.

3.1 Basic Characteristics of Explanations

Our Orator experiment generated 6,910 audio recordings with a median duration of 26 seconds. We find substantial variation in length: the 10th percentile is 11 seconds and the 90th percentile 55 seconds. The audio quality of recordings is high. Analyses of the audio files show that only 1.1% of recordings are unusable, typically because of a technical microphone problem or because respondents submitted it too early by mistake.¹³ We use transcripts of the recordings that preserve details and nuances of spoken language, notably filler words such as “um” and “eh.” The median length of the resulting transcripts is 55 words.

To parse basic features of the scripts, human coders classify them using a simple coding scheme (see Appendix B). We find that 13.1% of explanations are pure restatements of the

¹²In accordance with our pre-registration, we determine orators gave valid responses if not all their recordings were blank and if they did not indicate that they looked up answers online. We similarly drop receivers who self-reported looking answers up online.

¹³Incomprehensible messages or high background noise appear very rarely and are therefore not relevant concerns for our study.

question and/or the answer, without adding any content matter. These may both be due to people not trying or not having any explanation for their answer. We characterize a negligible minority of 2.6% of recordings as nonsensical. Looking at the cases that reflect some form of actual explanation, we find that 8.6% of all explanations contain *no substantive arguments* while 74.3% of all explanations contain *substantive arguments*. Finally, 13.7% of recordings contain explicit expressions of the speaker’s confidence.

This first look at basic descriptives suggests the Orator experiment provides a rich and varied database of heterogeneous explanations for our set of tasks. In Section 5, we go much further in examining their characteristics.

3.2 Explanations and Optimality

We start by analyzing the effects of our treatments on the frequency of correct choices, which we refer to as the *optimality rate*. For comparability with additional treatments and to maximize statistical power, we pool observations for *Choice Only* obtained from different between-subject collections that use this exact same control condition (see Sections 4.2 and 4.3). The prior optimality rate reflects receivers’ knowledge about a task before learning from another respondent. The posterior optimality rate captures accuracy after receivers observe another respondent’s answer only (*Choice Only*) or additionally listen to their verbal explanation (*Explanation*).

Figure 1a shows these optimality rates pooled across all 15 tasks. Prior to exposure, 55.4% and 55.2% of respondents provided correct answers in the *Choice Only* and *Explanation* conditions, respectively ($p = 0.88$). We document two main findings on posterior optimality. First, just observing another’s choice increases optimality rates by 4.1 p.p. ($p < 0.01$), creating an aggregate improvement. Second, additionally listening to another person’s explanation raises the size of the improvement to 7.5 p.p. (0.15 SD, $p < 0.01$). This difference in improvement rates between the *Choice Only* and *Explanation* conditions is statistically significant ($p < 0.01$) but quantitatively modest. Importantly, this aggregate treatment effect reflects that a large fraction of receivers encounter confirmatory advice (58.5%), which plausibly creates limited scope for social learning. Moreover, it masks important variation across initially correct and incorrect listeners, different tasks and explanations, which we turn to below.

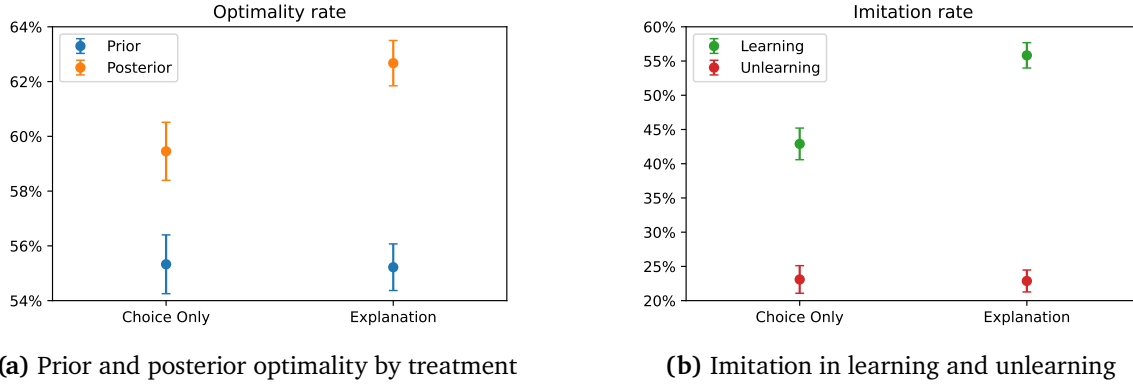


Figure 1: Effect of *Explanation* on optimality and imitation. *Notes:* Left panel shows share of correct receivers before and after exposure to the orator's choice or explanation. Right panel shows share of receivers picking the same answer as the orator in learning and unlearning situations. *Explanation* sample is the main Receiver experiment (1,103 receivers, 13,111 obs.), *Choice Only* is pooled from all collections (2,733 receivers, 8,232 obs.). Whiskers show 95% CIs.

3.3 Explanations and Imitation Rates

Our sample is composed of structurally distinct sets of orator-receiver matches. Specifically, pairs vary along two margins relevant for social learning: the initial accuracy of the listener and the accuracy of the orator. This creates four distinct groups, characterized by whether a receiver was initially correct, and whether they were subsequently exposed to a *confirming* or *conflicting* signal. Since the optimality rate is only modestly above 50% and matching is random, these four situations occur with broadly similar frequencies. Intuitively, situations where receivers hear conflicting advice should have the biggest scope for learning. We start by analyzing these.

Imitation in response to conflicting signals. Among respondents who receive conflicting signals, we distinguish between two distinct situations: those with initially incorrect choices who are exposed to correct ones, and those with initially correct choices who are exposed to incorrect ones. We refer to the former as *learning opportunities* and the latter as *unlearning opportunities*.¹⁴ If the probability of being correct is p for both receivers and orators, under random matching, learning and unlearning situations both occur with frequency $p(1 - p)$: indeed, in our sample, there are 21.2% learning and 20.3% unlearning opportunities.

Figure 1b displays the frequency of imitation in learning and unlearning opportunities. It illustrates two key findings. First, the unlearning rate does not differ significantly between *Choice*

¹⁴We will also refer to corresponding explanations as *learning explanations* and *unlearning explanations*.

Only and *Explanation*, at 23.1% vs. 22.9% ($p = 0.87$). About one of every four receivers with a correct prior confronted with another respondent's wrong answer switches away from the correct one. Thus, participants in unlearning opportunities do not, on average, infer information from explanations that systematically helps them identify the answer as wrong.

Second, we do find a quantitatively large treatment effect on the learning rate. Learning opportunities are far more likely to be seized in *Explanation*, where people imitate in 55.8% of cases, than in *Choice Only*, with 42.8%. This 13.0 p.p. ($p < 0.01$) increase in the learning rate shows that, on average, explanations help listeners identify the correct answer.

Imitation in response to confirmatory signals. To benchmark effect sizes in learning and unlearning contexts, we next examine imitation when receivers are exposed to confirming signals. Appendix Figure D4 displays optimality and imitation rates in these situations. When both the orator and the receiver are initially correct, imitation rates are extremely high, at 99.1% in *Choice Only* and 99.2% in *Explanation* ($p = 0.77$). By construction, posterior optimality rates are identical. This indicates that “destructive” arguments, agreeing with a listener's correct choice but nevertheless prompting them to switch to an incorrect one, are essentially absent in our data.

On the other hand, when both the orator and the receiver are initially incorrect, imitation rates stand at 82.6% and 82.2%, respectively ($p = 0.73$). Corresponding aggregate posterior optimality rates are quite small at 2.0% in *Choice Only* and 3.8% in *Explanation*, but do display a small 1.8 p.p. ($p < 0.01$) treatment effect. For this specific analysis, the distinction between two- and three-option tasks plays an important role and provides additional insights. In our twelve three-option tasks, explanations make receivers more likely to select the correct answer when the orator gave the same wrong answer as the receiver, but also when they supported a different wrong answer. Although these effects are small, we therefore find that arguments can play an “enabling” role, i.e., support the same or a different initial wrong choice as the receivers' but lead them to switch to the correct answer.¹⁵

Decomposing the aggregate effect. The 1.8 p.p. effect when both are wrong is an order of magnitude smaller than the 13.0 p.p. learning effect, while both situations occur similarly often (23.5% vs. 20.3%). Decomposing the 3.2 p.p. increase in posterior optimality in *Explanation* relative to *Choice Only*, we find that 80% of it is driven by learning, 12% by situations where both are wrong and 8% by unlearning.

¹⁵See Online Appendix C.2 for details.

Result 1. *Listening to another respondent’s explanation somewhat increases the average optimality rate, relative to just observing their answer. The treatment effect is strongly asymmetric: explanations increase imitation in learning opportunities but do not decrease it in unlearning opportunities.*

Robustness. In Online Appendix C, we find that the asymmetric effects of explanations are robust to excluding the shortest and longest recordings, to distinguishing only by orator optimality, and to separating tasks with two or three options.

3.4 Cross-Task Heterogeneity and Robustness

The previous analysis pooled data across tasks, potentially obscuring task-level heterogeneity. Appendix Figure D6 shows optimality and imitation rates across tasks. Optimality rates vary from more than 90% for “Nominal Illusion” to less than 20% for “Disposition effect”, with the difference in optimality after receiving advice and between treatments being almost an order of magnitude smaller than cross-task heterogeneity. We see this variability as a useful feature of our selection of tasks from the literature, since both harder and easier questions naturally occur in economic decision-making. In turn, imitation rates range from around 60% in learning situations to around 10% in unlearning situations, both for “Nominal Illusion”. Tasks with higher optimality rates exhibit a larger gap between learning and unlearning, showing that, in both treatments, easier tasks make it easier to change incorrect beliefs and harder to change correct ones.

Turning to the effect of explanations, Figure 2 illustrates cross-task variation in our main findings. The left panel shows a positive treatment effect of *Explanation* on optimality in 14 of the 15 tasks.¹⁶ All 95% confidence intervals contain the aggregate effect of 3.2 p.p., though the treatment effect is statistically significant in only 6 out of 15 tasks, reflecting lower power at the individual task level.

To separate the share of variation reflecting true heterogeneity rather than sampling variation, we perform Cochran’s Q-test which yields a statistic of 10.69 with 14 degrees of freedom, failing to reject the null of homogeneity ($p=0.71$). The corresponding I^2 index is 0%, suggesting all variability should be attributed to sampling error. However, with only 15 tasks, power to detect modest variation is limited. Despite our large data collection of nearly 50,000 individual decisions, the noisy nature of social learning makes precise estimation at the task level difficult: though it should be stressed we are not very well-powered to measure it, we find no evidence to

¹⁶This improvement rate is not significantly correlated with the prior optimality rate in a given task ($r = -0.07$, $p = 0.81$), and neither is the net learning effect ($r = 0.13$, $p = 0.65$).

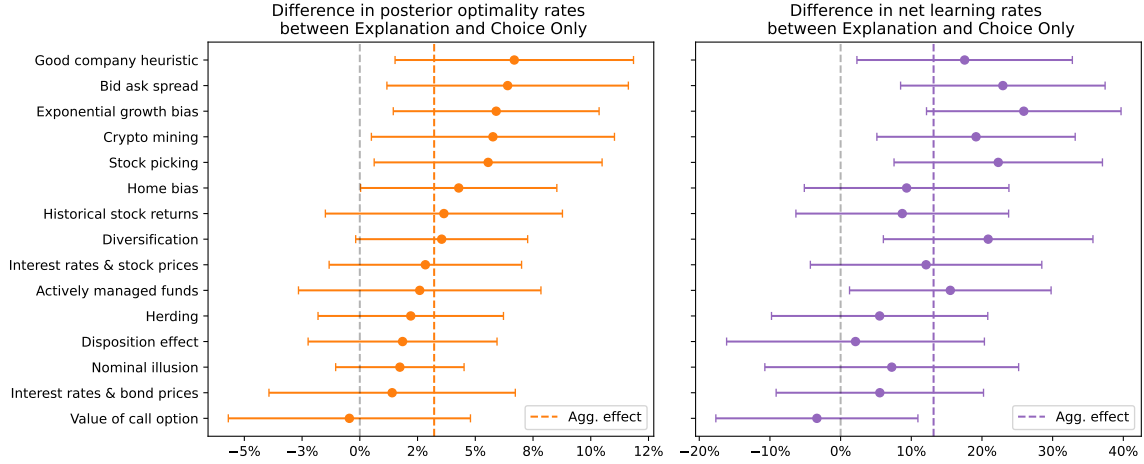


Figure 2: Difference in posterior optimality rates between *Explanation* and *Choice Only* by task, and difference in net learning rates between *Explanation* and *Choice Only* by task. *Notes:* The net learning rate is defined as the difference in imitation rates between learning and unlearning situations. Dashed vertical lines show aggregate effects across tasks, of 3.2 p.p. and 13.3 p.p., respectively. *Explanation* sample is the main Receiver experiment, *Choice Only* is pooled from all collections. Whiskers show 95% CIs.

suggest strong heterogeneity in the effects of explanation on optimality.

This conclusion is more nuanced for the asymmetric benefit of explanations. The right panel of Figure 2 shows the net learning effect of explanations, defined as the difference in learning rates between *Explanation* and *Choice Only* minus the corresponding difference in unlearning rates, is similarly pervasive. It is positive in 14 tasks, with confidence intervals also containing the 13.3 p.p. aggregate effect in 14 tasks, though it is statistically significant in only 7 tasks. The figure displays substantial heterogeneity, with estimates ranging from a maximum of +25.9 p.p. in “Exponential growth bias” to a median of +12.1 p.p. in “Interest rates and stock prices” to a minimum of -3.4 p.p. in “Value of call option.” For net learning, Cochran’s Q stands at 18.38 ($p = 0.19$) and the I^2 index is 24%, suggesting that roughly one-quarter of observed variation likely reflects genuine task-level heterogeneity.

3.5 Confidence and Social Learning

Our findings so far are based on actual imitation decisions and the implied optimality rates only. Our design also provides more granular data from orators’ and receivers’ confidence statements. We now leverage this confidence data to shed light on who imitates and who gets imitated.

Confidence data. In our experiments, we asked both orators and receivers to report their confidence in their answer on a scale from 0% to 100%. It stands at 73.0% for correct and 62.0% for incorrect ($p < 0.01$) receiver prior choices. It is very similar at 75.0% and 63.0% ($p < 0.01$), respectively for orator choices.¹⁷

Heterogeneity by receiver confidence. We investigate how heterogeneity in receiver confidence interacts with the effect of explanations. One intuitive possibility is that explanations reduce the confidence threshold below which individuals are willing to imitate others. Figure 3a displays the imitation rate by bins of receiver prior confidence in *Choice Only* and *Explanation*, separately for learning and unlearning situations. As one would expect, imitation generally slopes down in receiver prior confidence. Just as there is no average effect of *Explanation* in unlearning situations, there is no statistically significant effect within any of the confidence bins. On the other hand, in learning situations, effects are relatively weak in the first bins up to 60% confidence, after which the treatment effect becomes much stronger. More precisely, splitting the sample by the overall median confidence of 74%, the net learning rate of explanations is 10.0 p.p. ($p < 0.01$) for unconfident receivers and about two times larger at 19.2 p.p. ($p < 0.01$) for confident ones, a significant 9.1 p.p. difference ($p = 0.02$). The learning benefit of explanations is therefore even greater for confident but wrong receivers.

Orator confidence. We now turn to the role of orator confidence in shaping social learning. Figure 3b shows that imitation generally slopes up in orator confidence for learning situations, though it is almost flat in unlearning situations. Moreover, among these, there is no explanation effect at any confidence level. Finally, although learning effects appear weaker up to 60% confidence, they are strong and growing above this threshold. For listeners exposed to orators with confidence below the median, the learning effect is 8.1 p.p. ($p < 0.01$), but two times larger at 16.2 p.p. ($p < 0.01$) above the median, also a significant 8.8 p.p. difference ($p = 0.05$). The learning benefit of explanations is thus amplified by confident and correct orators. Online Appendix G provides additional results on heterogeneity by confidence.

Taken together, these findings point to a central role of orator and receiver confidence in shaping imitation decisions. In the next section, we conduct a more formal decomposition of the effects of explanations into underlying forces that leverage the richness of the confidence data.

¹⁷Because of an error in the survey which allowed respondents to skip the question, prior confidence is missing for 0.6% of the sample. We drop these observations in this Section.

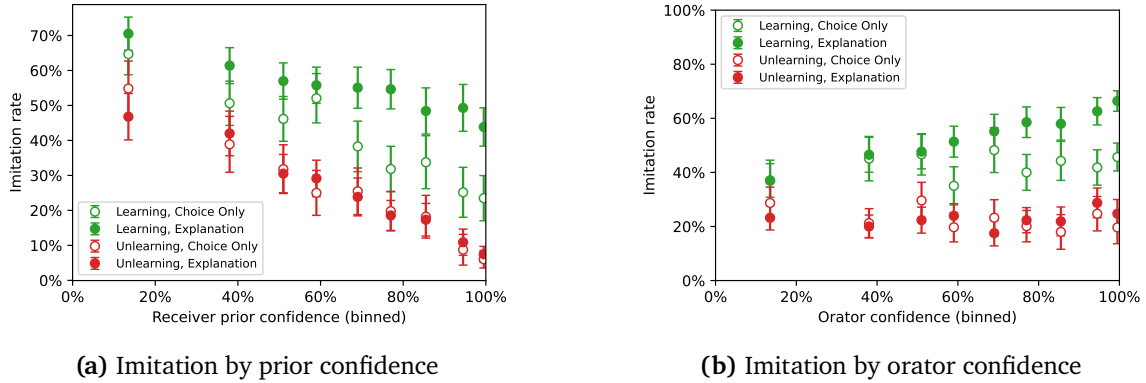


Figure 3: Effect of prior and orator confidence on imitation in learning and unlearning situations. *Notes:* *Explanation* sample is the main Receiver experiment (1,103 receivers, 13,111 obs.), *Choice Only* is pooled from all collections (2,733 receivers, 8,232 obs.). Whiskers show 95% CIs.

4 Interpreting the Treatment Effect of Explanations

Having documented a strongly asymmetric treatment effect of explanations as our main reduced-form finding, we now attempt to better understand the drivers of this treatment effect. To structure our analyses, we first illustrate the role of explanations in a canonical belief formation framework. We then present additional experiments that help characterize the treatment effect.

4.1 A Model-Based Decomposition

How can explanations be represented in a canonical updating framework? We present a simple model that directly motivates an empirical specification to decompose the treatment effect.

Model summary. We outline the setup and intuition of our framework and relegate all details and derivations to Appendix A. We directly build on Augenblick et al. (2025), who propose a Bayesian model of over- and under-inference due to imprecise information about, or imperfect integration of, signal strength.

In our setting, respondents face questions with correct answer $\theta \in \{-1, 1\}$, where 1 denotes the correct answer (without loss of generality). Their own reasoning about a question is modeled as a draw of a signal strength $S > 0$ and a direction d with $\mathbb{P}(d = \theta) = \Lambda(S)$, where Λ is the logistic function, so that stronger signals are more likely to be correct.

Receivers then observe the answer of an orator, which is an additional directional signal d , but only have imprecise information about its strength S . In *Choice Only*, the receiver does not get any information about signal strength, so they must rely on its unconditional distribution. In

Explanation, the verbal explanation delivers a noisy signal $\tilde{S}$ about signal strength S , which the receiver uses to modulate the magnitude of their belief update. We model this as standard log-normal Bayesian updating, where $\log S \sim \mathcal{N}(\log \bar{S}, \sigma^2)$ and $\log \tilde{S} = \log S + \varepsilon$ with $\varepsilon \sim \mathcal{N}(0, \sigma_\varepsilon^2)$, so that the receiver forms a posterior that shrinks the imprecise signal toward their prior about signal strength:

$$\log S \mid \tilde{S} \sim \mathcal{N}(\log \bar{S} + \lambda(\log \tilde{S} - \log \bar{S}), (1 - \lambda)\sigma^2), \quad \lambda = \frac{\sigma^2}{\sigma^2 + \sigma_\varepsilon^2}.$$

How can this model shed light on the treatment effect of explanations? Its basic prediction is that, while receivers are entirely insensitive to the signal strength in *Choice Only*, they become responsive to it when given an explanation: they respond more to strong signals than to weak ones. However, the imprecision makes this response imperfect, leading to an attenuation pattern relative to the benchmark of observing signal strength *without noise*: receivers tend to overinfer from weak explanations and underinfer from strong explanations (as in Augenblick et al., 2025).

Appendix Figure A1 illustrates the receiver’s predicted belief update as a function of the orator’s signal strength, for *Choice Only* as well as high- and low-noise *Explanation*. All curves approximately intersect at the average signal strength $\mathbb{E}(S)$, mirroring Figure 1a in Augenblick et al. (2025). Crucially, as signals about signal strength become more informative, the slope of the curve steepens while their level at $\mathbb{E}(S)$ stays approximately constant, so that the curves pivot.

We therefore refer to this basic Bayesian effect of explanations in the model as the *pivot* effect. To the extent that explanations carry some information about true signal strength, the *Explanation* treatment makes receivers more sensitive than in *Choice Only* to the true knowledge that is shared, which translates into aggregate improvements.

We consider two potential deviations from this Bayesian framework that may contribute to the treatment effect. First, explanations could uniformly *shift* belief movement, e.g., by causing receivers to imitate correct answers more irrespective of the underlying signal strength. Such a “boost” to the perceived signal strength of correct answers in *Explanation* could account for the asymmetric treatment effect we observe. Second, explanations could affect the weight receivers put on their own *prior*, e.g., by causing receivers to neglect it more or less when listening to an explanation. Depending on average accuracy of priors in the population, this, too, could contribute to an aggregate treatment effect.

Our model offers a structured framework to think about belief updating from explanations, and helps us identify three channels that govern their effect on optimality: *pivot*, *shift* and *prior*.

Estimation. We propose to estimate our model via a canonical Grether (1980) regression on log-odds beliefs. In particular, Proposition 4 in Appendix A shows that a regression of the Bayesian update on orator signal strength S captures the pivot mechanism, i.e., has a level at $\mathbb{E}(S)$ that stays constant between *Choice Only* and *Explanation* with different levels of noise. In turn, this allows us to decompose the average treatment effect (ATE) into the *pivot*, *shift* and *prior* components.

While our previous analyses of treatment effects were based on binary imitation data, this analysis requires belief data. Without loss of generality, we define a respondent’s belief as the subjective probability they assign to the correct answer. We recover beliefs by leveraging our confidence data. We convert it to belief probabilities $\pi \in [0, 1]$ by mapping confidence from 0% to 100% to $[0.5, 1]$ for correct answers. Conversely, confidence from 100% to 0% is mapped to $[0, 0.5]$ for incorrect answers.¹⁸ Finally, we transform belief probabilities into belief log-odds $\ell = \text{logit}(\pi) \in \mathbb{R}$.¹⁹ Our key outcome is then log-odds assigned to the correct answer ℓ , with $\ell > 0$ for correct choices, $\ell < 0$ for incorrect choices, and larger $|\ell|$ reflecting greater confidence.

It should be stressed that, unlike in controlled belief updating tasks, the true signal strength is unobservable in our setting, and instead estimated from participants’ confidence statements. In the questions we study, higher confidence is predictive of accuracy: prior confidence is 61% on average for incorrect receivers and 72% for correct ones. However, in line with typical experimental patterns of overconfidence (see, e.g., Moore and Healy, 2008), our data also show that confidence is far less predictive of optimality than implied by the logit link structure.

In our model, we account for this by assuming that respondents’ beliefs inflate their signal strengths as $\ell = \omega \cdot d \cdot S$, with ω a common overconfidence parameter. In our data, we estimate $\omega \approx 10$, reflecting significant overconfidence. Since this is a linear re-scaling, the model-derived decomposition that applied to the Bayesian update carries over directly to belief movement. Importantly, the pivot for the empirical decomposition is then $\mathbb{E}(|\ell|)$, a very simple, model-free sample moment. This robustness reflects the fact that our decomposition only relies on pivots and shifts in the updating function across treatments, not on its overall shape or scale.

Moreover, the confidence statements underlying our approximations are possibly subject to noise, which can cause attenuation bias in our analysis (see, e.g., Gillen et al., 2019). In

¹⁸Robustness checks using alternative mappings yield qualitatively identical results. In tasks with three options, the two wrong options are effectively grouped. Dropping cases where a receiver with a wrong answer hears an orator with a different wrong answer likewise has no effect (cf. Tables A1–A2).

¹⁹To avoid dropping 0 and 1 beliefs, we winsorize probabilities to their 5th and 95th percentiles.

our estimation, these concerns forbid strong conclusions about over- vs. under-inference, i.e., statements suggesting a comparison to a normative Bayesian benchmark. Instead, we focus on comparisons of more vs. less inference *across treatments*.

Results. Our Grether regressions are shown in Appendix Table A1, with our main specification in column (3). It shows receiver posteriors regressed on orator beliefs and receiver priors, all interacted with orator optimality and a dummy for the *Explanation* treatment. Since beliefs are truth-signed log-odds, and we find an ATE of +0.185, explanations increase posterior optimality. This belief-based analysis replicates the core choice-based findings: explanations generate an asymmetric treatment effect, with little impact when orators are incorrect but substantial gains when they are correct. This lends credibility to the use of confidence-based beliefs as an outcome.

Turning to the decomposition, we document three main findings. First, the *pivot* effect—reflecting the Bayesian response to imprecise information about signal strength as in Augenblick et al. (2025)—accounts for 20% of the treatment effect. Explanations thus make receivers somewhat more sensitive to our proxy for signal strength, though the effect is modest in size. Second, the *prior* effect contributes −36%: explanations make receivers less sensitive to their own priors, which reduces optimality given that priors are, on average, informative. Finally, the *shift* effect accounts for 116% of the treatment effect: correct explanations are uniformly more likely to be imitated regardless of orator confidence. This large boost dominates the decomposition and effectively explains the entire aggregate treatment effect.

To illustrate the findings on belief movement (pivot and shift), Figure 4 plots receiver belief movements, i.e., the change in log-odds between a receiver’s prior and posterior answer, as a function of orator beliefs, also expressed as log-odds. Lines are fitted using column (3) of Appendix Table A2, which repeats our analysis but for belief movement, by subtracting the prior from the posterior on the left-hand side instead of using it as a covariate on the right-hand side. Dots represent a bin-scatter and show that the prediction lines up quite well.

It makes clear that the belief-based analysis replicates our main choice-based result. In *Choice Only*, receiver beliefs move by moderate, offsetting amounts when the orator is correct and incorrect, while in *Explanation* they shift far more when the orator is correct, driving an average treatment effect. Beyond replicating this asymmetry, the Figure also illustrates its decomposition. The slope difference between treatments reflects the *pivot* effect—receivers become more responsive to signal strength when given an explanation. At the same time, the vertical displacement between treatments for correct orators captures the large *shift* effect: even the least confident

correct explanations cause more belief movement than choices. Together, these patterns visually confirm the decomposition into a modest pivot effect and a dominant shift effect.

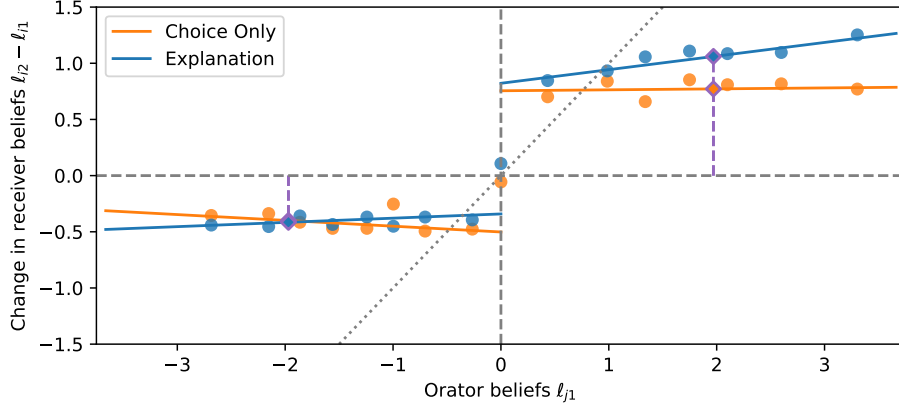


Figure 4: Change in receiver beliefs $\ell_{i2} - \ell_{i1}$ as a function of orator beliefs ℓ_{j1} . *Notes:* Lines plot results from column (3) in Table A2 and dots the corresponding bin-scatter. Purple dashed lines show $\pm \mathbb{E}|\ell_1| \approx \pm 1.97$ and diamonds the predicted change in beliefs.

Taken together, our model-guided analysis shows that explanations make listeners more sensitive to the orator’s signal strength in all cases, and that, more importantly, correct answers benefit from a substantial discrete “boost” to perceived signal strength. This suggests there is additional informational content embedded in correct explanations, over and above their role in transmitting belief strength.

Before turning to our analysis of the substance of explanations in Section 5, we validate this conclusion with two additional experiments. In particular, we examine whether the learning benefit of explanations can be replicated with a one-dimensional numerical confidence signal, or whether it instead reflects the unique features of verbal argumentation.

4.2 Are Explanations Equivalent to Numerical Confidence Statements?

To answer this question empirically, we conduct an additional Receiver experiment that allows us to benchmark the effect of explanations against directly observing the orator’s confidence.

Design. This additional experiment closely follows the baseline Receiver experiment and also relies on the orator data collected in the baseline Orator experiment. Condition *Choice Only* is identical to its baseline version. Condition *Choice & Confidence* is identical to *Choice Only* except that the listener also sees the level of the orator’s stated posterior confidence, a number between 0% and 100%. Example screens from this experiment are provided in Online Appendix Figure

K20. In each task, we randomly assign respondents to the *Choice Only* (20%) treatment or the *Choice & Confidence* treatment (80%).

Logistics. This experiment was run with 860 U.S. respondents in January 2024, of whom 713 provided valid responses.

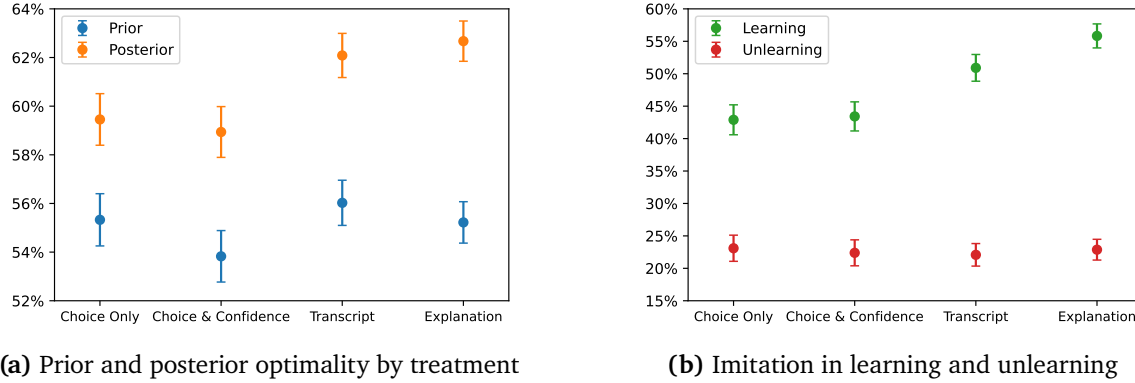


Figure 5: Effect of *Choice & Confidence* and *Transcript* on optimality and imitation rates. *Notes:* Left panel shows share of correct receivers before and after exposure to the orator’s choice, confidence & choice, explanation transcript or explanation speech. Right panel shows share of receivers picking the same answer as the orator in learning and unlearning. Samples are the corresponding Receiver experiments for *Explanation* (1,103 receivers, 13,111 obs.), *Choice & Confidence* (713 receivers, 8,522 obs.) and *Transcript* (917 receivers, 10,964 obs.), while *Choice Only* is pooled from all collections (2,733 receivers, 8,232 obs.). Whiskers show 95% CIs.

Results. We compare the treatment effect of the *Choice & Confidence* treatment on optimality and imitation rates to the treatment effect of *Explanation*. The results are visualized in Figure 5. Panel (a) shows that the *Choice & Confidence* treatment also induces a substantial, 5.1 p.p. ($p < 0.01$) improvement of the average optimality rate. Yet, adding confidence does *not* create a significant treatment effect on the posterior optimality rate, which is at 58.9% in *Choice & Confidence* compared to 59.5% in *Choice Only* ($p = 0.50$).²⁰ Results for optimality across treatments are summarized by regressions in Appendix Table E8. Turning to imitation, we find that *Choice & Confidence* has virtually no effect on both the learning and unlearning rate. At 22.4% and 23.1%, respectively, the unlearning rates of *Choice & Confidence* and the control *Choice Only* are

²⁰The prior optimality rate in *Choice & Confidence*, at 53.8%, lies marginally below that in *Choice Only* at 55.4% ($p = 0.05$) and *Explanation* at 55.2% ($p = 0.05$). We attribute these small differences to sampling noise across data collections. Our conclusion of a non-significant treatment effect in *Choice & Confidence* also holds when analyzing the improvement (difference between posterior and prior, thereby accounting for the variation in priors), instead of the posterior optimality rate ($p = 0.10$).

virtually identical ($p = 0.61$). Learning rates are similarly close at 43.4% and 42.9% ($p = 0.75$), especially in comparison to the 55.8% learning rate in *Explanation*. Appendix Table E9 regresses imitation on all treatments and learning.

From the absence of treatment effects in *Choice & Confidence* we conclude that explanations operate differently from merely conveying a quantitative signal of the orator’s confidence. There are various possible reasons. For example, explanations can convey information above and beyond a confidence level: they may provide objective justifications for an answer that the listener can evaluate independently. This confidence result suggests that the high-dimensional nature of messages may play an important role, motivating our mechanism analyses in Section 5.

Result 2. *The effect of explanations on social learning differs from that of merely observing a sender’s confidence. Unlike explanations, confidence observations (i) do not have a treatment effect on the optimality rate, and (ii) do not affect learning and unlearning rates.*

4.3 The Effect of Explanations: What Is Said Versus How It Is Said

The drivers of the treatment effect can be broken down into two factors (e.g., Mehrabian, 1971): the content of the explanation (*what* is said) and its delivery through the speaker’s voice (*how* it is said). This distinction matters because it speaks to whether the benefits of explanations for social learning are likely to be limited to oral conversations or may occur similarly, for example, in written exchanges. To distinguish the effects of content and delivery, we run an additional experiment in which receivers read the transcript of an explanation, instead of listening to it. This effectively shuts down the effect of oral delivery, while keeping the content channel constant. This treatment can be thought of as lowering the dimensionality of the message space, while keeping the substantive content identical.

Design. We transcribe the explanations from our Orator experiment in a way that preserves the nuances of the spoken text, including filler words such as “um” and “eh”. The design is identical to our baseline Receiver experiment except that *Explanation* is replaced with a *Transcript* treatment, in which participants read the transcript of a recording rather than listening to it. In each task, we randomly assign respondents to *Choice Only* (20%) or *Transcript* (80%). To keep the *Explanation* and *Transcript* treatments as comparable as possible, the text is displayed progressively. Example screens are provided in Online Appendix Figure K21.

Logistics. This experiment was run with 1,266 U.S. respondents in January 2024, of whom 917 provided valid responses.

Results. Panel (a) of Figure 5 shows that explanation transcripts also strongly increase optimality rates relative to the *Choice Only* condition, with nearly similar effect sizes as the corresponding voice recordings. *Transcript* induces a posterior optimality rate of 62.1%, significantly above *Choice Only* (59.5%, $p < 0.01$) and not significantly different from *Explanation* (62.7%, $p = 0.37$). Looking at improvements, which net out the minor across-treatment differences in the prior optimality rate, *Transcript* produces a 2.0 p.p. ($p < 0.01$) larger increase from prior to posterior than *Choice Only*. This corresponds to approximately 59% of the size of the additional improvement in *Explanation* (at 3.4 p.p.), a significant difference ($p < 0.01$, cf. Table E8).

Panel (b) shows that a strong asymmetric effect between learning and unlearning also emerges in the *Transcript* treatment. While transcripts have a strong effect of 8.1 p.p. on the learning rate (at 50.9%, $p < 0.01$), the unlearning rate is virtually unaffected relative to *Choice Only*, at 22.0% ($p = 0.43$). The size of the treatment effect of *Transcript* on the learning rate corresponds to 62% of the treatment effect in *Explanation*, also a significant gap ($p = 0.03$, cf. Table E9). This evidence shows that listening to a spoken explanation leads to somewhat more imitation than just reading the same explanation in learning opportunities, though the asymmetric treatment effects qualitatively emerge in both *Transcript* and *Explanation*. The gap between these treatments highlights that the dimensionality of the message space also matters for social learning.²¹

Result 3. *Both substantive content features and the oral delivery of explanations matter for social learning, with content driving the majority of the effect.*

5 The Supply and Interpretation of Explanations

Our findings on explanations so far rely on experimental variation rather than on the content of the explanations themselves. In this section, we open this black box to better understand why explanations increase imitation in learning opportunities but do not decrease it in unlearning ones. We organize the analysis around an annotation of domain-general features, substantive arguments and an aggregate measure of richness (Section 5.1), discuss content-analysis results (Sections 5.2 and 5.3), and conclude by summarizing additional results on the role of respondent characteristics (Section 5.4) and the dimensionality of communicable information (Section 5.5).

²¹Note that the *Transcript* treatment still relies on text that was originally produced in *spoken* format. In Section 2 we reviewed the systematic differences between written and spoken text production.

5.1 Dissecting Explanations

To study the role of explanations’ content, we examine the transcripts of the recordings. Such data are difficult to analyze comprehensively because language is high-dimensional: each sentence and its oral delivery have innumerable features and possible interpretations.

Our analysis follows a two-pronged approach based on the following distinction: on the one hand, explanations are characterized by the substantive content of the answer to a question. Specifically, explanations frequently invoke *arguments*, defined as a series of statements with the purpose of establishing a conclusion. This content tends to be domain-specific, i.e., it directly relates to a specific question and the chosen answer. On the other hand, an explanation is also characterized by text features: it exhibits speech and text metrics, markers of certainty and linguistic features, etc. We think of such features as domain-general, i.e., applying to explanations for different questions and answers. These two ways of analyzing the data provide complementary perspectives that may shed light on central questions, such as whether imitation is affected more by the substantive content of an explanation or by specific linguistic features.

5.1.1 Argument Annotation

Identifying arguments. To identify arguments from the unstructured text data, we develop a coding scheme detailed in Appendix B. First, we provide a state-of-the-art Large Language Model (LLM), OpenAI’s GPT-4, with all explanations for a given task and make it identify all distinct arguments. This extraction encompasses any type of argument: not only valid or sound ones, but also fallacious and irrelevant ones. Second, based on the initial list of arguments identified by the LLM, we manually fine-tune the categories, e.g., to avoid duplicates or distinguish between variants. Third, a team of six graduate-level research assistants annotates 100 responses in each of the different tasks; whenever they encounter arguments not captured by our scheme, we add them to it. This yields the final list of arguments.

Annotating explanations. The team of research assistants then annotates the presence of all arguments in the scheme across all 6,910 explanations. To assess the quality of the main annotation, the manual annotation is then performed again, with each task allocated to a new research assistant who is blind to the previous results. Inter-rater reliability is high. If one coder identifies a specific argument, there is a 72% chance the other coder does so as well. If one coder does not identify an argument, there is a 95% chance the other coder does not either. Cohen’s κ is 0.67, indicating “substantial agreement” (Cohen, 1960; Landis and Koch, 1977).

Inter-rater reliability is even higher for argument categories. When one coder identifies “any argument”, there is a 100% chance that the other coder does so as well; when one coder does not identify “any argument”, there is a 0% chance the other coder does so as well. These chances are 82% and 89% for “any fallacious argument” and 83% and 89% for “any sound argument”. As a second test, we performed the annotation again using GPT-4. When a human coder identifies an argument, there is a 79% chance GPT-4 does so as well. If a human coder does not identify an argument, there is a 90% chance GPT-4 does not either. Cohen’s κ is 0.61, again indicating “substantial agreement”. Agreement on categories is similarly high. We view these benchmarks as validating our annotation approach.

5.1.2 Feature Annotation

The second part of our approach leverages 31 domain-general text features that apply across all explanations, independent of the specific question or answer. Using GPT-4, we annotate 25 features drawn from prior work. These include explicit uncertainty markers (modal verbs such as could, might; epistemic stance markers such as I believe; hedges such as probably, perhaps), relative and absolute language (almost, always), and certainty references (definitely, certainly). We also capture implicit markers of uncertainty (hesitations, filled pauses, repetitions, self-corrections), as well as mentions of sources, personal experience, authority, direct addresses, and apologetic phrases. In addition, we compute six simple text and speech metrics, including word count, delivery speed, and the Flesch–Kincaid complexity score. Appendix Table B3 provides an overview of all features.

5.2 The Content of Explanations

We first discuss the descriptive results from our annotation approach. We then estimate how content differences affect imitation rates among receivers. We begin with task-specific arguments before turning to the domain-general text features of explanations.

5.2.1 Arguments: The Substance of Explanations

Illustration of results: Actively managed funds. To illustrate the argument annotation, consider the results on *Actively managed funds*, shown in Figure 6.²² The left-hand panel shows the frequency of a given argument separately for the sample of explanations for correct and

²²Analogous results for all other tasks are provided in Appendix Figure D8. The wording of the questions and answer options can be found in Appendix Table E6.

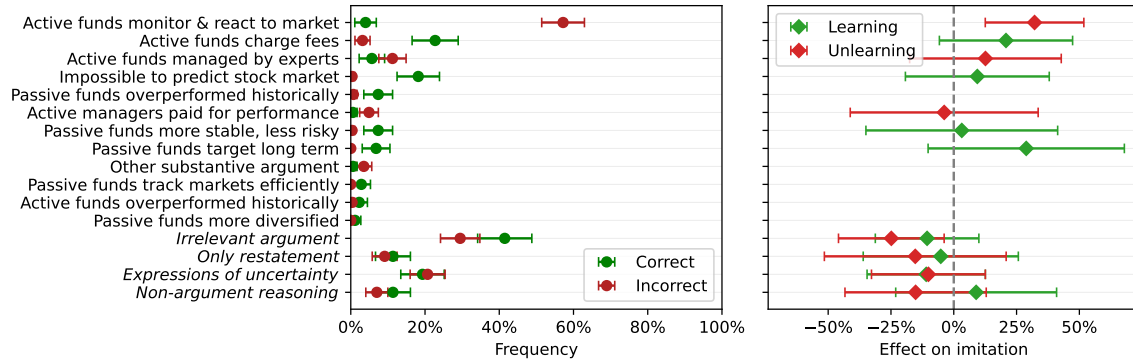


Figure 6: Argument frequency and effects for *Actively managed funds* task. *Notes:* Left panels show the frequency arguments in correct and incorrect explanations. Sample is the Orator experiment. Right panels show the difference-in-differences of the imitation rate between *Explanation* and *Choice Only*, between explanations with and without the argument, in learning and unlearning situations. Only arguments appearing in more than 5% of corresponding explanations are shown. *Explanation* sample is the main Receiver experiment, *Choice Only* is pooled from all collections. Whiskers show 95% CIs, with standard errors clustered at the orator and receiver levels.

incorrect answers, ordered by total frequency in our data. The bottom of the panel also shows the frequency of irrelevant arguments, pure restatements of the answer, any expressions of the speaker’s certainty, and any non-argument reasoning. The right-hand panel displays the estimated effect of a given argument on the likelihood of imitation, separately for learning and unlearning situations. To ensure sufficient statistical power, we only show effects for arguments occurring in at least 5% of explanations in the corresponding situation.

The dominant argument is that active funds can adapt quickly to market changes—common in incorrect explanations (57.2%) but rare in correct ones (4.0%). By contrast, the claim that active funds charge higher fees is frequent in correct explanations (22.7%) and nearly absent in incorrect ones (3.2%). A third theme highlights expert management (skewed toward incorrect answers), while a fourth stresses market unpredictability ($\approx 20\%$ of correct, absent from incorrect). Irrelevant arguments are frequent, somewhat more so for correct (41.5%) than incorrect (29.5%) answers; restatements occur in about 10%; and certainty markers in about 20%.

In the right-hand panel, adaptability arguments raise imitation in unlearning situations by 32.1 p.p., and fee arguments raise imitation in learning situations by 20.7 p.p.. Irrelevant arguments reduce imitation in both, while restatements increase it in learning but reduce it in unlearning. Uncertainty has no systematic effects.

Variation across tasks. Explanations vary widely across tasks (see Appendix Figure D8). Some tasks generate many distinct arguments, others only a few; in some consensus is elusive, in others a single line of reasoning dominates. Arguments also differ sharply in their persuasive power, sometimes encouraging imitation even when wrong and discouraging it even when correct. These patterns highlight the variability of financial reasoning, but also the difficulty of comparing arguments across tasks, motivating us to construct a systematic way to analyze them.

Categorizing arguments across tasks. To draw more general conclusions about differences between explanations for correct and incorrect choices, we define four domain-general argument categories. First, we code the absence of any argument. Second, we define an argument as irrelevant if the premises are unrelated to the question or its answer, i.e., an argument might be entirely off-topic. Third, an argument might be relevant but fallacious: one or more of the premises are false, or the conclusion is not valid given the premises. Finally, we classify a sound argument as one with true premises and a valid conclusion. In classifying explanations, we embrace the fact that there are often several explanations for the correct answer that are sound. We also include “weakly sound” arguments in the “sound” category where, from a strict logician’s perspective, the premises might not quite be sufficient for the conclusion. Online Appendix Table F1 lists all arguments and their categorization in each task.

Analyzing the prevalence of different arguments classes is important as it is *ex ante* unclear whether right or wrong answers are supported by different kinds of arguments. For example, it is in principle possible to give the right answer based on fallacious or irrelevant arguments or to give a wrong answer even if some part of the explanation relies on a weakly sound argument.

To classify each explanation, we treat these four categories as hierarchical: conditional on having any argument, an explanation will be coded based on the category of the “highest-quality” argument it contains. For example, if an explanation contains both a sound and a fallacious argument, we will assign this explanation to the sound bucket. In practice, 91.8% of explanations contain at most one argument type.

The argument gap. The left panel of Figure 7 shows the frequency of different classes of arguments encountered in learning versus unlearning opportunities. A large fraction of explanations in unlearning opportunities contain no (21.8%), irrelevant (22.6%) or, most often, fallacious arguments (51.0%). All three types of arguments are significantly less common in learning opportunities, at 16.0% for none, 17.7% for irrelevant and 10.5% for fallacious arguments, respec-

tively. This means that the three categories of “lower-quality” explanations are more frequent in unlearning situations, with the most pronounced gap in the case of fallacious arguments. Sound arguments, by contrast, are practically absent in unlearning explanations (4.7%),²³ yet they constitute the dominant category in learning explanations (55.8%). We refer to this stark imbalance in the distribution of argument types as the *argument gap*: learning explanations contain “better” types of arguments than unlearning explanations according to this taxonomy.

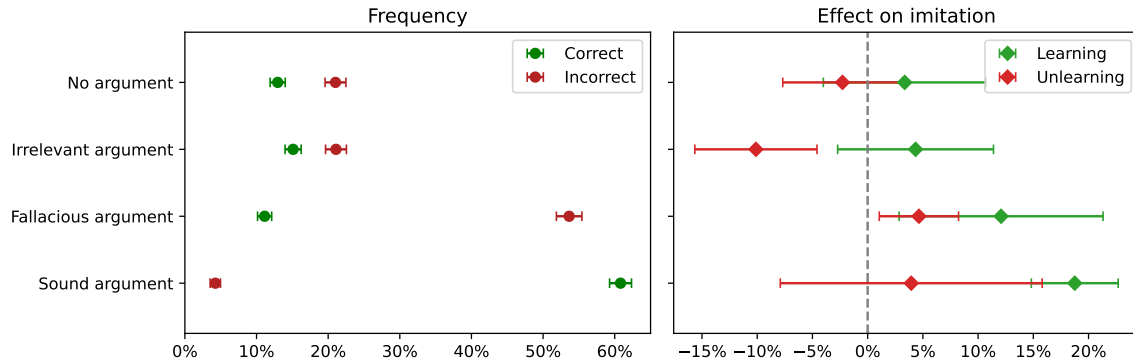


Figure 7: The argument gap. *Notes:* Left panel shows frequency of argument qualities in correct and incorrect explanations. Sample is the Orator experiment. Right panel shows difference in imitation rate between *Explanation* and *Choice Only* by argument quality in learning and unlearning situations. *Explanation* sample is the main Receiver experiment, *Choice Only* is pooled from all collections. Whiskers show 95% CIs.

Argument types and the asymmetric treatment effect. We next examine whether these different classes of arguments are associated with different effects on imitation rates. The right panel of Figure 7 displays the treatment effects associated with each category of argument separately for learning and unlearning situations. Recall that the treatment effect is calculated as the difference in the imitation rates between the *Explanation* treatment and the corresponding matches in the *Choice Only* treatment. We make the following observations.

First, consider treatment effects in unlearning situations. Figure 1b showed a precisely estimated null effect in the aggregate. This could mean that listeners do not adjust their choices in response to explanations, or that the average masks heterogeneity across argument types. Figure 7 confirms the latter: two of four categories exhibit significant effects. Fallacious arguments—which account for more than half of explanations in unlearning—increase the likelihood of

²³This small occurrence stems from our definition of soundness that includes arguments in which the premises might not strictly be true under all circumstances or only weakly establish the conclusion.

switching to a wrong answer by 4.6 p.p. ($p = 0.01$). By contrast, irrelevant arguments reduce imitation by 10.1 p.p. ($p < 0.01$), while no argument has a small and insignificant negative effect (-2.3 p.p., $p = 0.41$). Thus, the aggregate null conceals sharply offsetting effects across explanation types.

Second, turning to learning situations, we find a positive treatment effect on imitation across all categories. It is strongest in the most common category of sound arguments (18.8 p.p., $p < 0.01$), less pronounced for fallacious arguments (12.1 p.p., $p = 0.01$), and about the same for explanations with no (3.5 p.p., $p = 0.35$) or irrelevant arguments (4.5 p.p., $p = 0.21$). This suggests that, if it supports the right answer, *any* explanation tends to help, but better arguments are more persuasive.

Third, we compare treatment effects across learning and unlearning situations. In every argument category, learning effects exceed unlearning effects, though the size of the gap varies: 14.9 p.p. ($p = 0.02$) for sound arguments, 14.7 p.p. ($p < 0.01$) for irrelevant ones, 7.4 p.p. ($p = 0.14$) for fallacious, and 5.8 p.p. ($p = 0.21$) when no argument is given.

Finally, we combine the heterogeneity results with the argument gap—the differing frequencies of argument types across learning and unlearning—to assess how much of the asymmetric effect is explained by argument composition. Comparing columns 1 and 2 of Table 1, we find that differences in argument categories account for up to 25% of the overall asymmetry.

Why does an asymmetric effect persist across the whole range of argument types? In the following subsection, we investigate whether explanations in learning and unlearning opportunities differ beyond the arguments they contain, for example, in terms of their linguistic richness.

5.2.2 The Features of Explanations

We now turn to our second perspective on the content of explanations. Figure 8 summarizes the results from our annotation of domain-general characteristics of explanations, separately for learning and unlearning situations. The left-hand panel displays the frequency with which each feature occurs in learning and unlearning explanations. We make two main observations.

First, the results confirm a number of intuitions about how explanations for correct and incorrect choices might compare. For example, low certainty markers—indicating low confidence—are more common among unlearning explanations but high certainty markers are more common among learning explanations. Low certainty markers appear more than twice as often overall as high certainty markers, plausibly reflecting that people understand the absence of confidence statements as indicating high confidence. Many features that are plausibly associated with a

Table 1: Decomposition of differential learning effects

	<i>Dependent variable: Imitation</i>						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Explanation	-0.002 (0.013)	0.042** (0.018)	-0.166*** (0.046)	-0.128*** (0.048)	-0.208*** (0.065)	0.051*** (0.015)	-0.111* (0.065)
Learning	0.199*** (0.017)	0.199*** (0.021)	0.200*** (0.018)	0.128*** (0.016)	0.112*** (0.021)	0.207*** (0.018)	0.114*** (0.021)
Explanation $\times$ Learning	0.133*** (0.021)	0.099*** (0.026)	0.091*** (0.022)	0.153*** (0.021)	0.101*** (0.026)	0.054** (0.022)	0.070*** (0.026)
Richness						-0.011 (0.009)	-0.007 (0.010)
Explanation $\times$ Richness						0.107*** (0.012)	0.085*** (0.014)
Argument controls		✓			✓		✓
Orator controls			✓		✓		✓
Receiver controls				✓	✓		✓
Observations	8803	8803	8803	8803	8803	8803	8803
R^2	0.093	0.100	0.107	0.166	0.186	0.112	0.195

Notes: Sample is the main Receiver experiment for *Explanation* and all collections for *Choice Only*, both restricted to learning and unlearning situations. *Explanation* is a dummy for the *Explanation* treatment, *Learning* a dummy for learning situations, *Richness* is standardized explanation richness. All controls contain the variable and an interaction with *Explanation*. *Argument controls* denotes dummies for *No argument*, *Irrelevant argument*, *Fallacious argument* and *Sound argument*. Orator and receiver controls are: *Republican*, *Higher education*, *Black*, *Working*, *Age above 35*, *Male*, *(Prior) Confidence*, *Optimality on all others tasks*. We drop the 0.6% of observations with missing receiver prior confidence from all regressions.

higher quality of explanations, such as empirical statements or indications of sources, are indeed more common in learning explanations.

Do the differences in the features of explanations we document predict imitation? The right panel of Figure 8 estimates the treatment effect of each feature on the imitation rates in learning and unlearning situations.²⁴ There is substantial heterogeneity in the degree to which specific features are associated with increases or decreases in imitation rates. A higher speaking pace and markers for questions are consistently associated with stronger imitation. Conversely, low certainty markers are correlated with less imitation. A substantial number of features do not significantly predict imitation. Overall, we do not find that the raw features are jointly associated with more or less imitation in learning versus unlearning situations (in a joint F-test, $F = 0.33$ and $p = 0.56$). We only find significant (albeit small) differences in the feature coefficients for

²⁴These estimates are obtained from multiple regressions for learning and unlearning situations that include all features, relative to *Choice Only*. We only report estimates for features present in at least 5% of the corresponding explanations.

learning versus unlearning situations in 1 of the 32 variables.

Second, we observe that for the vast majority of features (24 out of 31, or 77.4%), explanations in learning situations exhibit *more occurrences*. Moreover, learning explanations feature higher scores in all of the quantitative text metrics, such as language complexity scores or sentence length. This pattern in the feature analysis may suggest that explanations for correct answers are *richer*, a point we examine systematically in turn.

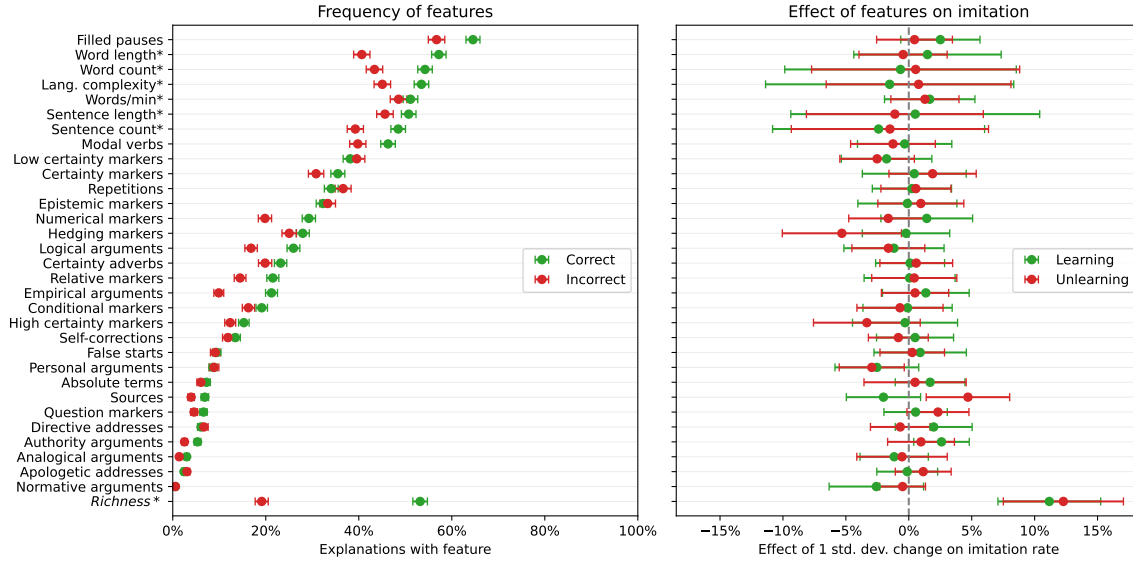


Figure 8: Frequency of explanation features and effects on imitation. *Notes:* Left panel shows share of explanations with features, split by orator optimality. Features with a * instead show the fraction above the overall median. Right panel shows the coefficients on $Explanation \times Feature$ in a multiple regression of imitation on $Explanation$, $Feature$ and $Explanation \times Feature$, for all listed features, applied separately to learning and unlearning. Whiskers show 95% CIs.

5.3 The Richness of Verbal Explanations

We now explore the concept of the richness of a verbal explanation. The motivation is that (i) if explanations in learning opportunities are indeed richer and (ii) richness itself is associated with imitation, the richness gap may partly explain the asymmetric treatment effect of explanations.

5.3.1 The Richness Gap

We set out to characterize the richness of the content of a given message in natural language.²⁵ We apply the following pre-registered definition in our coding instructions: “A rich explanation

²⁵The term richness is used in different disciplines and economics fields, perhaps most commonly to characterize the space of numerical messages in models of communication. While various definitions of

is detailed, comprehensive, logically structured, nuanced, and tailors the argument to fit the context. A sparse explanation is basic, narrow, unclear or disorganized, presents only surface-level understanding, lacks depth or specific details and fails to clearly relate to the context.” Our coding approach relies on both human and machine coding, and follows similar procedures as our main annotation (Section 5.1). We obtain richness scores on an 11-point Likert scale, ranging from 0 to 10 (both inclusive).

We document a systematic richness gap: explanations in learning situations score 0.77 SD ($p < 0.01$) higher than in unlearning, and 0.60 SD ($p < 0.01$) after controlling for transcript length. Appendix Figure D5 shows this pattern within each argument category: the gap is 0.28 SD ($p < 0.01$) for none, 0.46 SD ($p < 0.01$) for irrelevant, 0.74 SD ($p < 0.01$) for fallacious, and 0.29 SD ($p < 0.01$) for sound arguments.

What does the richness score capture? In Appendix Figure D7, we systematically investigate which attributes of a text are most predictive of its richness score. Our analysis accommodates a wide array of metrics, spanning lexical features, part-of-speech and phrase structure, readability metrics, syntactic features, complexity and cohesion measures, as well as entity metrics. While many of these features influence richness, we document that *lexical* richness—the complexity, variety, and uniqueness of vocabulary—is a key determinant.

The effect of richness on imitation. The richness score of an explanation is by far the most potent predictor of imitation (Figure 8). A 1 SD increase in richness is associated with 11.3 p.p. ($p < 0.01$) and 12.4 p.p. ($p < 0.01$) increases in imitation in learning and unlearning situations, respectively, after controlling for all other features, including the length of the recording.

Does the richness gap explain the asymmetric treatment effect of explanations?

Given that learning explanations are richer across the board and that richness is a strong determinant of imitation, a larger treatment effect of explanations might naturally emerge in learning situations. We examine which fraction of the asymmetric treatment effect is explained by differences in the richness of explanations encountered in learning versus unlearning situations.

Comparing regression analyses in columns 1 and 6 of Table 1 shows that 59% of the asymmetric effect is explained away by the richness gap. Richness remains a powerful determinant of the asymmetric effect once we also account for the role of argument categories. In fact, after

richness are used in the literature, they often relate to the cardinality and/or granularity of the message space as well as the mapping between messages and states. Here, we attempt to characterize the richness of a given message (rather than a hypothetical message space) in natural language.

accounting for richness, the estimated asymmetric treatment effect remains unchanged when additionally controlling for different argument types.

5.3.2 Exogenous variation in richness

The previous section presents correlational evidence that richness accounts for some of the asymmetric effects between learning and unlearning, even conditioning on the argument gap, and points to the relevance of linguistic aspects of richness. To shed further light on this mechanism, we conduct an additional pre-registered experiment in which we exogenously vary linguistic richness, while holding the arguments and facts of the explanation constant.

Design. The experiment is identical to the *Transcript Receiver* experiment presented in Section 4.3 and relies on the same set of original explanations from the main orator experiment. The key difference is that we randomly assign respondents to either a *Rich version* or a *Sparse version* condition at the task level. We generate rich and sparse versions of each original transcript using an LLM (OpenAI’s GPT-4.1), closely following the pre-registered definition of richness that we employed in Section 5.3.1. For the sparse version, the LLM is instructed to mimic conversational uncertainty by employing mid-sentence self-corrections, informal vocabulary, and fragmented sentence structures lacking clear logical progression. Conversely, for the rich version, the model uses precise terminology, explicit logical connectors (such as “because” and “therefore”), illustrative examples, and contextual framing designed to facilitate comprehension. Importantly, the LLM is instructed to preserve key arguments, factual statements, and references to external sources in both versions. Online Appendix I provides additional details, including the prompt used to create the rich and the sparse versions of the original transcript.

Results. As illustrated by Figure 9b, we document a large positive effect of being assigned to the *Rich version* condition on imitation rates. In learning situations, imitation rates increase from 39.7% to 58.4% ($p < 0.01$). In unlearning situations, imitation rates rise from 15.0% to 26.3% ($p < 0.01$). When receivers with a wrong prior receive a confirming transcript, imitation rates increase from 78.8% to 81.8% ($p = 0.03$), and remain largely unchanged at 98.2% and 98.9% when both orator and receiver are correct ($p = 0.06$). Finally, the overall optimality rate increases from 60.3% in the *Sparse version* to 62.4% in the *Rich version* ($p = 0.01$).

Robustness. A key assumption required to isolate the effect of linguistic richness is that we successfully hold argument content constant. To assess this, we employ an LLM to compare the argument content of rich and sparse transcripts and find substantial agreement. As a conservative

robustness check, we restrict the sample to transcripts with exact argument overlap and obtain significant results of similar magnitude to those in the full sample. Online Appendix I provides further evidence on the features and richness of the LLM-generated versions.

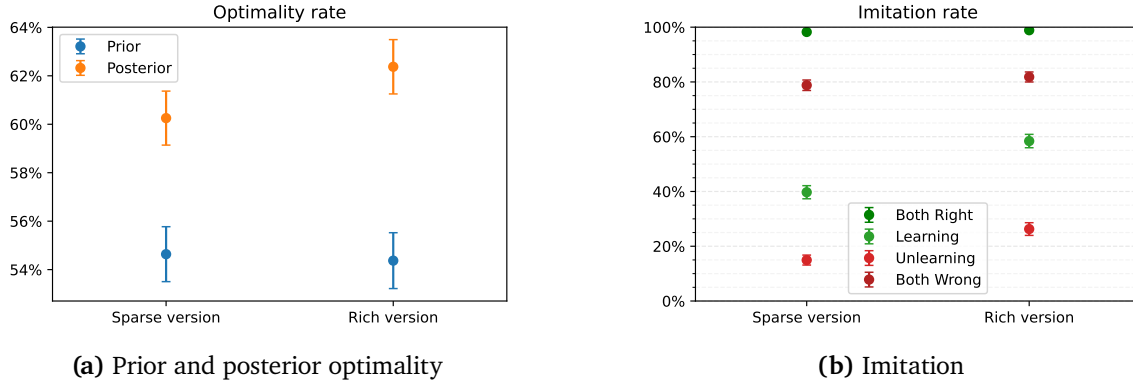


Figure 9: Effect of richness manipulation on optimality and imitation. *Notes:* Sample is the Richness receiver survey (972 receivers, 14,580 obs.). Whiskers show 95% CIs.

Effect size. To better interpret the effect sizes, we start by rating the richness of each version with an LLM just as for the original explanation (cf. Section 5.2.2). On a scale from 0 to 10, the richness of original explanations was 3.1 on average, while it is 2.9 for *Sparse version* ($p < 0.01$) and 5.9 for *Rich version* ($p < 0.01$). This implies rich versions are 1.71 SD (of original richness) richer than sparse versions. For comparison, the richness gap between correct and incorrect original explanations is 0.77 SD.

In turn, we find that across learning and unlearning situations, the *Rich version* condition increases imitation by 15.4 p.p. ($p < 0.01$). We can interpret the treatment assignment as an instrumental variable for richness, which implies that an experimentally induced 1 SD increase in linguistic richness has a $15.4 / 1.71 = 9.0$ p.p. ($p < 0.01$) effect on imitation. This is about two thirds of the 13.0 p.p. increase associated with naturally occurring variation in richness among original explanations.

Result 4. *Learning explanations are richer and contain higher quality arguments than unlearning ones. Richness is the key predictor of imitation and explains about 60% of the asymmetric effect. An additional experiment underscores that linguistic richness is causally related to imitation.*

5.4 The Role of Orator and Receiver Characteristics

We complement the content analyses by analyzing whether differences in orator and receiver characteristics help explain the asymmetric effect of explanations. This asymmetry reflects heterogeneity across an endogenous margin: orators in learning and receivers in unlearning situations have correct priors, while the reverse hold incorrect priors. One possibility is that individuals with correct priors are systematically different—e.g., more influential as orators or less responsive as receivers. Online Appendix H shows, however, that demographic differences across these groups do not account for the asymmetry once content differences are taken into account.

5.5 The Dimensionality of Communicable Information

Our evidence comes from tasks in which explanations convey high-dimensional information, combining facts and arguments in applied, real-world contexts. The central result is that the richness of explanations is crucial for their effectiveness. A natural question is whether explanations also matter when communicable information is low-dimensional. In other words, is high-dimensional communicable information a necessary precondition for explanations to matter?

In the final step of our analysis, we tackle this question by extending our analysis to an unfamiliar, abstract problem: a balls-and-urns belief-updating task (Edwards, 1968). In this task, the signal is plausibly one-dimensional and there might be little real-world knowledge or arguments to bring in. Under the hypothesis that there is indeed little high-dimensional information to communicate, explanations may be less effective.²⁶

Design. We design a standard balls-and-urns task. Two bags contain colored balls: one holds 80% blue and 20% red, the other 20% blue and 80% red. One bag is randomly selected, with the prior probability of choosing the blue-majority bag set to either 40% or 60% (varied across participants). A single ball is then drawn from the chosen bag, and its color is revealed to the participant.²⁷ The participant’s task is to state the likelihood with which they think the bag with more blue balls was selected. In the Orator experiment, participants are given instructions on this task with an example. They record an explanation, select their answer on a continuous scale

²⁶An examination of explanations in the Balls-and-urns experiment shows that they typically contain similar, largely intuition-based arguments about inference, reflecting a more low-dimensional message space compared to our financial reasoning tasks.

²⁷We chose these parameters so that (i) the two possible priors (40% or 60%) sit symmetrically around 50% and have roughly similar space to move on either side; (ii) the diagnosticity of 80% yields a strong signal, yet not so extreme that responses hit ceiling or floor effects; and (iii) limiting the evidence to one draw keeps the task one-dimensional while still illustrating a non-trivial Bayesian update.

from 0% to 100% and state their confidence. We choose a continuous outcome measure rather than a discrete one (as in our other main tasks) in order to keep our implementation of this task comparable to the experimental literature.

In the Receiver experiment, a separate sample of participants is given instructions of the task with an example. They first state their prior responses and their confidence. They then either (i) learn about another respondent’s choice (*Choice Only* treatment) or (ii) *additionally* listen to a verbal explanation behind the choice (*Explanation* treatment). Subsequently, respondents again state their choice and confidence. Receivers have a 40% probability of being assigned to the *Choice Only* treatment and a 60% probability of being assigned to the *Explanation* treatment.

Results. We compare the prior and posterior accuracy rates between the *Choice Only* and *Explanation* treatments. To account for stratified assignment, we recover the population average treatment effect by reweighting observations according to their expected frequency under fully random assignment. Following our main results, we examine imitation separately for learning and unlearning opportunities. Online Appendix Figure J13 documents muted effects of explanations on various metrics of imitation: an indicator for no imitation, an indicator for full imitation and a continuous imitation measure. We find some evidence that receiving an explanation somewhat increases the likelihood of full imitation, but this effect does not differ across learning and unlearning conditions. Online Appendix J provides additional details on both the design and analysis of the balls-and-urns task. Taken together, our findings are consistent with the idea that explanations are less effective in settings where communicable information is more low-dimensional.

6 Discussion and Conclusion

We examine how explanations influence the propagation of truths and falsehoods in the context of 15 financial decision-making problems. In our first experiment, participants record an explanation for each of their answers with incentives for the accuracy of their listeners’ responses. In a second experiment, a separate set of respondents either only observes an orator’s choice on a question or also hears one of the over 6,900 verbal explanations before potentially updating their own decisions. We find that explanations increase aggregate optimality. Notably, this improvement is entirely driven by the greater spread of truths, whereas falsehoods do not become less contagious. Our model-guided decomposition indicates that the treatment effect is driven by a uniform increase in the credibility of explanations for correct answers. A comprehensive

analysis of underlying mechanisms reveals that explanations for truths contain fewer fallacious and more sound arguments, and are far richer than explanations for falsehoods. These richness differences account for approximately 60% of the asymmetric treatment effect. An additional experiment that exogenously varies the linguistic richness of messages, holding the underlying arguments constant, points to a causal interpretation.

Future directions. The evidence in this paper may be extended in various directions. We find that explanation richness is correlated with truth, which is a central relationship underlying the overall beneficial effect of explanations. This relationship may be specific to explanations in settings with aligned incentives. Our setup might fruitfully serve as a blueprint for studying analogous patterns in the case of *persuasive messages*, where the orator wants the receiver to take a specific action. In the case of persuasion, it is conceivable that the richness-truth association in the supply of arguments weakens, or, in some situations, even reverses.

Finally, our LLM-based annotation approach provides a blueprint for analyzing high-dimensional language data to analyze mechanisms underlying economic decisions. The two-step identification of arguments, the extraction of features and the measurement of richness could all be applied to field settings, such as social media posts explaining financial decisions. This opens up valuable opportunities to validate experimental findings in more naturalistic contexts.

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APPENDIX FOR “EXPLANATIONS”

Thomas Graeber

Christopher Roth

Constantin Schesch

A Conceptual Framework

We briefly set out a framework that casts our experimental setup as a standard belief formation model that speaks to the existing economics literature. It conceptualizes our reduced-form findings and provides a structure for our mechanism analyses. At the same time, it is not meant to be a micro-foundation of the structure of explanations in natural language and their interpretation.

Prior beliefs and choice. We model a receiver i that has to respond to a question, whose correct answer is modeled as a state $\theta \in \{-1, 1\}$. We assume, without loss of generality, that the true state is always $\theta = 1$.²⁸ Participants start with an ignorance prior $\pi_0 = \mathbb{P}(\theta = 1) = 1/2$, which in log-odds maps to $\ell_{i0} = \text{logit}(\pi_0) = 0$.

The receiver then thinks about their answer, which we model as a noisy signal about the state. Later on, they will hear from an orator j whose answer comes from the same signal technology. The diagnosticity of posterior beliefs, and their distribution, are then critical objects. We therefore model signals through a log-normal strength combined with a logistic link.

Assumption 1. *The respondent receives a signal comprising a direction $d \in \{-1, 1\}$ and a strength $S \in \mathbb{R}_+$. The strength is log-normal with $\log S \sim \mathcal{N}(\log \bar{S}, \sigma^2)$, while the sign depends on S via:*

$$\mathbb{P}(d = \theta \mid S) = \Lambda(S),$$

with $\Lambda(x) = 1/(1 + e^{-x})$ the logistic function.

Lemma 1. *The log-likelihood ratio (LLR) of observing (d, S) is exactly $d \cdot S$.*

Proof. Let g be the density of S and $f_{\pm}$ the densities of $d \cdot S$:

$$\log \frac{f_+(d \cdot S)}{f_-(d \cdot S)} = \log \frac{g(S)\Lambda(d \cdot S)}{g(S)\Lambda(-d \cdot S)} = \log \frac{\Lambda(d \cdot S)}{1 - \Lambda(d \cdot S)} = d \cdot S.$$

²⁸In tasks with multiple options, we simply map all incorrect options to -1. Columns (5) in Tables A1 and A2 show our results are robust to dropping observations where a receiver with a wrong answer hears from an orator with a different wrong answer.

□

Since respondents start from $\ell_{i0} = 0$, their first choice is simply $d_i = d$. The overall probability of being correct is then:

$$p = \mathbb{P}(d = \theta) = \mathbb{E}[\Lambda(S)].$$

As expected, the optimality rate increases with median signal diagnosticity $\bar{S}$. Correspondingly, their first posterior should be $d \cdot S$. To account for the well-documented overstatement of confidence in experimental data, we assume that respondents inflate their signal strength.²⁹

Assumption 2. *Respondents inflate their signal strength by a common knowledge factor ω .*

Stated beliefs are then $\ell_{i1} = \omega \cdot d \cdot S$. Calibration of variance is immediate as $\sigma^2 = \mathbb{V}(\log S) = \mathbb{V}(\log |\ell_1|) \approx 0.61$. Matching the optimality rate $p \approx 55.3\%$ then yields $\bar{S} \approx 0.16$. Finally, we get $\omega = \exp(\mathbb{E}(\log |\ell_1|))/\bar{S} \approx 1.60/0.16 \approx 10$, meaning that subjects report confidence levels that overstate diagnosticity by roughly an order of magnitude.

Learning from choices and explanations After forming their own opinion, the receiver sees the choice or hears the explanation of an orator. We make the following critical assumption.

Assumption 3. *The orator formed their belief ℓ_{j1} via an independent draw from the same signal.*

If the orator could perfectly transmit ℓ_{j1} , the receiver would naturally update to $\ell_{i2} = \ell_{i1} + \ell_{j1}$. However, under *Choice Only*, the receiver observes only the orator's choice d_j .

Proposition 1. *If the orator only transmits their choice d_j , the receiver updates to*

$$\ell_{i2}^C = \ell_{i1} + \omega \cdot d_j \cdot \text{logit}(p).$$

Proof. The orator's choice is a binary signal with $\mathbb{P}(d_j = \theta) = p$, so its LLR is $d_j \cdot \text{logit}(p)$. □

In *Explanation*, the receiver additionally hears the explanation behind the orator's choice, which can convey a noisy signal about the orator's confidence. We model this learning from signals with imperfectly known diagnosticity by closely following Augenblick et al. (2025).

²⁹One could alternatively model a bias in reported beliefs. This would, however, obscure the interpretation of S , which is strictly positive in our setting. Importantly, the distinction does not affect our empirical results: when outcomes are measured as belief changes before and after an explanation (see Table A2), we obtain qualitatively identical findings, namely that explanations are dominated by a uniform *shift*.

Assumption 4. Explanations contain a noise-free choice signal d_j and a noisy belief strength signal $\log \tilde{S}_j = \log S_j + \varepsilon$, with disturbances $\varepsilon \sim \mathcal{N}(0, \sigma_\varepsilon^2)$ independent of ℓ_{i1} and θ .³⁰

After observing $\tilde{S}_j$, the receiver forms the posterior $\log S \mid \tilde{S}_j \sim \mathcal{N}(\log \bar{S}_{\text{post}}, \sigma_{\text{post}}^2)$, with:

$$\log \bar{S}_{\text{post}} = \log \bar{S} + \lambda(\log \tilde{S}_j - \log \bar{S}), \quad \sigma_{\text{post}}^2 = (1 - \lambda)\sigma^2, \quad \lambda = \frac{\sigma^2}{\sigma^2 + \sigma_\varepsilon^2}.$$

Proposition 2. If the orator transmits an explanation, the receiver updates to

$$\ell_{i2}^E = \ell_{i1} + \omega \cdot d_j \cdot \text{logit}(\mathbb{E}[\Lambda(S) \mid \tilde{S}_j]).$$

Proof. Let $f_\pm$ denote the densities of $(d_j, \tilde{S}_j)$ under $\theta = \pm 1$. Since ε is state-independent,

$$\log \frac{f_+(d_j, \tilde{S}_j)}{f_-(d_j, \tilde{S}_j)} = \log \frac{g(\tilde{S}_j)\mathbb{P}(d_j \mid \theta = 1, \tilde{S}_j)}{g(\tilde{S}_j)\mathbb{P}(d_j \mid \theta = 0, \tilde{S}_j)} = \log \frac{\mathbb{E}[\Lambda(d_j S) \mid \tilde{S}_j]}{1 - \mathbb{E}[\Lambda(d_j S) \mid \tilde{S}_j]} = \text{logit}(\mathbb{E}[\Lambda(d_j S) \mid \tilde{S}_j]).$$

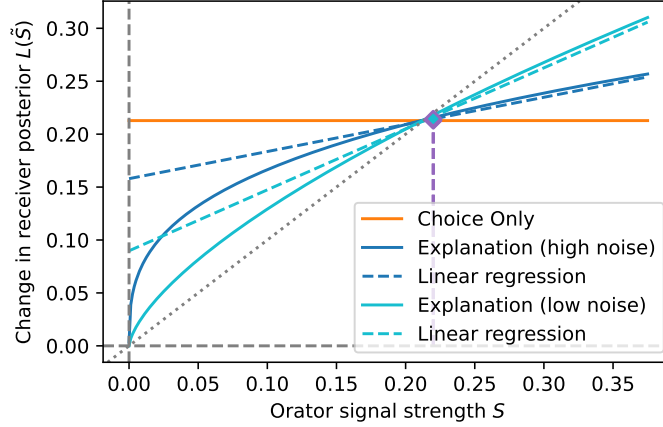
If $d_j = 1$, the result is clear. If $d_j = -1$, this is $\text{logit}(1 - \mathbb{E}[\Lambda(S) \mid \tilde{S}_j]) = -\text{logit}(\mathbb{E}[\Lambda(S) \mid \tilde{S}_j])$. $\square$

Belief movement therefore separates into a perfectly-known direction d_j and an imperfectly-known magnitude $L(\tilde{S}) = \text{logit}(\mathbb{E}[\Lambda(S) \mid \tilde{S}])$. As $\sigma_\varepsilon^2 \rightarrow 0$, $\lambda \rightarrow 1$ and the receiver perfectly recovers S_j so that the increment tends to $d_j \cdot S_j$, i.e., the noise-free benchmark. As $\sigma_\varepsilon^2 \rightarrow \infty$, $\lambda \rightarrow 0$ and $\tilde{S}_j$ becomes completely uninformative so that the increment tends to $d_j \cdot \text{logit}(\mathbb{E}[\Lambda(S)])$, i.e., the *Choice Only* benchmark.

Pivot Figure A1 plots the belief update $L(\tilde{S})$, using our calibrated values $\bar{S} \approx 0.16$ and $\sigma^2 \approx 0.61$, for *Choice Only* (i.e., $\lambda = 0$), high-noise *Explanation* ($\lambda = \frac{1}{3}$) and low-noise *Explanation* ($\lambda = \frac{2}{3}$). It is directly comparable to Figure 1a in Augenblick et al. (2025). As they only contain a noisy signal about the orator’s belief strength, receivers move too little when hearing a confident explanation, and too much when hearing an unconfident explanation. This reproduces the pattern of over-inference from weak signals and under-inference from strong signals identified in Augenblick et al. (2025).

As signals about belief strength become more precise, the curves’ level at their intersection stays approximately constant, while their slope increases, so that the curves pivot. We can characterize this behavior analytically in the small signal informativeness $\bar{S} \rightarrow 0$ limit, which is

³⁰Note we could equivalently have assumed explanations contain a signal reflecting (over-)stated confidence $\omega \cdot S$. Because ω is common knowledge, the update would simply subtract $\log \omega$.



Appendix Figure A1: Change in receiver beliefs $L(\tilde{S})$ as a function of orator belief strength S . *Notes:* Parameters are $\bar{S} \approx 0.16$ and $\sigma^2 \approx 0.61$, as well as $\lambda = \frac{1}{3}$ for high-noise and $\lambda = \frac{2}{3}$ for low-noise explanations. Purple dashed line indicates $\mathbb{E}(S) = \bar{S}e^{\sigma^2/2}$, blue dashed lines show output of a linear regression of $L(\tilde{S})$ on S .

appropriate in our setting where the optimality rate is 55.3%.³¹

Proposition 3. *As λ increases, the LLR curve $L(\tilde{S})$ pivots approximately around $\mathbb{E}(S)$, in the sense that the effect of λ on the level at $\mathbb{E}(S)$ is third order in $\mathbb{E}(S)$:*

$$L(\mathbb{E}(S)) = \mathbb{E}(S) + \frac{1}{12}\mathbb{E}(S)^3(1 - e^{3(1-\lambda)\sigma^2}) + O(\bar{S}^5).$$

Proof. Recall the Taylor expansions around $x = 0$:

$$\Lambda(x) = \frac{1}{2} + \frac{x}{4} - \frac{x^3}{48} + O(x^5), \quad \text{logit}\left(\frac{1}{2} + x\right) = 4x + \frac{16}{3}x^3 + O(x^5).$$

Plugging these into $\mathbb{E}(\Lambda(S) | \tilde{S})$ and $L(\tilde{S}) = \text{logit}(\mathbb{E}(\Lambda(S) | \tilde{S}))$ yields:

$$\mathbb{E}[\Lambda(S) | \tilde{S}] = \frac{1}{2} + \frac{1}{4}\mathbb{E}[S | \tilde{S}] - \frac{1}{48}\mathbb{E}[S^3 | \tilde{S}] + O(\bar{S}^5),$$

$$L(\tilde{S}) = \mathbb{E}[S | \tilde{S}] + \frac{1}{12}(\mathbb{E}[S | \tilde{S}]^3 - \mathbb{E}[S^3 | \tilde{S}]) + O(\bar{S}^5).$$

Under the log-normal posterior,

$$\mathbb{E}[S^k | \tilde{S}] = \bar{S}^{k(1-\lambda)} \tilde{S}^{k\lambda} \exp\left(\frac{\sigma^2}{2} k^2 (1-\lambda)\right).$$

³¹As shown in Section 3.4, optimality within tasks varies more widely, from 20% to 90%. The small- $\bar{S}$ characterization should thus be interpreted as capturing the average financial reasoning environment.

Evaluating at $\tilde{S} = \mathbb{E}(S)$ gives:

$$\mathbb{E}[S \mid \tilde{S} = \mathbb{E}(S)] = \bar{S}e^{\sigma^2/2} = \mathbb{E}(S), \quad \mathbb{E}[S^3 \mid \tilde{S} = \mathbb{E}(S)] = \bar{S}^3 \exp(3 \cdot \sigma^2(3/2 - \lambda)),$$

and gathering terms then yields the stated result. $\square$

The first term is $\mathbb{E}(S)$ and independent of λ , while the only λ -dependence is at cubic order and quite small. In Figure A1, the numerical difference in $L(\mathbb{E}(S))$ between $\lambda = \frac{2}{3}$ and $\lambda = \frac{1}{3}$ is indeed only +0.002, while the difference in intercepts a^* is only +0.001. This explains why the noise-free benchmark, low- or high-noise *Explanations* and *Choice Only* all approximately intersect at $\mathbb{E}(S)$. In turn, we can show that coefficients in a linear regression of $L(\tilde{S})$ on S also reflect and identify this pivot.

Proposition 4. *A regression of the LLR $L(\tilde{S})$ on $\{1, S - \mathbb{E}(S)\}$ yields a slope b^* and an intercept a^* where the latter only depends on λ up to third order in $\mathbb{E}(S)$:*

$$a^* = \mathbb{E}(S) + \frac{1}{12}\mathbb{E}(S)^3(e^{3\lambda\sigma^2} - e^{3\sigma^2}) + O(\bar{S}^5).$$

Proof. Since we regress $L(\tilde{S})$ on a constant and a demeaned $S - \mathbb{E}(S)$,

$$a^* = \mathbb{E}[L(\tilde{S})] = \mathbb{E}[\mathbb{E}[S \mid \tilde{S}]] + \frac{1}{12}(\mathbb{E}[\mathbb{E}[S^3 \mid \tilde{S}]] - \mathbb{E}[\mathbb{E}[S^3]] + O(\bar{S}^5)).$$

By the tower property, $\mathbb{E}[\mathbb{E}[S \mid \tilde{S}]] = \mathbb{E}[S]$ and $\mathbb{E}[\mathbb{E}[S^3 \mid \tilde{S}]] = \mathbb{E}[S^3]$. The only new moment is:

$$\mathbb{E}[\mathbb{E}[S \mid \tilde{S}]^3] = \mathbb{E}[\bar{S}^{3(1-\lambda)} \cdot \bar{S}^{3\lambda} \cdot e^{3(1-\lambda)\frac{\sigma^2}{2}}] = \bar{S}^{3(1-\lambda)} \cdot e^{3(1-\lambda)\frac{\sigma^2}{2}} \cdot \bar{S}^{3\lambda} e^{\frac{9}{2}\lambda^2(\sigma^2 + \sigma_\epsilon^2)} = \mathbb{E}[S]^3 e^{3\lambda\sigma^2},$$

where we used $\lambda(\sigma^2 + \sigma_\epsilon^2) = \sigma^2$. Gathering terms yields the result. $\square$

One can further prove that, as expected, the slope b^* is increasing in λ . We have therefore shown that more informative signals, meaning a higher λ , make the belief update $L(\tilde{S})$ pivot; we have shown that this pivot is approximately at $\mathbb{E}(S)$; and we have shown that a linear regression of $L(\tilde{S})$ on S also reflects this pivot mechanism. In Figure A1, dashed lines display the result of such a regression, confirming that predictions made in the small- $\bar{S}$ limit hold true in our setting.

In our regressions, outcomes are beliefs ℓ directly so that we use $|\ell| = \omega \cdot \mathbb{E}(S) = \mathbb{E}(|\ell_1|)$. Our model therefore motivates a test of its key effect in a canonical linear Grether regression,

using only an extremely simple sample moment. Moreover, it justifies our decomposition of the effect of explanations into a Bayesian component and deviations from this benchmark.

Deviations from Bayesian benchmark Our Bayesian model of explanations as noisy transmitters of confidence therefore predicts that, compared to *Choice Only*, belief movement as a function of confidence in the *Explanation* treatment acts as a pivot: low-confidence explanations are imitated less than choices, while high-confidence explanations are imitated more. If there is at least some knowledge to be shared, so that confidence correlates with optimality, this translates into aggregate improvements. More precisely, truth-signed log-odds beliefs should be higher in *Explanation* than in *Choice Only*. We examine deviations from this Bayesian benchmark in two directions: First, explanations could uniformly *shift* belief movement, e.g., by causing correct explanations to be imitated more or less irrespective of confidence. Second, explanations could affect weight put on *priors*, e.g., by causing receivers to neglect their prior more or less when hearing an orator speak. Since we shed light on the asymmetry between correct and incorrect explanations, we allow for different pivots, shifts and prior sensitivities when receivers face correct or incorrect answers.

Estimation We model the posterior belief of receiver i faced with the correct (+) or incorrect (−) choice ($E_i = 0$) or explanation ($E_i = 1$) of orator j as:

$$\ell_{i2} = (\delta_{\pm}^C + \delta_{\pm}^E E_i) \ell_{i1} + (\kappa_{\pm}^C + \kappa_{\pm}^E E_i) + (\gamma_{\pm}^C + \gamma_{\pm}^E E_i) (\ell_{j1} \mp \bar{\ell}) + \varepsilon_i.$$

The $\delta_{\pm}^C$ etc. identify the effect of choices while the $\delta_{\pm}^E$ etc. identify the additional effect of explanations. The conditional treatment effect of a correct or incorrect explanation is then:

$$\mathbb{E}[\ell_{i2}^E - \ell_{i2}^C \mid d_j = \pm 1] = \delta_{\pm}^E \bar{\ell}_{i1} + \kappa_{\pm}^E + \gamma_{\pm}^E (\bar{\ell}_{\pm} \mp \bar{\ell}).$$

Here, we have defined average beliefs conditional on being correct or incorrect $\bar{\ell}_{+} = \mathbb{E}[\ell_{j1} \mid d_j = 1]$ and $\bar{\ell}_{-} = \mathbb{E}[\ell_{j1} \mid d_j = -1]$. Moreover, we call $\bar{\ell}_{i1+} = \mathbb{E}[\ell_{i1} \mid d_j = 1]$ and $\bar{\ell}_{i1-} = \mathbb{E}[\ell_{i1} \mid d_j = -1]$ the average conditional receiver beliefs.³² Recall that $p = \mathbb{P}(d_j = 1)$. The average treatment

³²Within a task, these are identical in population due to random matching, but may differ in finite samples. Across tasks, they could co-vary due to heterogeneity in optimality rates. We track both to keep the decomposition exact.

effect (ATE) can then be broken down into three components:

$$\begin{aligned}
\text{ATE} &= \mathbb{E}[\ell_{i2}^E - \ell_{i2}^C] \\
&= p(\delta_+^E \bar{\ell}_{i1+} + \kappa_+^E + \gamma_+^E(\bar{\ell}_+ - \overline{|\ell|})) + (1-p)(\delta_-^E \bar{\ell}_{i1-} + \kappa_-^E + \gamma_-^E(\bar{\ell}_- + \overline{|\ell|})) \\
&= \underbrace{p\kappa_+^E + (1-p)\kappa_-^E}_{\text{shift}} + \underbrace{p\gamma_+^E(\bar{\ell}_+ - \overline{|\ell|}) + (1-p)\gamma_-^E(\bar{\ell}_- + \overline{|\ell|})}_{\text{pivot}} + \underbrace{p\delta_+^E \bar{\ell}_{i1+} + (1-p)\delta_-^E \bar{\ell}_{i1-}}_{\text{prior}}.
\end{aligned}$$

In practice, to avoid opaque variable demeaning, our regression is simply specified as:

$$\begin{aligned}
\ell_{i2} &= (\beta + \beta^E E_i) + (\beta_c + \beta_c^E E_i) c_j + (\beta_\ell + \beta_\ell^E E_i) \ell_{j1} + (\beta_{c\ell} + \beta_{c\ell}^E E_i)(c_j \cdot \ell_{j1}) \\
&\quad + (\beta_p + \beta_p^E E_i) \ell_{i1} + (\beta_{cp} + \beta_{cp}^E E_i)(c_j \cdot \ell_{i1}) + \varepsilon_i,
\end{aligned}$$

where $c_j = \mathbb{1}_{\{d_j=1\}}$ is the choice with correct/incorrect coded as $\{1, 0\}$. These coefficients map to linear model parameters as $\gamma_-^E = \beta_\ell^E$, $\gamma_+^E = \beta_\ell^E + \beta_{c\ell}^E$, $\kappa_-^E = \beta^E - \overline{|\ell|} \beta_\ell^E$, $\kappa_+^E = \beta^E + \beta_c^E + \overline{|\ell|}(\beta_\ell^E + \beta_{c\ell}^E)$, $\delta_-^E = \beta_p^E$ and $\delta_+^E = \beta_p^E + \beta_{cp}^E$. Note that the decomposition always sums to the ATE, and that the choice of a pivot $\overline{|\ell|}$, which is motivated by our model, only affects its breakdown.

Results are reported in Table A1. Each column re-computes $\overline{|\ell|}$ for the decomposition using its variable coding and sample restrictions, for which we pool orator and receiver priors for increased precision. Our main specification is presented in column (3). It shows the following decomposition of the effect of explanations on truth-signed beliefs:

- The *pivot* effect accounts for 20%: explanations make receivers more sensitive to orator beliefs, which improves optimality since orators are correct on average,
- The *prior* effect accounts for -36%: explanations make receivers less sensitive to their prior, which hurts optimality since receivers are also correct on average,
- The *shift* effect accounts for 116%: correct explanations are uniformly more likely to be imitated, irrespective of orator confidence; moreover, this effect is very large while *pivot* and *prior* effects cancel out, so that it accounts for virtually the entire treatment effect.

Figure A1 illustrates our approach by plotting receiver belief movement as a function of orator beliefs. It effectively replicates Figure A1 with data, separately for correct (on the $\ell_{j1} > 0$ pane) and incorrect ($\ell_{j1} < 0$) explanations. Lines are fitted using column (3) of Table A2, which repeats our previous analysis but for belief movement, by subtracting the prior from the

Appendix Table A1: Grether regression

	<i>Dependent variable: Posterior log-odds</i>				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.701*** (0.027)	-0.382*** (0.029)	-0.485*** (0.040)	-0.351*** (0.039)	-0.411*** (0.042)
Explanation	0.168*** (0.031)	0.209*** (0.041)	0.167*** (0.054)	0.100* (0.055)	0.093* (0.056)
Prior log-odds		0.829*** (0.010)	0.888*** (0.011)	0.918*** (0.014)	0.943*** (0.014)
Explanation $\times$ Prior log-odds		-0.096*** (0.013)	-0.010 (0.015)	-0.035* (0.018)	-0.028 (0.019)
Orator correct		1.251*** (0.057)	1.298*** (0.058)	1.087*** (0.057)	1.147*** (0.060)
Explanation $\times$ Orator correct		-0.079 (0.081)	-0.030 (0.081)	0.150* (0.082)	0.157* (0.083)
Orator log-odds		0.014 (0.012)	-0.045** (0.020)	-0.033 (0.023)	-0.042* (0.025)
Explanation $\times$ Orator log-odds		0.114*** (0.018)	0.092*** (0.028)	0.081** (0.032)	0.078** (0.034)
Orator correct $\times$ Prior log-odds			-0.104*** (0.017)	-0.125*** (0.020)	-0.150*** (0.021)
Explanation $\times$ Orator correct $\times$ Prior log-odds			-0.151*** (0.022)	-0.140*** (0.026)	-0.146*** (0.027)
Orator correct $\times$ Orator log-odds			0.098*** (0.027)	0.053* (0.029)	0.062** (0.031)
Explanation $\times$ Orator correct $\times$ Orator log-odds			0.038 (0.036)	0.015 (0.040)	0.017 (0.042)
ATE	0.168	0.187	0.185	0.168	0.173
% shift	100%	103%	116%	144%	147%
% pivot	0%	19%	20%	12%	10%
% prior	0%	-22%	-36%	-56%	-57%
Observations	21199	21199	21199	13213	12658
R^2	0.001	0.678	0.687	0.698	0.693

Notes: Outcome is the receiver posterior belief in log-odds ℓ_{i2} . *Prior log-odds* is ℓ_{i1} . *Explanation* is a dummy for the *Explanation* treatment, *Orator correct* a dummy for the orator being correct, *Orator log-odds* is the orator's belief in log-odds ℓ_{j1} . *ATE*, *shift*, *pivot* and *prior* report the treatment effect of explanations and its decomposition, as detailed in the main text. In columns (1) to (3), confidence from 0% to 100% is mapped to belief probabilities in $[0.5, 1]$ for correct and $[0, 0.5]$ for incorrect answers. In column (4), confidences from 5% to 100% are mapped to $[0.5, 1]$ for correct and $[0, 0.5]$ for incorrect answers, while observations below 50% are dropped. In column (5), we further drop observations where a receiver with a wrong answer hears from an orator with a different wrong answer. Sample is the main Receiver experiment for *Explanation* and all collections for *Choice Only*, excluding 0.7% of observations with missing confidence. Standard errors are clustered at the orator and receiver levels.

posterior on the left-hand side instead of adding it as a covariate on the right-hand side. The bin-scatter shows our linearized model fits the data quite well, and again illustrates the *pivot* effect. They also reflect the strong contribution of the *shift*: the least confident correct explanations cause more belief movement than *Choice Only*.

Appendix Table A2: Belief movement regression

	<i>Dependent variable: Change in receiver log-odds</i>				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.257*** (0.019)	-0.435*** (0.030)	-0.502*** (0.041)	-0.370*** (0.042)	-0.434*** (0.045)
Explanation	0.185*** (0.021)	0.187*** (0.042)	0.161*** (0.055)	0.083 (0.057)	0.073 (0.059)
Orator correct		1.239*** (0.057)	1.257*** (0.057)	1.000*** (0.057)	1.064*** (0.060)
Explanation × Orator correct		-0.101 (0.083)	-0.094 (0.083)	0.038 (0.083)	0.048 (0.085)
Orator log-odds		-0.012 (0.012)	-0.052** (0.020)	-0.037 (0.023)	-0.045* (0.026)
Explanation × Orator log-odds		0.104*** (0.018)	0.089*** (0.028)	0.073** (0.033)	0.071** (0.034)
Orator correct × Orator log-odds			0.060** (0.027)	0.015 (0.029)	0.024 (0.031)
Explanation × Orator correct × Orator log-odds			0.023 (0.036)	0.018 (0.041)	0.020 (0.042)
ATE	0.185	0.189	0.189	0.177	0.182
% shift	100%	82%	82%	90%	91%
% pivot	0%	18%	18%	10%	9%
Observations	21199	21199	21199	13213	12658
R^2	0.003	0.201	0.202	0.183	0.194

Notes: Outcome is the change in receiver belief in log-odds $\ell_{i2} - \ell_{i1}$. See notes for Table A1.

B Annotation of explanations

Our annotation starts from transcripts generated by Phonic using Amazon Transcribe. Notably, these transcripts preserve disfluencies or hesitation markers like “um” or “eh” that are typically removed by speech-to-text software. We then annotate these transcripts using a combination of human coding by a team of RAs and machine coding by a Large Language Model (LLM). For the latter, we use the state-of-the-art OpenAI GPT-4, with a temperature set to 0 for reproducibility.

We annotate four different dimensions of explanations. First, we categorize explanations into broad categories, e.g., to distinguish restatements of the answer from non-substantive or substantive argumentation. Second, we identify a large set of 31 features in the explanations, e.g., the word count, the number of uncertainty markers or of analogical arguments. Third, we

rate the general richness of explanations using a pre-registered definition. Fourth, we identify the different arguments appearing in each task and tag their presence in each explanation.

B.1 Explanation categorization

We first categorize speeches into general categories to acquire a broad overview of the different types of explanations. For that, we asked a team of RAs to identify whether an explanation fell into one of the following categories: *Only Restatement*, *Any Uncertainty*, *Non-Substantive Explanation*, *Substantive Explanation*, *Correct Explanation*, *Incorrect Explanation*, *Unclear Explanation*, *Invalid Explanation* (see Table B4 for a detailed overview). They are not necessarily mutually exclusive.

To benchmark our fully manual categorization, we then performed the same categorization with GPT-4. When the human coder identified one of the categories, GPT-4 did so too in 79% of cases; when the human coder did not identify one of the categories, GPT-4 did so too in 82% of cases. Cohen’s κ is at 0.53, indicating ‘moderate agreement’. These statistics are higher for the more specific categories we rely on in our analyses, e.g., they stand at 56%, 96% and 0.55 for the *Only Restatement* category. Aggregate frequencies also seem more stable, e.g., with human coder finding 13.1% of explanations to be *Only Restatements* while GPT-4 identifies a close 11.1%.

B.2 Feature identification

We identify 31 text features in explanations, which are domain-general and were largely taken from the vast existing research on text analysis and natural language data. We extract 25 features in five categories: language markers, disfluencies, certainty markers, reasoning content and addresses to the Receiver. Some features potentially overlap, e.g., we simultaneously extract high confidence markers, low confidence markers and any confidence markers.

We instruct GPT-4 to identify all instances of each feature and return them as a JSON dictionary of lists. The annotation can then easily be audited, and appears sensible upon inspection. Instances are then counted, and counts are then standardized (intensive margin) or turned into dummies equal to 1 if any instance has been detected (extensive margin).

We generate 6 simple textual & speech features via direct computation. To investigate which features explain richness in Figure D7, we additionally generate 19 more advanced features, notably based on the distribution of words, part-of-speech tagging, named entity recognition and syntactic structure identification. Table B3 provides an overview of all features.

B.3 Richness rating

To assess the richness of explanations, we provide GPT-4 with the following, pre-registered definition of richness: *A rich explanation is detailed, comprehensive, logically structured, nuanced, and tailors the argument to fit the context. A sparse explanation is basic, narrow, unclear or disorganized, presents only surface-level understanding, lacks depth or specific details and fails to clearly relate to the context.* We instruct GPT-4 to rate each speech’s richness individually on a numerical scale from 0 to 10 (both inclusive).

B.4 Argument identification

Section 5.1.1 describes the argument identification and annotation scheme. It also provides statistics on inter-rater reliability, from a second blind human annotation and from an annotation via GPT-4, all showing substantial agreement. Online Appendix Table F1 shows all arguments appearing in the final scheme. Each has a title used to denote it in Figures D8 and a detailed description used in the annotation.

Table B5 further shows the four types of argument we have identified. Section 5.2.1 describes how each speech is then associated with a specific argument category based on the strongest type of argument it contains.

Appendix Table B3: Explanation features annotated via GPT-4 or computed directly

Feature	Description
Language Markers	
Modal verbs	Verbs indicating possibility, probability, or necessity. Example: “might”, “could”, “would”.
Certainty adverbs	Adverbs indicating certainty or doubt. Example: “possibly”, “probably”, “likely”.
Hedging language	Phrases indicating hedged claims. Example: “it seems”, “appears to be”, “to the best of our knowledge”.
Relative language	Words indicating qualifiers or comparisons. Example: “almost”, “nearly”, “more or less”.
Absolute language	Words indicating absolutes or superlatives. Example: “Always”, “Best”.
Epistemic stance markers	Phrases indicating subjective judgment. Example: “I believe”, “we assume”, “in my opinion”.
Conditional statements	Sentences indicating “If-Then” constructs. Example: “If we don’t act now, then”, “Assuming X, then Y”.
Interrogation markers	Words indicating questions or uncertainty. Example: “who”, “what”, “where”, “when”.
Numerical expressions	Phrases indicating quantitative or probabilistic information. Example: “more than 100 banks”, “95% chance that”.
Disfluencies	
Filled pauses	Instances of filled pauses. Example: “um”, “ah”, “er”.
False starts	Sentences starting but not completed. Example: “If you look at - I believe that”.
Repetitions	Instances of word or phrase repetition. Example: “I I mean”, “this is, this is wrong”.
Repairs	Instances where the speaker corrects themselves. Example: “I have two- three dogs”.
Certainty Markers	
Certainty markers	Statements indicating overall confidence. Example: “Without a doubt”, “I am certain that”.
High certainty markers	Statements indicating high confidence. Example: “I am certain that”, “I am sure that”.
Low certainty markers	Statements indicating low confidence. Example: “It might”, “I’m not sure but”.
Reasoning Content	
Indications of origin	Statements indicating information origin. Example: “According to”, “My grandmother has always said that”.
Personal experience args.	Arguments based on personal experience. Example: “I have often found that”.
External authority args.	Arguments based on external authority. Example: “My girlfriend works at a bank and said”.
Empirical args.	Arguments based on empirical facts. Example: “I remember reading a newspaper article saying”.
Analogical args.	Arguments based on analogies. Example: “Investments funds are like babies”.
Logical reasoning args.	Arguments based on logical reasoning. Example: “Since active managers put in more research”.
Normative args.	Arguments based on ethical considerations. Example: “It would not be fair if”.
Addresses to Receiver	
Directive addresses	Directives to the listener. Example: “You should definitely say that”.
Apologetic or humble addresses	Apologetic or humble addresses. Example: “I apologize for not knowing more”.
Simple Computed Features	
Word count	Total number of words.
Word length	Average length of words.
Words per minute	Average number of words per minute.
Sentence count	Total number of sentences.
Sentence length	Average length of sentences.
Language complexity	Flesch-Kincaid readability grade.
Lexical Metrics	
Lexical Diversity	Ratio of unique words to total number of words.
Entropy of Words	Entropy of distribution of words.
Hapax Legomena Ratio	Percentage of words that appear only once.
Share of long words	Percentage of words that have more than 10 letters.
Additional Readability Metrics	
Gunning Fog Index	Years of education required to understand the text, based on sentence length and percentage of complex words.
SMOG Index	Years of education required to understand the text, based on polysyllabic word counts.
Automated Readability Index	Years of education required to understand the text, based on characters per word and words per sentence.
Cohesion Metrics	
Referential Cohesion	Mean word overlap between sentence and following sentence.
Syntactic Complexity Metrics	
Part-of-Speech Tag Entropy	Entropy of parts of speech (e.g., nouns, verbs, adjectives) in the text.
Mean Length of T-units	Average length of T-units, i.e., a main clause plus any subordinate clauses.
Subordination Index	Ratio of subordinate clauses to main clauses.
Clause Density	Average number of clauses per sentence.
Named Entity Recognition	
Entity Count / Words	Ratio of number of named entities (e.g., people, organizations, locations) to total number of words.
Entity Type Count / Words	Number of different types of named entities (e.g., person, organization, location) to total number of words.
Sentence Structure and Syntax Metrics	
Number of Clauses	Total number of clauses.
Syntactic Tree Depth	Maximum depth of the syntactic dependency tree.
Syntactic Tree Branching	Average number of branches per node in the syntactic tree.
Noun Phrase Density	Ratio of number of noun phrases to total number of words.
Verb Phrase Density	Ratio of number of verb phrases to total number of words.

Appendix Table B4: Overview of explanation categories

Category	Description	Example
Only Restatement	The explanation is purely a restatement of the answer, without any arguments or elaborations.	"I think it's number one."
Any Uncertainty	The explanation contains any expressions of (un)certainity in the answer or arguments presented.	"Um, this one is more tricky. I think it's, um, I think it would be that they do not outperform passively managed ones. Um, I'm not really sure of an exact explanation because to be honest, I don't have any idea. Um, sorry"
Non-Substantive Explanation	The explanation only contains non-substantive justifications: appeals to authority, appeals to emotion, etc.	"I believe that passively managed funds perform better. And I'm gonna say that as uh uh as I remember Warren Buffett uh during an interview [...]"
Substantive Explanation	The explanation contains any substantive justification, e.g., any form of argument.	"If active funds outperformed, passive funds wouldn't exist."; "A fund is just like a plant, if you take more care of it, it will grow better."
Correct Explanation	The explanation is correct in meaning.	"I believe that actively managed funds do not outperform passively managed ones, the account for fees is too high when constantly monitoring an actively managed account."
Incorrect Explanation	The explanation is incorrect in meaning.	"Actively managed funds, do outperform, passive ones because you're actively making decisions about it and doing what makes you the most money."
Unclear Explanation	The explanation is very unclear or nonsensical.	"Passively managed funds, outperform, actively managed funds. And this is why hedge funds have a very short life spans. So question number two."
Invalid Explanation	The explanation is empty or entirely incomprehensible due to transcription errors.	"Yes, I conquer, actively managed form. I perform passively managed forms. Every time, every time I really conquer, I good choice."

Appendix Table B5: Overview of argument types

Type	Description	Example
Sound Argument	An argument that has correct premises and where the conclusion follows from the premises. The premises might not quite be sufficient for the conclusion.	"I believe that actively managed funds do not outperform passively managed ones, the account for fees is too high when constantly monitoring an actively managed account." (Active funds charge fees)
Fallacious Argument	An argument that is relevant to the question or its answer, but where one or more of the premises are false, or the conclusion is not valid given the premises.	"Actively managed funds will outperform passively managed ones because actively managed funds make more strategic decisions. While passively managed ones are kind of just going with the flow of the market. But actively managed funds can predict what the market is gonna do and make a decision based on that. So the answer is actively managed funds outperform, passively managed ones." (Active funds managed by experts)
Irrelevant Argument	An argument whose premises are unrelated to the question or its answer.	"Actively managed funds, outperform, passively managed ones because they are being actively managed. Whereas passively managed ones are being managed passively and actively sounds better than passively."
No Argument	No argument given at all.	"Um, actively managed funds outperform passively managed ones most times probably."

C Robustness checks

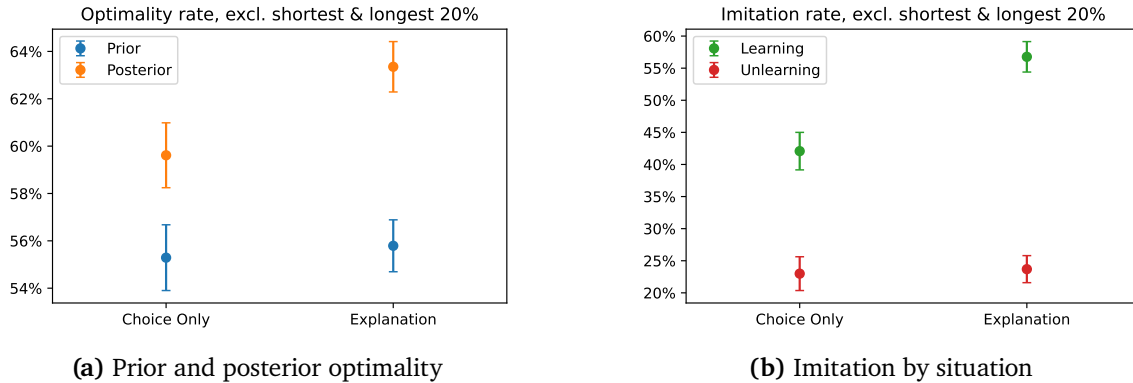
C.1 Excluding the shortest and longest recordings

To ensure our reduced-form findings are not driven by a small subsample of explanations, e.g., extremely succinct or long-winded, we verify that they are robust to excluding the shortest and longest 20% of recordings. We filter recordings based on the total duration of the audio file.

Figure C2b shows the resulting optimality rates, mirroring Figure 1b. The share of receivers giving the correct answer before having been exposed to the orator’s explanation is 55.3% in *Choice Only* and 55.8% in *Explanation* ($p = 0.61$). After being exposed to the orator’s explanation, the share of receivers giving the correct answer is 59.6% in *Choice Only* and 63.4% in *Explanation* ($p < 0.01$). Being exposed to an orator’s explanation instead of only their choice therefore increases the optimality rate by 3.3 p.p. ($p < 0.01$).

Figure C2b repeats the analysis by learning and unlearning situations as in Figure 1b. In unlearning situations, being exposed to an orator’s explanation increases the likelihood of imitating their answer an insignificant 0.7 p.p. ($p = 0.68$) relative to only seeing their choice. On the other hand, in learning situations, being exposed to an orator’s explanation in addition to their choice increases the likelihood of taking over their answer by 14.7 p.p. ($p < 0.01$).

In conclusion, both findings confirm that our results from Section 3 are robust to excluding the shortest and longest 20% of explanations from the sample.



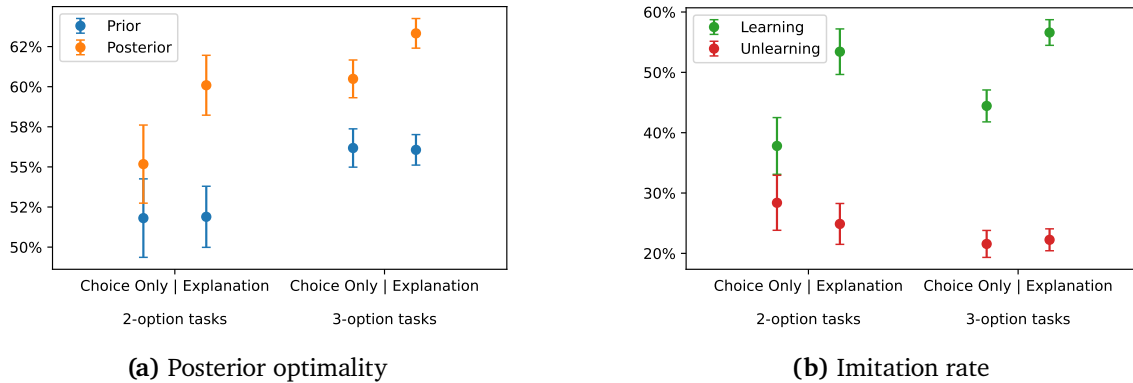
Appendix Figure C2: Robustness of main findings to dropping shortest and longest recordings. *Notes:* Analyses and starting samples are the same as in Figures 1a and 1b. We additionally drop the 20% of shortest and 20% of longest explanations. Whiskers show 95% CIs.

C.2 Distinguishing by number of options

While twelve of the tasks gathered from the literature have three answer options, three of them are effectively true/false questions and therefore only have two options: “Actively managed funds”, “Crypto mining” and “Stock picking” (cf. Table E6).

It is natural to expect different optimality rates if some respondents randomize between answers. In our case, however, the prior optimality rate is 51.8% for the two-option tasks but 56.2% for the three-option tasks ($p < 0.01$), showing that cross-task heterogeneity dominates this mechanism. Prior confidence is 63.2% on average for two-option tasks, against 68.8% for three-option tasks ($p < 0.01$). Posterior confidence exhibits a similar gap at 68.8% and 74.0%, respectively ($p < 0.01$).

Although the number of options is constant across conditions and should therefore not influence treatment effects, Figure C3 confirms that our main effects hold for both types of tasks. The left panel shows that *Explanation* increases posterior optimality by 4.9 p.p. relative to *Choice Only* among two-option tasks ($p < 0.01$), and by 3.0 p.p. among three-option tasks ($p < 0.01$). This difference in treatment effects between the two types of tasks is not statistically significant ($p = 0.18$). In the right panel, the effect of *Explanation* over *Choice Only* is not significant in unlearning situations for two- or three-option tasks ($p = 0.23$ and $p = 0.64$). On the other hand, in learning situations it is 15.8 p.p. for two-option tasks ($p < 0.01$) and 12.2 p.p. for three-option tasks ($p < 0.01$). As before, this difference is not statistically significant ($p = 0.32$).



Appendix Figure C3: Effect of *Explanation* on optimality and imitation by number of options.

Notes: See notes for Figure 1. Two-option tasks are “Actively managed funds”, “Crypto mining” and “Stock picking”, see Table E6. Whiskers show 95% CIs.

The fact that we use two- and three-option tasks introduces an interesting source of variation

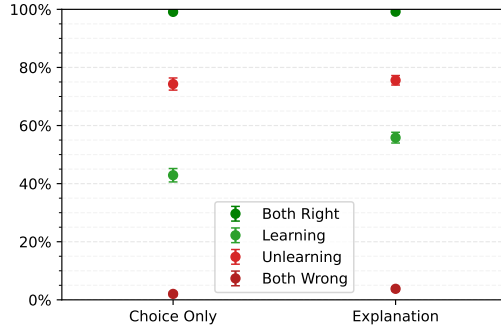
when analyzing receivers' reaction to confirmatory signals, as discussed in Section 3.3. Importantly, we define imitation as the receiver picking the exact same option as the orator. When the receiver and the orator are both right, they have necessarily chosen the same answer. However, when both are wrong, they will sometimes have chosen two different wrong answers.

When the receiver and orator are both wrong, imitation rates are 82.6% in *Choice Only* and 82.2% in *Explanation* ($p = 0.75$), substantially lower than when both are right. However, in tasks with only two options, imitation rates are 97.5% and 96.7%, respectively ($p = 0.44$). They are similarly high in tasks with three options when the orator chose the same wrong option as the receiver, at 97.7% and 96.3% ($p = 0.03$). On the other hand, imitation is much lower at 36.0% and 37.8% ($p = 0.52$) in three-option tasks when the orator chose a different wrong option. Interestingly, the imitation rate for an alternative wrong option is between the learning and unlearning rates. Explanations therefore slightly reduce imitation in three-option tasks when receiver and orator initially picked the same wrong answer.

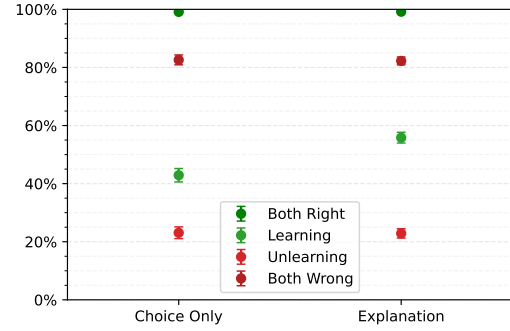
In the main analysis, we noted that aggregate posterior optimality rates display a small 1.8 p.p. ($p < 0.01$) treatment effect when both are wrong. Again breaking this down by number of options, we find an insignificant 0.8 p.p. ($p = 0.44$) effect on optimality in two-option tasks; a highly significant 1.8 p.p. ($p < 0.01$) effect in three-option tasks when the orator chose the same wrong option as the receiver; and a 2.5 p.p. ($p = 0.06$) effect in three-option tasks when the orator chose another wrong option.

Explanations therefore reduce imitation and increase posterior optimality when the orator chose the same wrong option as the receiver, meaning receivers switch away from their and the orator's choice to the correct answer. When the orator chose a different wrong option from the receiver's, explanations have no effect on imitation but increase optimality, so that they only make the receiver more likely to choose the correct answer. The coexistence of two- and three-option tasks therefore helps us identify the small but significant enabling role that arguments can play, by prompting incorrect listeners to think more deeply and switch to the correct answer.

D Additional figures

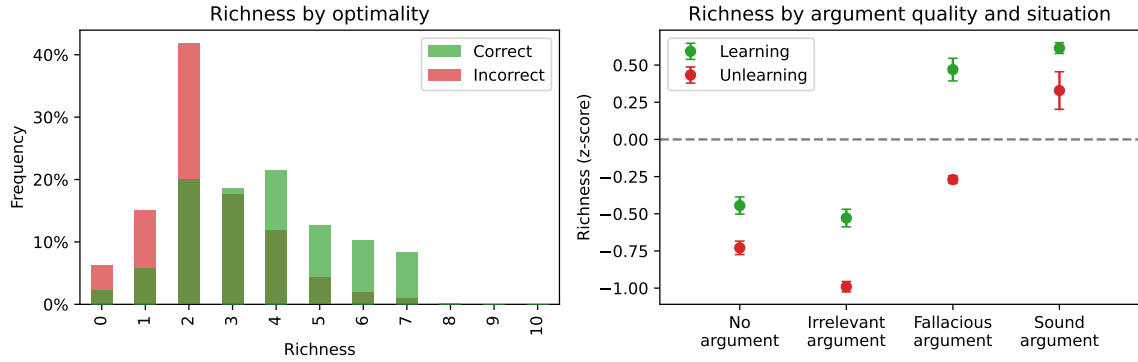


(a) Posterior optimality

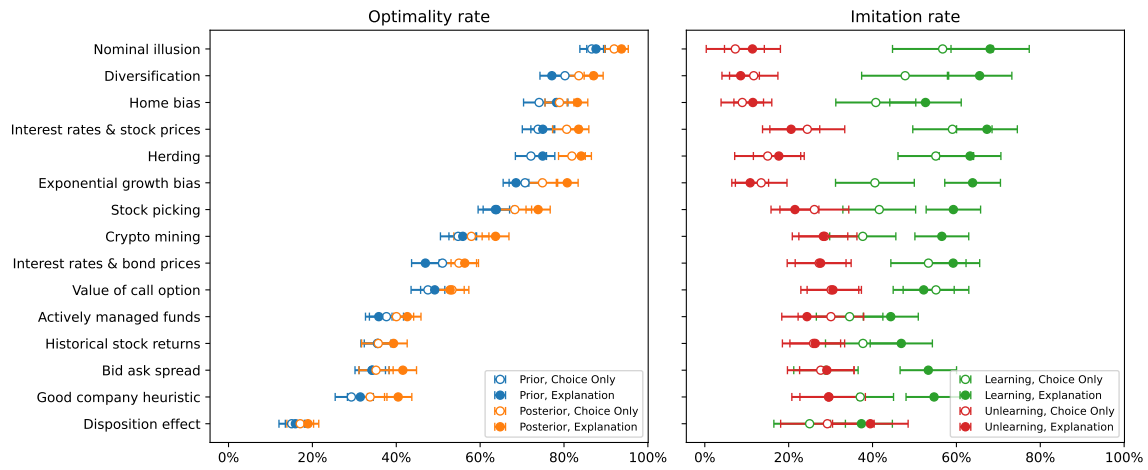


(b) Imitation rate

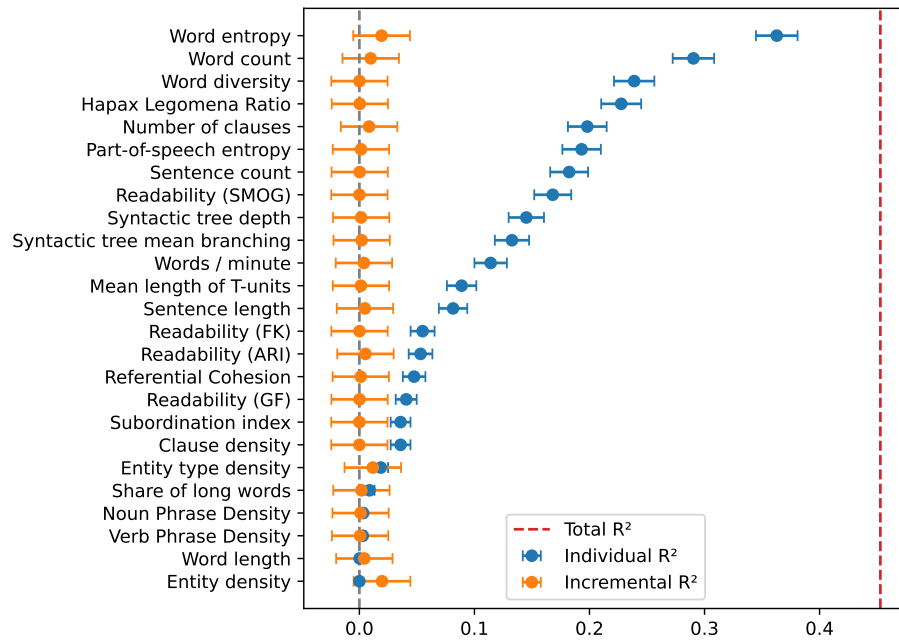
Appendix Figure D4: Effect of *Explanation* in conflicting and confirming situations. *Notes:* See notes for Figure 1. By construction, receiver prior optimality is 0% in *Learning* and *Both Wrong*, and 100% in *Unlearning* and *Both Right*. Whiskers show 95% CIs.



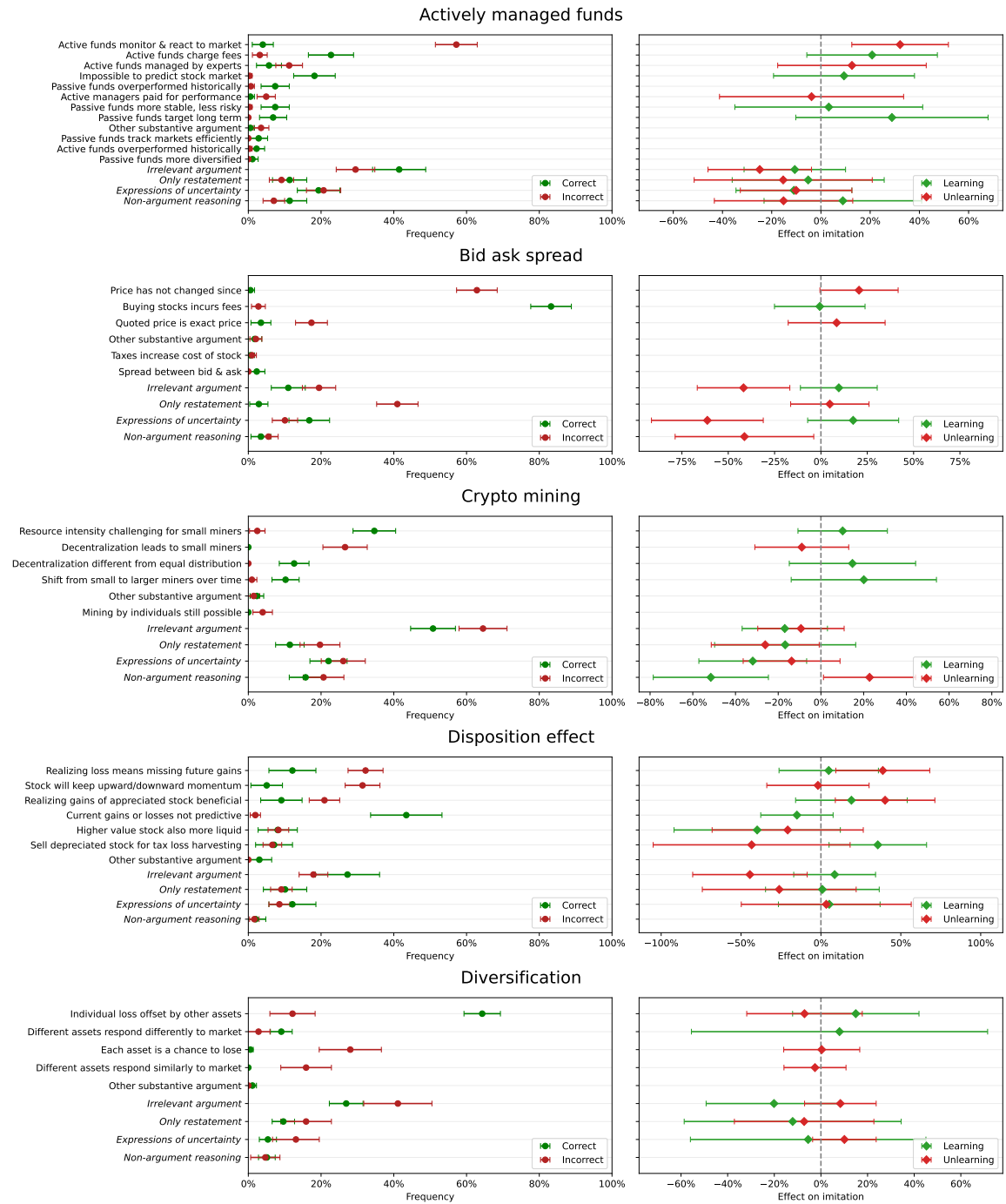
Appendix Figure D5: Richness gap by orator optimality, and by argument quality and situation. *Notes:* *Explanation* sample is the main Receiver experiment, *Choice Only* is pooled from all collections. See Appendix B for details on richness ratings. Whiskers show 95% CIs.



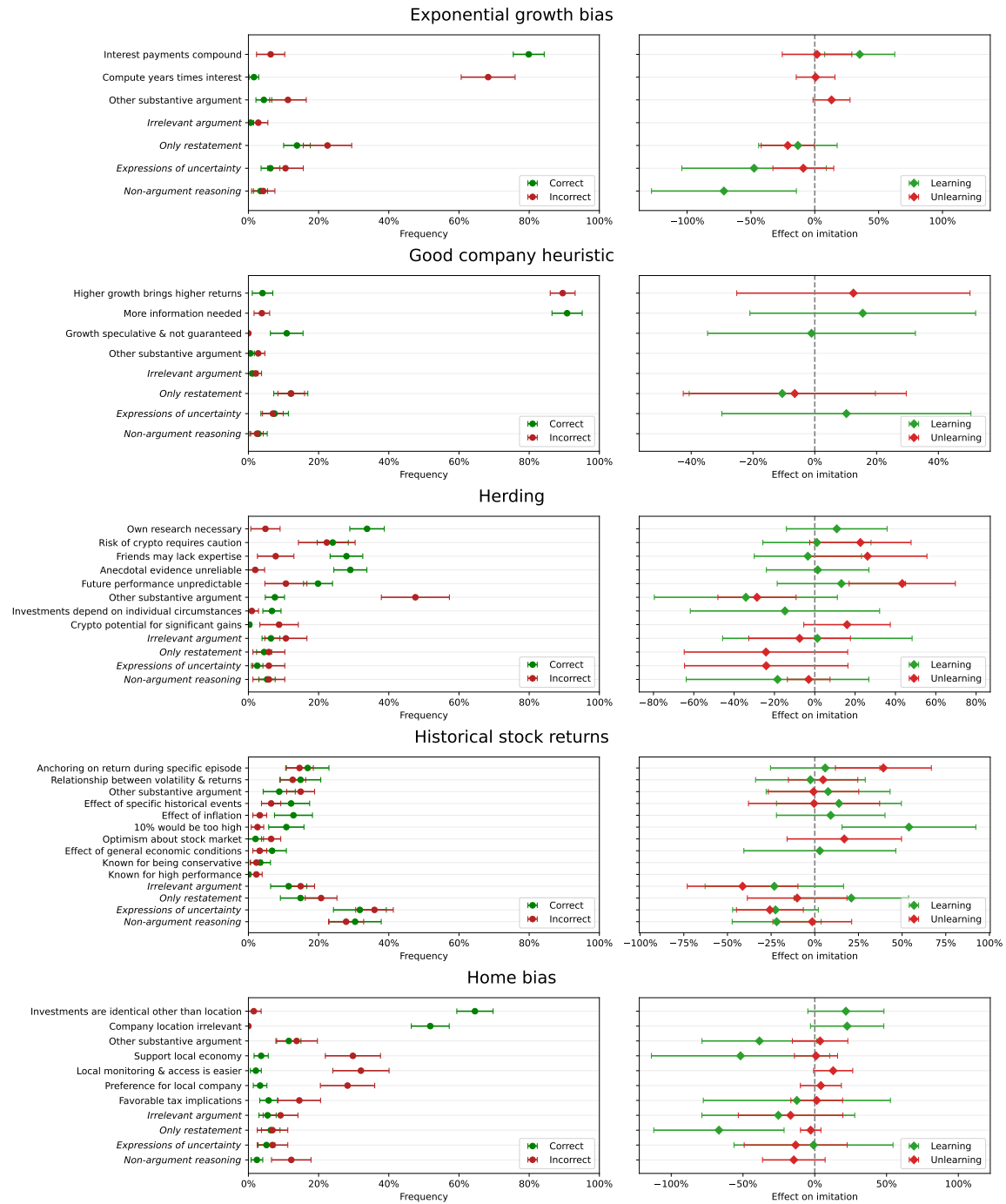
Appendix Figure D6: Effect of *Explanation* on optimality and imitation by task. *Notes:* See notes for Figure 1. Whiskers show 95% CIs.



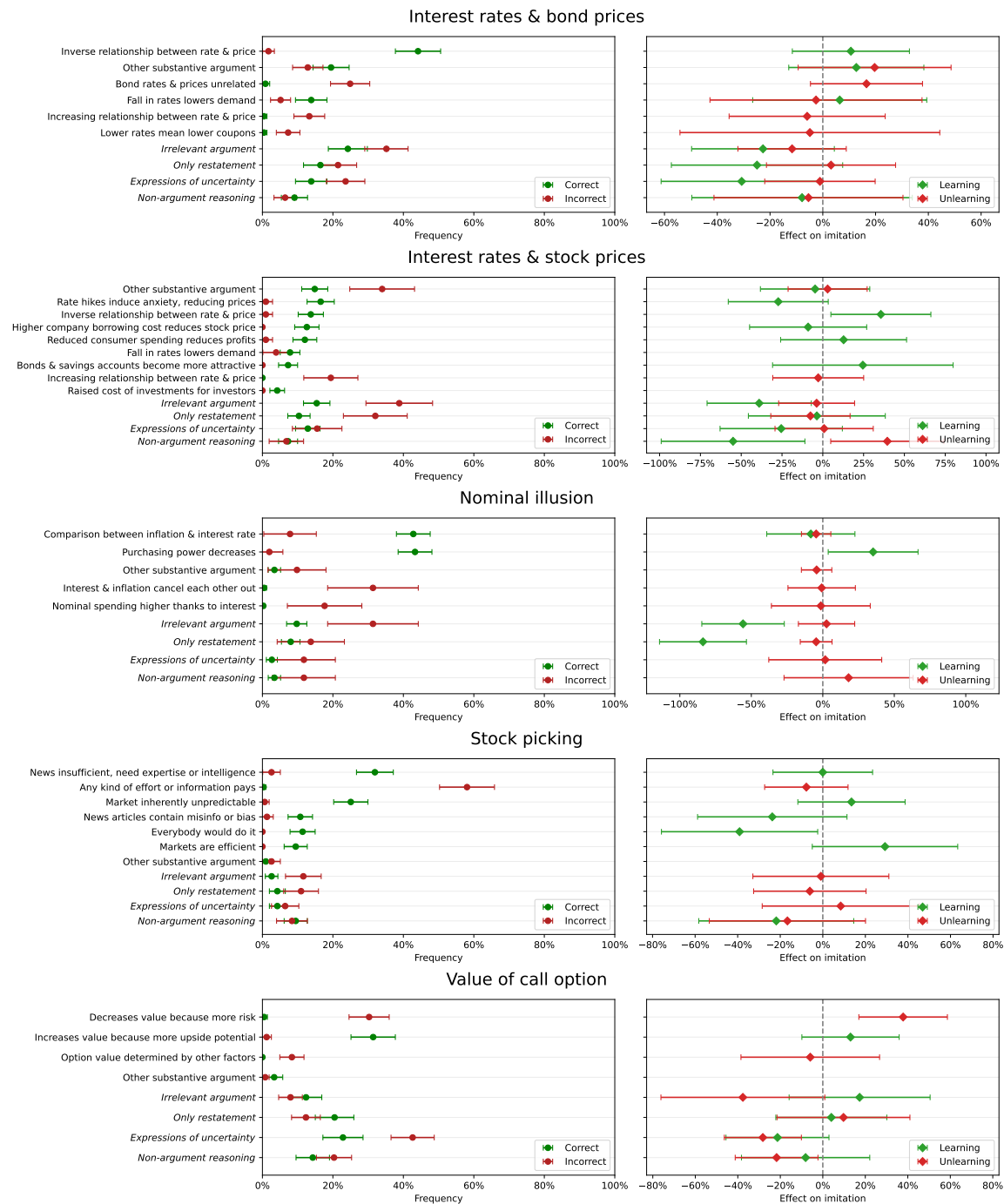
Appendix Figure D7: Explanatory power of explanation features for richness. *Notes:* *Individual R^2* is the R^2 in a regression of richness on a given feature and a constant. *Incremental R^2* shows the decrease in R^2 when removing a given feature from a regression of richness on all features and a constant. *Total R^2* shows the R^2 in a regression of richness on all features and a constant. Whiskers show 95% CIs.



Appendix Figure D8: Arguments by task I/III. Notes: See notes for Figure 6.



Appendix Figure D8: Arguments by task II/III. Notes: See notes for Figure 6.



Appendix Figure D8: Arguments by task III/III. Notes: See notes for Figure 6.

E Additional tables

Appendix Table E6: Financial Decision Questions

Task	Motivation	Question
Actively managed funds	Overestimating the return (after fees) of actively vs. passively managed funds. Adapted from Haaland and Næss (2023).	Do actively managed investment funds systematically outperform passively managed investment funds in terms of expected net returns, i.e., after accounting for investment fees? (i) Actively managed funds outperform passively managed ones. (ii) <u>Actively managed funds do not outperform passively managed ones.</u>
Bid-ask spread	Assessing knowledge about features of financial transactions.	You look up live stock prices on the internet and see that the current trading price of a stock you're interested in buying is \$30. You go to your online broker and buy that stock. Assuming the trading price hasn't changed in the meantime, how much do you have to pay for the stock? (i) Less than \$30 (ii) Exactly \$30 (iii) <u>More than \$30</u>
Crypto mining	Testing knowledge of the structure of the Bitcoin network.	Since the blockchain is decentralized, most Bitcoin mining is done by many small miners. (i) True (ii) <u>False</u>
Disposition effect	Failing to account for the random walk of stock prices. Investors have a stronger tendency to sell assets at a profit than to sell at a loss.	You have two stocks in your portfolio: one went up a lot in value since you bought it whereas the other one lost value. You need to sell one to raise cash. Is it optimal to sell the one that has lost value since you bought it? (i) Yes (ii) No (iii) <u>This does not make a difference</u>
Diversification	Assessing how investing in several different asset classes affects risk. Taken from Atkinson and Messy (2012).	When an investor spreads his money among different assets, does the risk of losing money: (i) Increase (ii) <u>Decrease</u> (iii) Stay the same
Exponential growth bias	Underestimating the exponential effects of compounding. Taken from Lusardi and Mitchell (2007).	Suppose you had \$100 in a savings account and the interest rate was 2 percent per year. After 5 years, how much do you think you would have in the account if you left the money to grow: (i) <u>More than \$110</u> (ii) Exactly \$110 (iii) Less than \$110
Good company heuristic	Failing to consider that market prices reflect available information, including growth prospects.	Imagine two hypothetical firms from the same industry, Firm A and Firm B, which have equal risk. However, Firm A has much higher growth prospects than Firm B. Imagine investing into one of the two firms. Which investment yields higher returns? (i) Firm A (ii) Firm B (iii) <u>Need to know more information</u>
Herding	Being influenced by "old news" from others, e.g., stories of friends, when investing.	Some of your friends with no prior experience or expert knowledge in financial markets tell you that they bought cryptocurrencies and made a lot of money with those cryptocurrencies; they mention that they bought after they came across an interesting newspaper article which describes the past price movements of cryptocurrencies. For your long-run investment strategy, how should the experience and information received from your friends influence your decision to invest (more) into cryptocurrencies? (i) Should invest more (ii) <u>Should invest less</u> (iii) Should not affect my decision
Historical stock returns	Estimating average historical returns of the S&P 500.	What is the average annual return of the S&P 500 stock market index over the past 20 years? (i) Less than 10% (ii) Between 10% and 15% (iii) <u>More than 15%</u>
Home bias	Believing that firms headquartered close to home outperform better investments.	Imagine two hypothetical companies that are identical in every possible way except that one is headquartered in your home state, whereas the other one is not. Assume you're deciding between investing in one firm or the other. Which one is the better investment? (i) The firm headquartered in my home state. (ii) The firm headquartered outside of my home state. (iii) <u>Given the assumptions, both are equally good investments.</u>
Interest rates & bond prices	Assessing the interaction between interest rates and bond prices. Taken from Lusardi and Mitchell (2007).	If the interest rate falls, what should generally happen to bond prices? (i) <u>Rise</u> (ii) Fall (iii) Bond prices are not affected
Interest rates & stock prices	Assessing the interaction between interest rates and stock prices. Adaptation from Lusardi and Mitchell (2007).	When the Fed increases interest rates more aggressively than expected by markets, what should happen to stock prices on average? (i) Stock prices will rise (ii) <u>Stock prices will fall</u> (iii) Stock prices will stay the same
Nominal illusion	Failing to assess purchasing power in real terms. Taken from Lusardi and Mitchell (2007).	Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, would you be able to buy: (i) More than today (ii) Exactly the same as today (iii) <u>Less than today</u>
Stock picking	Overconfidence in the value of free online news to "beat the market". Many investors actively pick stocks despite evidence that this leads to underperformance for most participants.	Most people could systematically outperform the stock market by carefully reading free online news articles about how recent events will affect different companies and picking the right stocks based on those readings. (i) True (ii) <u>False</u>
Value of a call option	Inferring how uncertainty affects the value of financial derivatives.	Holding everything else constant, how is the value of a call option for a stock generally affected by a higher volatility of that stock? (i) <u>Higher volatility increases the value of a call.</u> (ii) Higher volatility decreases the value of a call. (iii) Higher volatility has no effect on the value of a call.

Notes: Correct answers are underlined.

Appendix Table E7: Overview of data collections

Collection	Sample	Respondents	Treatments	Main outcomes	Pre-analysis plan
<i>Baseline experiments</i>					
Orator Experiment	Prolific	466	None	Choices in 15 financial decision tasks and voice recordings of explanations for choices	https://aspredicted.org/4t5b-42ws.pdf
Explanation Receiver Experiment	Prolific	1,103	<i>Choice Only Explanation</i>	Choices in 15 financial decision tasks	https://aspredicted.org/4t5b-42ws.pdf
<i>Additional experiments</i>					
Confidence Receiver Experiment	Prolific	713	<i>Choice Only Choice & Confidence</i>	Choices in 15 financial decision tasks	https://aspredicted.org/fwv8-3gzs.pdf
Transcript Receiver Experiment	Prolific	917	<i>Choice Only Transcript</i>	Choices in 15 financial decision tasks	https://aspredicted.org/y2f5-8zdp.pdf
Richness Receiver Experiment	Prolific	972	<i>Sparse version Rich version</i>	Choices in 15 financial decision tasks	https://aspredicted.org/9t49-kxbc.pdf
Balls-and-Urns Orator Experiment	Prolific	464	None	Estimate in standard balls-and-urns task	https://aspredicted.org/p6sd-p88k.pdf
Balls-and-Urns Receiver Experiment	Prolific	1,822	<i>Choice Only Explanation</i>	Estimate in standard balls-and-urns task	https://aspredicted.org/p6sd-p88k.pdf

Notes: Sample sizes refer to the final sample of respondents that satisfied the pre-specified inclusion criteria for each collection.

Appendix Table E8: Treatment effects on optimality

<i>Dependent variable: Posterior correct - Prior correct</i>	
Intercept	0.041*** (0.005)
Choice & Confidence	0.010* (0.006)
Transcript	0.019*** (0.006)
Explanation	0.033*** (0.006)
Observations	40859
R ²	0.001

Notes: *Choice Only* is the omitted category. The p-value in a t-test for equality between *Transcript* and *Explanation* is $p = 0.004$. Samples are the corresponding Receiver experiments for *Explanation* (1,103 receivers, 13,111 obs.), *Choice & Confidence* (713 receivers, 8,522 obs.) and *Transcript* (917 receivers, 10,964 obs.), while *Choice Only* is pooled from all collections (2,733 receivers, 8,232 obs.).

Appendix Table E9: Treatment effects on imitation in learning & unlearning situations

<i>Dependent variable: Imitation</i>	
Intercept	0.231*** (0.010)
Choice & Confidence	-0.007 (0.016)
Transcript	-0.010 (0.014)
Explanation	-0.002 (0.013)
Learning	0.198*** (0.017)
Learning $\times$ Choice & Confidence	0.012 (0.023)
Learning $\times$ Transcript	0.090*** (0.022)
Learning $\times$ Explanation	0.132*** (0.021)
Observations	16850
R ²	0.083

Notes: *Choice Only* is the omitted category. The p-value in a t-test for equality between *Learning $\times$ Transcript* and *Learning $\times$ Explanation* is $p = 0.018$. Samples are as in Table E8, restricted to learning and unlearning situations.

Appendix Table E10: Decomposition of differential learning effect in *Transcript* treatment

	<i>Dependent variable: Imitation</i>						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Transcript	-0.009 (0.014)	0.022 (0.018)	-0.092** (0.046)	-0.034 (0.054)	-0.053 (0.068)	0.039** (0.015)	0.028 (0.069)
Learning	0.199*** (0.017)	0.199*** (0.021)	0.200*** (0.018)	0.128*** (0.016)	0.112*** (0.021)	0.207*** (0.018)	0.114*** (0.021)
Transcript $\times$ Learning	0.090*** (0.022)	0.043 (0.027)	0.067*** (0.023)	0.092*** (0.022)	0.044 (0.027)	0.023 (0.023)	0.017 (0.027)
Richness						-0.011 (0.009)	-0.007 (0.010)
Transcript $\times$ Richness						0.095*** (0.012)	0.078*** (0.014)
Argument controls		✓			✓		✓
Orator controls			✓		✓		✓
Receiver controls				✓	✓		✓
Observations	7879	7879	7879	7879	7879	7879	7879
R^2	0.072	0.079	0.078	0.161	0.174	0.086	0.180

Notes: See notes for Table 1. *Explanation* sample is the *Transcript* survey, *Choice Only* sample is pooled from all collections. We drop the 0.3% of observations with missing receiver prior confidence from all regressions.

ONLINE APPENDIX FOR “EXPLANATIONS”

Thomas Graeber

Christopher Roth

Constantin Schesch

September 15, 2025

This Online Appendix contains a full list of identified arguments (Section F) and additional results on confidence (Section G) and respondent characteristics (Section H) in our main experiment. Furthermore, it provides additional results on our Richness (Section I) and Balls-and-urns (Section J) experiments. Finally, it contains survey screens (Section K) and full survey instructions (Sections L, M, N, O, P, Q, R).

F List of identified arguments

Table F1 shows all naturally-occurring arguments in the 15 financial reasoning tasks we study in our main experiment, as identified by our annotation scheme detailed in Appendix B.

O F1: Arguments Table

Argument	Description	Category
<i>Task: Actively managed funds</i>		
Active funds monitor & react to market	Actively managed funds can monitor and quickly adapt to market changes.	Fallacious
Impossible to predict stock market	Human inability to predict market movements, performance pressure, errors or over-confidence limit the effectiveness of active management.	Sound
Active funds managed by experts	Expertise in active management can lead to better investment decisions.	Fallacious
Active managers paid for performance	Active managers get paid because clients expect them to bring higher results than passive funds.	Fallacious
Active funds overperformed historically	References to historical data showing active management’s performance.	Fallacious

Continued on next page

Argument	Description	Category
Passive funds overperformed historically	References to historical data showing passive management's performance.	Fallacious
Passive funds more stable, less risky	Passively managed funds maintain stability by not frequently changing investments, while actively managed funds are risky investments.	Sound
Passive funds more diversified	Passive management benefits from diversification across a broad market index.	Sound
Active funds charge fees	Investment fees of actively managed funds are higher than for passive management. They reduce net returns and negate potential gains.	Sound
Passive funds target long term	Passively managed funds tack market trends over the longer term, so that they are better at delivering long-term growth.	Fallacious
Passive funds track markets efficiently	Passively managed funds can achieve long-term growth by following market trends. Passive management is efficient in tracking market performance with minimal intervention.	Sound
Other substantive argument	Any other substantive argument not part of the other categories.	Other
Irrelevant argument	Argument unrelated to the question; or no answer is implied by the argument.	Irrelevant
Task: Bid ask spread		
Spread between bid & ask	Stocks have a bid and an ask price, and one can only buy the stock at the ask price which is always higher than the midpoint.	Sound
Buying stocks incurs fees	Buying stock through an online broker incurs additional fees, leading to a cost higher than the stock's listed price.	Sound
Quoted price is exact price	The cost of purchasing a stock is exactly the listed trading price if no fees are applied.	Fallacious
Taxes increase cost of stock	The cost of purchasing the stock is higher because of taxes.	Fallacious
Price has not changed since	Since the price hasn't changed since it was quoted, the stock can be bought at this exact price.	Fallacious
Other substantive argument	Any other substantive argument not part of the other categories.	Other
Irrelevant argument	Argument unrelated to the question; or no answer is implied by the argument.	Irrelevant
Task: Crypto mining		
Resource intensity challenging for small miners	Bitcoin mining requires significant energy and resources, making it difficult for small miners. Large miners have an economic advantage in Bitcoin mining due to their scale and resources. Mining may not be profitable for small miners.	Sound
Mining by individuals still possible	Despite challenges, mining Bitcoin by individuals on a small scale is still possible, so that small miners dominate.	Fallacious
Decentralization different from equal distribution	Decentralization means that everyone can mine, but not that everyone mines equally, so that in practice large miners dominate.	Sound
Decentralization leads to small miners	Decentralization means there is no central planner, so that it leads to a diversity of miners, in which small miners dominate.	Fallacious
Shift from small to larger miners over time	There has been a historical shift from small miners to large mining operations over time.	Sound
Other substantive argument	Any other substantive argument not part of the other categories.	Other
Irrelevant argument	Argument unrelated to the question; or no answer is implied by the argument.	Irrelevant

Continued on next page

Argument	Description	Category
Task: Disposition effect		
Sell depreciated stock for tax loss harvesting	Selling a stock that has lost value can be beneficial for tax purposes, allowing for tax loss harvesting.	Sound
Realizing loss means missing future gains	A stock that has lost value may have the potential to increase in value in the future, making it unwise to sell. Avoid selling stocks at a loss to prevent realizing the loss and potentially missing out on future gains.	Fallacious
Realizing gains of appreciated stock beneficial	Selling a stock that has gained value realizes the profit, ensuring a positive return on investment.	Fallacious
Stock will keep upward/downward momentum	One should keep the stock that has gone up and sell the stock that has gone down, because these trends can be expected to continue in the future.	Fallacious
Current gains or losses not predictive	Stock values fluctuate, so current losses or gains do not reflect future performance.	Sound
Higher value stock also more liquid	The stock with the highest value will also be more liquid, one should therefore sell that one.	Fallacious
Other substantive argument	Any other substantive argument not part of the other categories.	Other
Irrelevant argument	Argument unrelated to the question; or no answer is implied by the argument.	Irrelevant
Task: Diversification		
Individual loss offset by other assets	Investing in multiple assets prevents total loss if one specific investment fails, akin to not putting all eggs in one basket.	Sound
Different assets respond differently to market	Different assets respond differently to market changes, so spreading investments can mitigate losses due to geopolitical or macroeconomic events.	Fallacious
Different assets respond similarly to market	Different assets usually respond similarly to market changes, so that it does not change much to invest in multiple assets instead of a single one.	Fallacious
Each asset is a chance to lose	Each asset is a chance to lose, so investing in multiple assets increases the chances of losing money.	Fallacious
Other substantive argument	Any other substantive argument not part of the other categories.	Other
Irrelevant argument	Argument unrelated to the question; or no answer is implied by the argument.	Irrelevant
Task: Exponential growth bias		
Interest payments compound	The total amount in the savings account increases due to compound interest, where interest is earned on both the initial principal and the accumulated interest from previous periods.	Sound
Compute years times interest	A simple calculation of 2% interest per year on the initial 100, <i>leading to a total of 110</i> after five years without considering compound interest.	Fallacious
Other substantive argument	Any other substantive argument not part of the other categories.	Other
Irrelevant argument	Argument unrelated to the question; or no answer is implied by the argument.	Irrelevant
Task: Good company heuristic		
Higher growth brings higher returns	Investing in the firm with higher growth prospects will yield higher returns due to its potential for growth.	Fallacious

Continued on next page

Argument	Description	Category
Growth speculative & not guaranteed	Growth prospects are speculative and not a guaranteed indicator of future success, thus more information is needed.	Fallacious
More information needed	More information is needed to make a decision because the provided details are insufficient.	Sound
Other substantive argument	Any other substantive argument not part of the other categories.	Other
Irrelevant argument	Argument unrelated to the question; or no answer is implied by the argument.	Irrelevant
Task: Herding		
Future performance unpredictable	Past performance of cryptocurrencies does not guarantee future results. Timing the market correctly when investing in cryptocurrencies is not possible.	Sound
Own research necessary	It is important to conduct one's own research before investing in cryptocurrencies.	Fallacious
Risk of crypto requires caution	High volatility, risk of scams, lack of backing and other risks associated with cryptocurrencies are a reason for caution.	Fallacious
Friends may lack expertise	Friends providing advice may lack expertise in financial markets or cryptocurrencies.	Sound
Anecdotal evidence unreliable	Anecdotal evidence from friends is not a reliable basis for investment decisions, can be coincidence, luck etc.	Sound
Investments depend on individual circumstances	Investment decisions should be based on individual circumstances and not influenced by others. Cryptocurrencies may not be suitable for all investors.	Sound
Crypto potential for significant gains	Cryptocurrencies have the potential for significant gains from investing.	Fallacious
Other substantive argument	Any other substantive argument not part of the other categories.	Other
Irrelevant argument	Argument unrelated to the question; or no answer is implied by the argument.	Irrelevant
Task: Historical stock returns		
Effect of inflation	Arguments that consider the impact of inflation on the average annual return.	Other
Relationship between volatility & returns	Arguments about how economic volatility affects the stock market's performance.	Other
Optimism about stock market	Arguments expressing a general optimism about the stock market's performance and long-term growth.	Other
Effect of general economic conditions	Arguments considering the general economic conditions and their impact on the stock market.	Other
Effect of specific historical events	Arguments considering the impact of specific historical economic events on the stock market, such as COVID-19 pandemic, recessions and subsequent recoveries etc.	Other
Anchoring on return during specific episode	Arguments where some remembrance of a specific or general stock returns is used as an anchor for the average return of the S&P 500.	Other
Known for high performance	The S&P500 is known for its high performance, which is why it has a historical average return above 10%.	Other
Known for being conservative	The S&P500 is known for being a popular, steady and conservative investment, which is why it has a historical return below 10%.	Other

Continued on next page

Argument	Description	Category
10% would be too high	Arguments based on the idea that a historical return above 10% seems too high. This can also involve the idea that, if that were true, everybody would be investing in the S&P500, which is not true and/or would reduce the return.	Other
Other substantive argument	Any other substantive argument not part of the other categories.	Other
Irrelevant argument	Argument unrelated to the question; or no answer is implied by the argument.	Irrelevant
Task: Home bias		
Company location irrelevant	The location of a company's headquarters does not impact its investment value.	Sound
Support local economy	Investing in a company headquartered in one's home state supports the local economy and community. This can also happen via taxes being paid in one's home state.	Fallacious
Local monitoring & access is easier	Investing in a company in one's home state allows for easier monitoring and access to the company.	Fallacious
Favorable tax implications	The choice between investing in a home state or out-of-state company may be influenced by different tax implications.	Fallacious
Preference for local company	A preference or bias towards investing in companies headquartered in one's home state.	Fallacious
Investments are identical other than location	Both investment options are considered equally good due to the companies being identical except for location.	Sound
Other substantive argument	Any other substantive argument not part of the other categories.	Other
Irrelevant argument	Argument unrelated to the question; or no answer is implied by the argument.	Irrelevant
Task: Interest rates and bond prices		
Inverse relationship between rate & price	Since there is an inverse relationship between interest rates and bond prices, bond prices will increase when the interest rate falls.	Sound
Increasing relationship between rate & price	Since there is a relationship in the same direction between interest rates and bond prices, bond prices will fall when the interest rate falls.	Fallacious
Fall in rates lowers demand	A fall in the interest rate leads to less demand and therefore a higher price of bonds.	Fallacious
Bond rates & prices unrelated	Bond prices remain stable and are not influenced by fluctuations in interest rates.	Fallacious
Lower rates mean lower coupons	Since the interest rate determines the interest payment that bondholders get from holding the bond, the bond's value will go down if the interest rate goes down.	Fallacious
Other substantive argument	Any other substantive argument not part of the other categories.	Other
Irrelevant argument	Argument unrelated to the question; or no answer is implied by the argument.	Irrelevant
Task: Interest rates and stock prices		
Inverse relationship between rate & price	Since there is an inverse relationship between interest rates and stock prices, stock prices will increase when the interest rate falls.	Sound
Increasing relationship between rate & price	Since there is a relationship in the same direction between interest rates and stock prices, stock prices will fall when the interest rate falls.	Fallacious
Fall in rates lowers demand	A fall in the interest rate leads to less demand and therefore a lower price of stocks.	Fallacious
Higher company borrowing cost reduces stock price	Higher interest rates increase borrowing costs for companies, reducing their profitability and negatively affecting stock prices.	Sound

Continued on next page

Argument	Description	Category
Bonds & savings accounts become more attractive	Higher interest rates make bonds and savings accounts more attractive compared to stocks, leading investors to shift their investments.	Fallacious
Reduced consumer spending reduces profits	Higher interest rates reduce consumer spending (e.g. due to borrowing constraints), negatively affecting company profits and stock prices.	Sound
Raised cost of investments for investors	Interest rate increases raise the cost of investments, making it more expensive for investors and negatively affecting stock prices.	Fallacious
Rate hikes induce anxiety, reducing prices	Interest rate hikes make market participants uncertain and anxious, which reduces stock prices.	Fallacious
Other substantive argument	Any other substantive argument not part of the other categories.	Other
Irrelevant argument	Argument unrelated to the question; or no answer is implied by the argument.	Irrelevant
Task: Nominal illusion		
Comparison between inflation & interest rate	Since the inflation rate is higher than the interest rate, one would be able to buy less tomorrow than today. This argument is distinct from PurchasingPowerDecrease because it displays no understanding of the mechanisms behind inflation and interest, and is based solely on a comparison of numbers.	Sound
Purchasing power decreases	Even though the amount of money in a savings account has increased thanks to the interest rate, the price at which one needs to buy goods and services will have increased more because of the comparatively higher inflation, so that the net effect on real purchasing power is higher. This argument is distinct from NumericalComparison because it displays an understanding of the mechanisms behind inflation and interest, not just a comparison of numbers.	Sound
Nominal spending higher thanks to interest	Because the amount of money in the savings account has increased thanks to the interest rate, one would be able to spend more than today.	Fallacious
Interest & inflation cancel each other out	Because the interest rate and inflation rate both cancel out, one would be able to buy exactly as much tomorrow as today.	Fallacious
Other substantive argument	Any other substantive argument not part of the other categories.	Other
Irrelevant argument	Argument unrelated to the question; or no answer is implied by the argument.	Irrelevant
Task: Stock picking		
Everybody would do it	If it was possible to outperform the stock market by reading free online news, everybody would be doing it.	Sound
Markets are efficient	All publicly available information is already factored into stock prices, so that markets will already have adjusted to stale news.	Sound
News articles contain misinformation or bias	News articles can contain misinformation or bias, leading to poor investment decisions.	Sound
Market inherently unpredictable	The stock market is inherently volatile and unpredictable, making systematic outperformance difficult.	Sound
News insufficient, need expertise or intelligence	News are not enough for everyday people to outperform the stock market, since, for example, they also need to be specially smart, to have financial expertise and/or to have access to other sources of information.	Fallacious

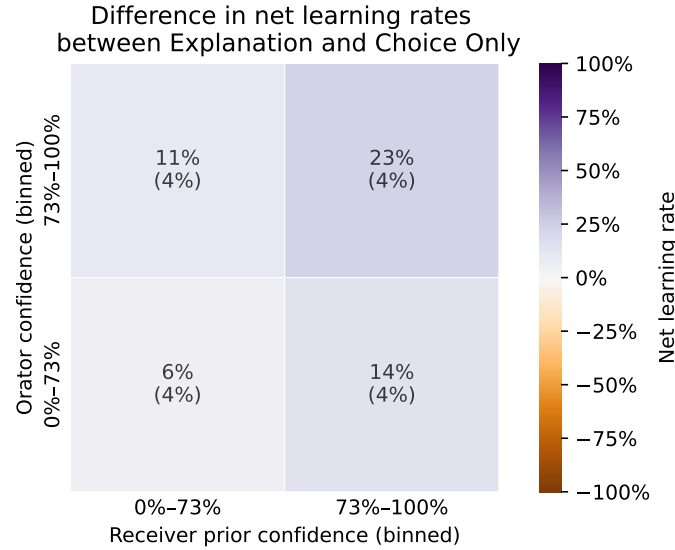
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Argument	Description	Category
Any kind of effort or information pays	Any kind of effort, research or information will help to outperform the stock market.	Fallacious
Other substantive argument	Any other substantive argument not part of the other categories.	Other
Irrelevant argument	Argument unrelated to the question; or no answer is implied by the argument.	Irrelevant
Task: Value of call option		
Increases value because more upside potential	Higher volatility in a stock increases the potential for larger price movements, which can be advantageous for call option holders seeking to profit from upward stock movements.	Sound
Decreases value because more risk	Higher volatility is seen as increasing risk, making the call option less attractive and decreasing its value due to the unpredictability of stock price movements.	Fallacious
Option value determined by other factors	The volatility of a stock has no direct effect on the value of a call option because the call option's value is determined by other factors, not just the stock's volatility.	Fallacious
Other substantive argument	Argument unrelated to the question; or no answer is implied by the argument.	Other
Irrelevant argument	Any other substantive argument not part of the other categories.	Irrelevant

G Additional results on confidence

G.1 Differences in net learning rates

Figure G1 shows how imitation by receiver and orator confidence combine by showing the difference in net learning rate between *Explanation* and *Choice Only* by orator and receiver prior confidence. The net learning rate is defined as the difference in imitation rates between learning and unlearning situations. We split both variables by the aggregate median confidence of 74%. We find that confidence effects largely compound: the explanation effect on net learning is not significant when both orator and receiver are below the median; it is significant and of similar magnitude when either one is above the median; and it is highest when both are confident.



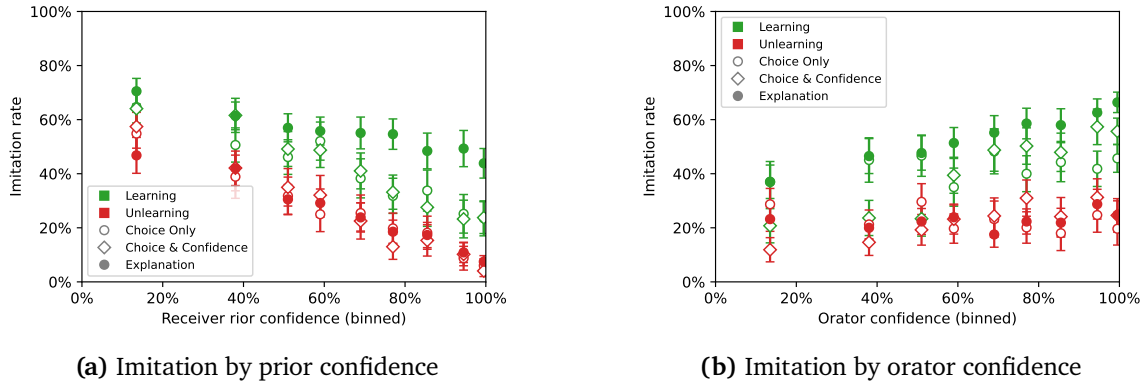
Online Appendix Figure G1: Effect of prior and orator confidence on imitation. *Notes:* Parentheses show SEs. *Explanation* sample is the main Receiver experiment (1,103 receivers, 13,111 obs.), *Choice Only* is pooled from all collections (2,733 receivers, 8,232 obs.).

G.2 Confidence and the content of explanations

We shed light on the mechanism behind these patterns by analyzing the interplay of confidence on the content of explanations.

We first repeat our previous analysis while also including the *Choice & Confidence* treatment. In Figure G2a, the effect of *Choice & Confidence* and *Choice Only* by receiver prior appears identical. Confidence signals do not help confident but wrong receivers

adjust their answer. Although Figure G2b may appear to show a slightly larger effect of *Choice & Confidence* relative to *Choice Only* for confident orators in learning situations, the difference is not significant above ($p = 0.37$) or below ($p = 0.08$) median confidence. Numerical certainty statements therefore do not explain the effect of confidence, highlighting the importance of explanation content.³³



Online Appendix Figure G2: Effect of prior and orator confidence on imitation in *Choice & Confidence* treatment. *Notes:* See notes for Figure G1. Sample for *Choice & Confidence* is the corresponding receiver experiment (713 receivers, 8,522 obs.). Whiskers show 95% CIs.

We therefore turn to the role of orator confidence on content differences in explanations. Figure G3a plots the average number of high certainty markers (e.g., “I am certain that”, “I am sure that”) by orator confidence. The number of markers increases with confidence, but there is no clear difference between correct and incorrect explanations. Low certainty markers (e.g., “It might”, “I’m not sure but”), shown in Figure G3b, conversely decrease with confidence, though right and wrong explanations do not significantly differ over most of the confidence range.

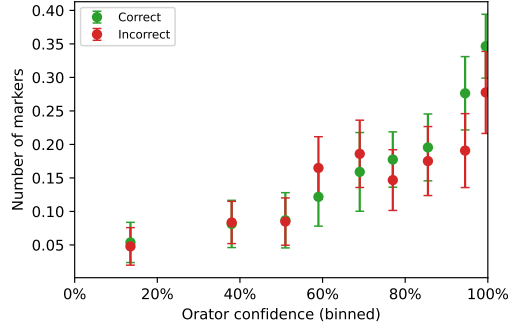
We then examine the effect of confidence on intellectual content by computing the shares of argument qualities in Figure G3c. The presence of sound arguments for correct explanations and of fallacious arguments for incorrect explanations clearly trend up in orator confidence. Other categories, and in particular no argument, in turn trend down, though there is no significant differentiating pattern between situations or confidence.

Finally, we focus on our main predictive variable by displaying richness by orator confidence in Figure G3c. We document three patterns. First, richness slopes up in orator confidence. Second, there is a richness gap between correct and incorrect explanations at all levels of confidence. Third, this gap becomes larger when orators become more

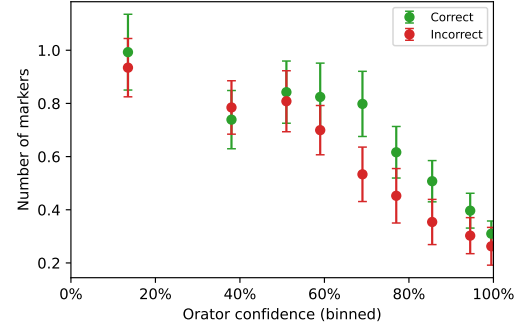
³³Interestingly, even in the *Choice & Confidence* treatment which makes the latter very salient, there is no effect of orator confidence on imitation in unlearning situations.

confident. More precisely, the richness gap between correct and incorrect explanations is 0.48 SD ($p < 0.01$) for orators with a confidence below the median against 0.91 SD ($p < 0.01$) with a confidence above it, a 0.42 SD difference ($p < 0.01$) which is slightly more than half the size of the unconditional richness gap.

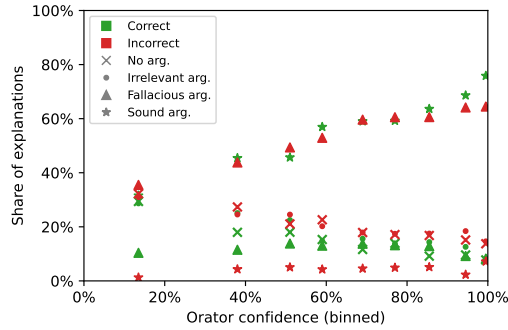
In conclusion, even within learning and unlearning situations, we uncover important differences in the content of explanations given by orators with differing certainties.



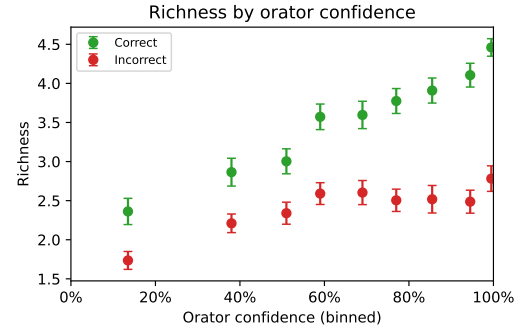
(a) High certainty markers by orator confidence



(b) Low certainty markers by orator confidence



(c) Argument quality by orator confidence



(d) Richness by orator confidence

Online Appendix Figure G3: Explanation content differences by orator confidence in learning and unlearning situations. *Notes:* Sample is the Orator experiment (466 orators, 6,910 obs.). For (c), see argument categorization in Section 5.2.1. Whiskers show 95% CIs. In Figure (c), CIs are not shown for legibility, but all SEs are smaller than 4.4%.

G.3 Richness imitation and confidence

Just as there are substantial content differences driven by the orator side, receivers could differentially imitate explanations depending on their own and the orator's confidence. In particular, they could react differently to richness, which summarizes a broad range of explanation features.

Table G2 repeats our main decomposition, from Columns (1) and (7) in Table 1, separately for confident and unconfident receivers. Columns (1) and (2) reflect our

earlier finding that explanations have a learning effect for both, but that it is about two times larger for confident receivers. Columns (2) and (4) show that the imitation of (standardized) richness is approximately the same for both, around 10 p.p., with an insignificant difference ($p = 0.09$). Since the richness gap between correct and incorrect explanations experienced by receivers is the same in both groups, richness therefore drives the same amount of learning asymmetry, of approximately $0.1 \times 0.744 = 7.4$ p.p.. This means it effectively explains the entire learning asymmetry for unconfident receivers, but only half of it for confident receivers. Put differently, confident receivers receive a benefit from explanations that is not explained by differential imitation of richness.

Turning to orators, we repeat the same decomposition separately for confident and unconfident orators in Table G3. Columns (1) and (2) again reflect our finding that explanations have a roughly two times larger learning effect when given by confident orators. Columns (2) and (4) establish that the imitation of richness is approximately the same in both samples in this case too, around 10 p.p., also with an insignificant difference ($p = 0.31$). Since we have found that the richness gap is 0.48 SD among unconfident orators but two times larger at 0.91 SD among confident ones, richness drives a two times larger learning effect among the latter. In turn, the residual not explained by richness is also roughly two times larger. In conclusion, the difference in explanation richness accounts for about half of the higher imitation of confident correct orators.

In conclusion, we have found that explanations have a learning benefit for confident and unconfident receivers, that this benefit is larger for more confident receivers, but that this effect is not driven by differential imitation of richness. It therefore reflects either content differences other than richness or a greater propensity to change their answer based on the arguments contained in explanations. In parallel, we have documented that explanations also have a larger learning benefit when they are delivered by confident orators, and that about half of this effect is driven by the fact that the richness gap between correct and incorrect orators is larger when they are more confident, which leads listeners to imitate correct and confident orators more.

O G2: Richness imitation by prior confidence

	<i>Dependent variable: Imitation</i>			
	Receiver prior confidence $\leq 73\%$ (1)	Receiver prior confidence $\leq 73\%$ (2)	Receiver prior confidence $> 73\%$ (3)	Receiver prior confidence $> 73\%$ (4)
Intercept	0.347*** (0.017)	0.339*** (0.019)	0.118*** (0.011)	0.122*** (0.012)
Explanation	-0.008 (0.022)	0.055** (0.023)	0.007 (0.014)	0.048*** (0.016)
Learning	0.165*** (0.023)	0.175*** (0.025)	0.169*** (0.024)	0.163*** (0.025)
Explanation $\times$ Learning	0.098*** (0.030)	0.013 (0.031)	0.196*** (0.030)	0.126*** (0.031)
Richness		-0.016 (0.013)		0.008 (0.012)
Explanation $\times$ Richness		0.122*** (0.016)		0.085*** (0.017)
Observations	4849	4849	3940	3940
R^2	0.054	0.077	0.133	0.155

Notes: Sample is the main Receiver experiment for *Explanation* and all collections for *Choice Only*, both restricted to learning and unlearning situations. *Explanation* is a dummy for the *Explanation* treatment, *Learning* is a dummy for learning situations, *Richness* is standardized explanation richness. 73% is the median pooled orator and receiver prior confidence. We drop the 0.6% of observations with missing receiver prior confidence from all regressions.

O G3: Richness imitation by orator confidence

	<i>Dependent variable: Imitation</i>			
	Orator confidence $\leq 73\%$ (1)	Orator confidence $\leq 73\%$ (2)	Orator confidence $> 73\%$ (3)	Orator confidence $> 73\%$ (4)
Intercept	0.244*** (0.013)	0.226*** (0.016)	0.208*** (0.016)	0.210*** (0.017)
Explanation	-0.029* (0.017)	0.035* (0.020)	0.036* (0.022)	0.072*** (0.022)
Learning	0.176*** (0.024)	0.192*** (0.024)	0.225*** (0.023)	0.221*** (0.025)
Explanation $\times$ Learning	0.086*** (0.029)	0.030 (0.030)	0.156*** (0.030)	0.077** (0.032)
Richness		-0.033** (0.014)		0.005 (0.013)
Explanation $\times$ Richness		0.113*** (0.018)		0.089*** (0.016)
Observations	4583	4583	4206	4206
R^2	0.061	0.073	0.124	0.144

Notes: See notes for Table G2.

H Additional results on orator & receiver characteristics

We examine how orator and receiver characteristics across learning and unlearning situations, as well as differential imitation based, e.g., on sociodemographics, may contribute to the asymmetric treatment effect of explanations.

We first document the heterogeneity of participants on observable characteristics. We then study which *orator* characteristics predict imitation, and whether this helps explain the asymmetric effect above and beyond the language differences associated with different groups of orators. We then test whether the characteristics of *receivers* predict their responsiveness to explanations, and to what extent this contributes to the asymmetric effect in the aggregate.

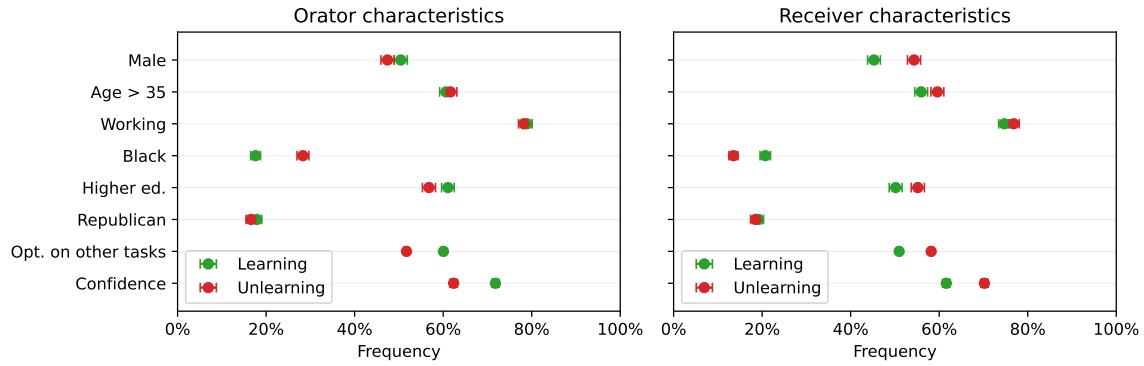
H.1 Participant Characteristics in Learning and Unlearning

Because receivers and orators are drawn from the same population and because learning and unlearning are determined by the same endogenous variable—receiver prior accuracy—, orators in learning and receivers in unlearning situations *should* have the same characteristics on average; similarly, orators in unlearning and receivers in learning situations should be similar. Figure H4 shows the full set of observable characteristics we elicit in the study, for orators in the left panel and receivers in the right panel, separately for learning and unlearning situations.

Among orators, we find significant differences across seven of the eight characteristics we examine between those in learning and unlearning situations. The first six characteristics capture participant sociodemographics. Orators with a correct answer have more education, are more likely to be male, less likely to be Black, and similarly likely to be Republican, to be older than 35 (the approximate median in our dataset) and to be working. The remaining two features characterize participants within the context of our study: orators with correct answers have a substantially higher prior accuracy rate in the 14 remaining tasks (61% vs. 52%) and a higher confidence on the present task (72% vs. 62%). Among receivers, we find very similar patterns for those with correct and incorrect priors.

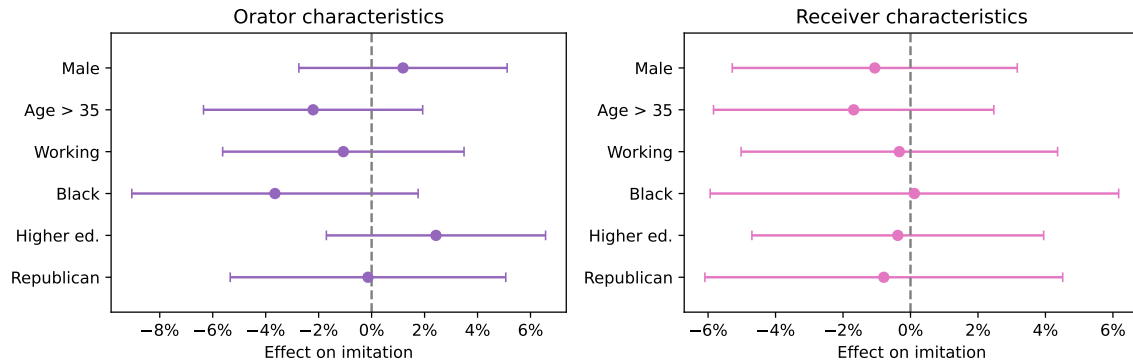
H.2 The Role of Orator Characteristics

Heterogeneous treatment effects by orator characteristics. We ask whether orator characteristics drive imitation patterns. We begin by examining the raw relationship between orator characteristics and the treatment effect of explanations based on the *Choice Only* and *Explanation* conditions. In the left panel of Figure H5, we show the



Online Appendix Figure H4: Characteristics of orators and receivers in learning and unlearning situations. *Notes:* Optimality on other tasks is the average optimality in the 14 other tasks. Confidence is rescaled from [0, 100] to [0, 1]. 35 is the approximate median age in our data. Sample for both panels is the main Receiver experiment, matched with the Orator experiment for the left panel. Whiskers show 95% CIs.

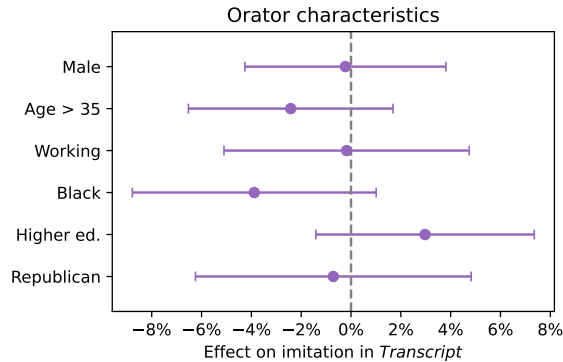
effect of orator characteristics on imitation, controlling for the orator’s and receiver’s accuracy. For example, the imitation rate is 1.2 p.p. higher if the orator is male than when they are female. Point estimates suggest that that explanations from male and highly educated speakers tend to increase imitation, while explanations from Black or older speakers result in less imitation, but none are significant.



Online Appendix Figure H5: Effect of orator and receiver characteristics on imitation in *Explanation*. *Notes:* Left panel shows coefficients on *Explanation* interacted with orator characteristics, in a linear regression of imitation on orator and receiver optimality, *Explanation*, orator characteristics, and *Explanation* interacted with orator characteristics. Right panel shows the same results for receiver characteristics. Sample for *Explanation* is the main Receiver experiment, *Choice Only* is pooled from all collections. Whiskers show 95% CIs.

Do orator characteristics operate via content differences? Orator characteristics could drive imitation via their content, via their oral delivery, or because the orator’s voice sig-

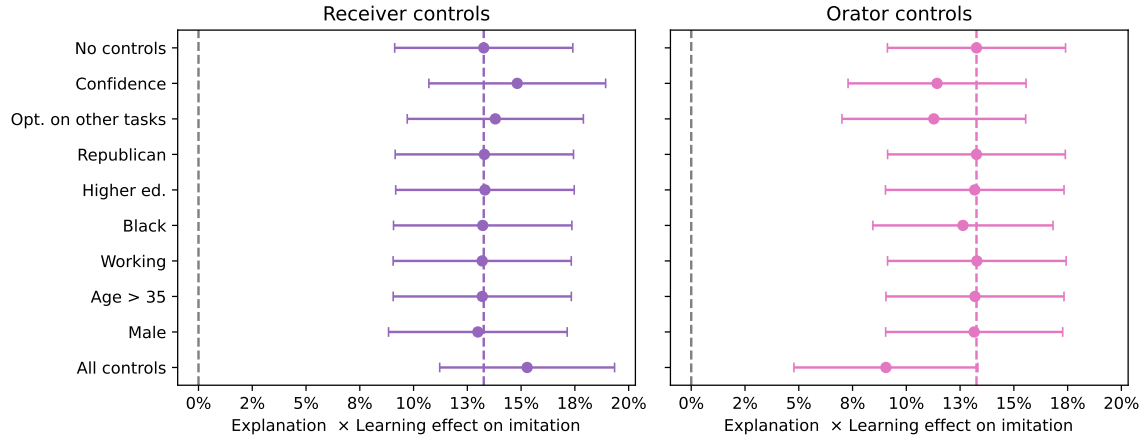
nals sociodemographic features that could influence imitation. To separate the role of content difference, we can focus on the transcript of each explanation and repeat the previous analysis while contrasting *Choice Only* with the *Transcript* treatment. In Figure H6, we can see that the effects of orator characteristics in *Transcript* are very close to those in *Explanation*, and that none of the differences between effects are statistically significant. This suggests that the effect of orator characteristics arises not from the orator's identity as revealed by speech, but from the different kinds of explanations different demographics use.



Online Appendix Figure H6: Effect of orator characteristics on imitation in *Transcript* treatment. *Notes:* See notes in Figure H5. *Transcript* sample is the corresponding Receiver experiment, *Choice Only* is pooled from all collections. Whiskers show 95% CIs.

Do orator characteristics explain away the asymmetric effect? Intuitively, orators in learning situations may signal characteristics through their voice, e.g., gender, which could make them more or less likely to be imitated. However, they also deliver different explanatory content. The preceding estimates should be interpreted as encapsulating *every* feature correlated with orator characteristics, both those contained in words and in their oral delivery.

Column 3 of Table 1 shows that orator characteristics explain away 32% of the differential effects, far below the 59% explained by richness. Moreover, columns 6 and 7 show that, once richness is controlled for, adding controls for orator characteristics does not further decrease the size of the unexplained learning effect. Figure H7 examines which orator characteristics explain away the differential effect. It shows that prior confidence and accuracy in the other tasks are most predictive, consistent with our finding that the effects of orator characteristics primarily operate through the content of explanations, though these effects are again very weak.



Online Appendix Figure H7: Learning asymmetry after controlling for orator or receiver characteristics. *Notes:* Coefficient on *Explanation* $\times$ *Learning* in a regression of imitation on *Explanation*, *Learning*, *Explanation* $\times$ *Learning*, *Control* and *Explanation* $\times$ *Control*. *Control* is a receiver control in the left panel and an orator control on the right. All regressions except 'No controls' and 'All controls' contain a single control. *Explanation* sample is the main Receiver experiment, *Choice Only* is pooled from all collections, both restricted to learning and unlearning situations. *Explanation* sample is the corresponding Receiver experiment, *Choice Only* is pooled from all collections. Whiskers show 95% CIs.

H.3 The Role of Receiver Characteristics

Heterogeneous treatment effects by receiver characteristics. We plot the effect of receiver characteristics on imitation in the left panel of Figure H5. For example, after controlling for orator and receiver accuracy, a male receiver is 1.1 p.p. less likely to imitate. Again, it should be stressed that these effects are relatively weak since none of them are significant. Unlike in our analogous study of the orator side, the receiver analysis is not affected by content differences, since the content is controlled by orators, who are randomly assigned to receivers.

Do receiver characteristics explain away the asymmetric effect? From column 4 of Table 1, we can see that receiver characteristics, if anything, *increase* the asymmetric treatment effect between learning and unlearning. This is consistent with the idea that receivers with higher prior accuracy, i.e., those with unlearning opportunities, actually have a *better* assessment of whether another respondent's choice is right or wrong after listening to their explanation. Appendix Figure H7 studies the effect of controlling for each characteristic separately, finding that accounting for prior confidence and accuracy in the other tasks slightly increases this gap.

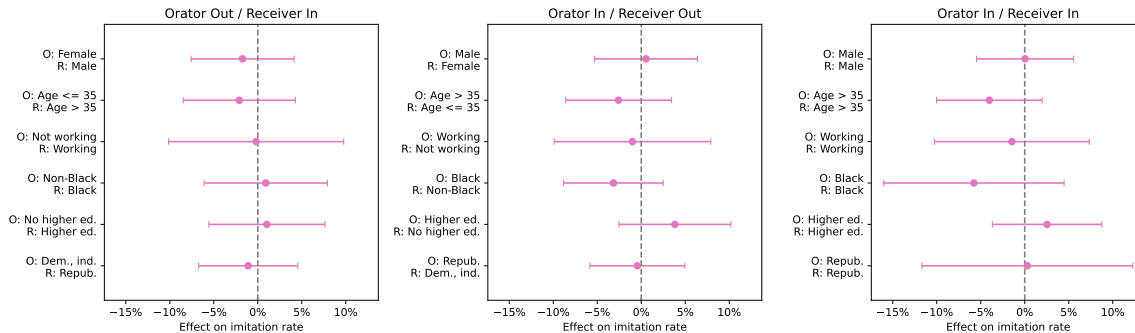
H.4 The Role of Interacted Orator and Receiver Characteristics

We have studied orator and receiver characteristics separately, and found relatively mild effects, but it could be that their interaction produces strong effects. For example, men might be more likely to imitate other men, women might be less likely to imitate men, etc. This example shows that, for binary characteristics like ours, there are four relevant configurations, depending on whether the orator or receiver are in the in- or out-group.

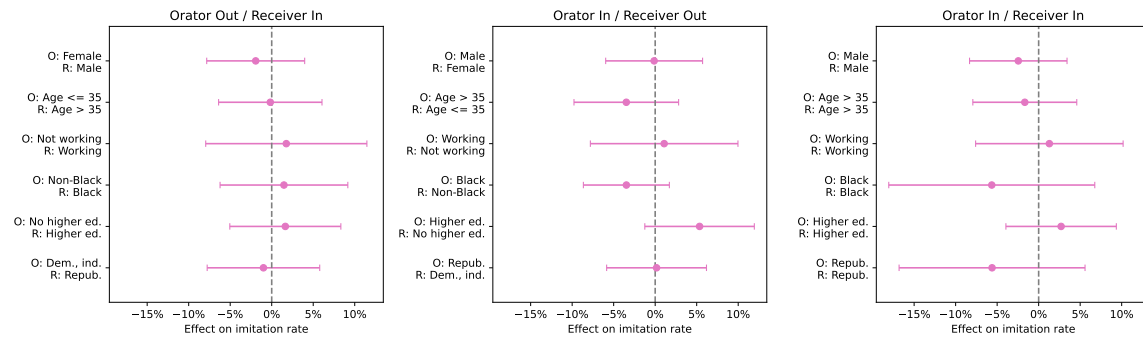
For example, when a male receiver is 2.5 p.p. less likely to imitate a female orator, while a woman is 1.9 p.p. more likely to imitate a man and a man is 0.1 p.p. more likely to imitate a man. All of these effects are relative to a woman listening to a woman, contrast *Explanation* with *Choice Only*, and control for orator and receiver accuracy. However, much like before, none of these effects appear strong enough to be significant.

Figure H9 repeats the same analysis but contrasts *Transcript* with *Choice Only*. Estimates are very similar and not statistically different from the previous one. This suggests that the effects of orator-receiver characteristics, if at all, seem to operate mainly through the content of explanations rather than pure signaling of socioeconomic characteristics.

In conclusion, although online speech-based surveys are promising to study bias in social learning or even discrimination, we do not find strong effects of orator or receiver characteristics when discussing financial reasoning tasks.



Online Appendix Figure H8: Effect of orator-receiver characteristics on imitation in *Explanation* treatment. *Notes:* Coefficients on *Explanation* interacted with orator-receiver characteristics, in a linear regression of imitation on orator and receiver optimality, *Explanation*, orator-receiver characteristics and *Explanation* interacted with orator-receiver characteristics. *Explanation* sample is the main Receiver experiment, *Choice Only* is pooled from all collections. Orator-receiver characteristics are an *Orator Out / Receiver In* dummy equal to 1 if the receiver has the characteristic but not the Orator; *Orator In / Receiver Out* and *Orator In / Receiver In* are analogously defined; *Orator Out / Receiver Out* is left out and serves as reference level. Whiskers show 95% CIs.



Online Appendix Figure H9: Effect of orator-receiver characteristics on imitation in *Transcript* treatment. *Notes:* See notes in Figure H8. *Transcript* sample is the corresponding Receiver experiment, *Choice Only* is pooled from all collections. Whiskers show 95% CIs.

I Additional results from Richness experiment

This Section summarizes additional details about the experiment exogenously manipulating linguistic richness.

I.1 Details on the generation of rich & sparse versions

Our experimental design aims to take each explanation given by a respondent and generate a rich and a sparse variant that (i) preserve the informational content, and (ii) remain as close as possible to the natural tone of respondents.

We address (i) by heavily emphasizing in our prompt that the informational content, and in particular “all arguments, facts or references” should be exactly preserved. An inspection of original explanations and generated versions shows this works quite well. The ex-post argument identification exercise described below confirms this finding.

Achieving (ii) is more challenging because LLMs are pre-trained on corpora of written text and fine-tuned to be maximally intelligent and helpful assistants. We therefore give the model examples, for each question, of 20 explanations randomly drawn from the 50 with the lowest richness rating (to avoid having only extremely sparse explanations), and the 5 with the highest richness rating (since these are longer).

We then prompt it to generate a maximally sparse and a maximally rich version by imitating the style of the examples while keeping the informational content constant. We instruct the LLM to pay close attention to specific features when imitating the sparse and rich examples. These features are informed by our analysis of the content of explanations and of the determinants of richness (cf. Section 5.2).

To generate the versions, we used GPT-4.1 (more specifically, `gpt-4.1-2025-04-14`), OpenAI’s “flagship model for complex tasks” as of June 2025. Below, we reproduce the full prompt used to generate both versions at once:

Survey respondents were asked the following financial literacy question: {question}

They also recorded oral responses to explain their choice. A rich explanation is detailed, comprehensive, logically structured, nuanced, and tailored to the context. A sparse explanation is basic, narrow, unclear or disorganized, presents only surface-level understanding, lacks depth or specific details, and fails to relate clearly to the context. Richness is measured as an integer between 0 and 10, both inclusive. If the explanation provides no argument, it is 0. Richness should not depend on whether the respondent’s answer or their premises are factually correct—only the quality of explanation matters.

To give some examples, here are twenty maximally sparse and five maximally rich explana-

tions given by respondents:

{20 sparse examples}

{5 rich examples}

We now focus on a specific respondent, who chose the following answer: {answer}

The respondent also gave the following oral response to explain their choice: {speech}

Please produce two versions of the above explanation, one that is maximally sparse (richness score: 1/10) and one that is maximally rich (richness score: 9/10). Each version should exactly preserve the informational content of the original explanation. In particular, it should preserve all arguments, facts or references of the original explanation, and not add to them. Instead, your re-writings should focus on structure, coherence, presentation and wording of the explanation, and very closely imitate the corresponding examples given above.

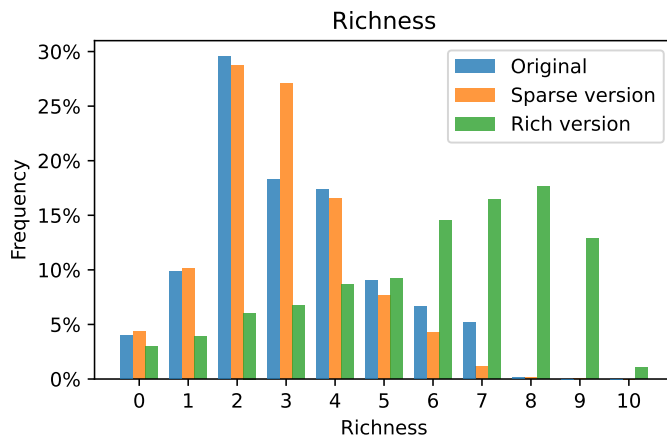
Both versions should closely imitate the oral style of corresponding explanations. In particular, you should pay close attention to filler words (“uh”, “um”, “huh”), false starts (“So, uh, I think, maybe...”), repetitions and restarts (“I believe that, um, I believe that...”), rhetorical questions (“Why do they outperform?”) and first-person framing (“I believe...”) and meta-commentary (“This is an easy/difficult question”, “To answer this question”, “To maximize your chances of getting it right” etc.).

The maximally sparse version should not be a pure summarization of the explanation. When imitating the given examples, you should pay close attention to contradictions or self-corrections mid-sentence (“I think it’s one—no wait, maybe two...”), vague or circular language, replacement of specific vocabulary with informal terms (“stuff”, “thing”), fragmented or run-on sentences (“So I say one, because, like, I think...”), clauses connected without logical links (“I think, it has to be that, I mean clearly”), abrupt cutoffs or trailing thoughts (“So yeah, number one, because they...”), disconnected or illogical flow, introduction of arguments without relating to the overall context and over-reliance on the prompt.

The maximally rich version should not be a mere rewording of the explanation. When imitating the given examples, you should pay close attention to their clear logical sequence and explicit connectives (“because”, “therefore”, “for instance”), clarification of underlying assumptions and concepts, specific vocabulary and avoidance of vague words, illustrative examples and real-world analogies, contextual framing of arguments (“Let’s say the interest rate is 2%...”), and structure designed to help someone else choose the correct answer rather than just restating their own.

I.2 Richness of rich & sparse versions

We display the distribution of richness scores in Figure I10, which shows that the sparse versions are indeed sparser and the rich versions richer than the originals. Moreover, all distributions appear relatively well-behaved, with no extreme clustering at either end.³⁴



Online Appendix Figure I10: Distribution of richness of original, rich & sparse versions. *Notes:* Sample is the Orator experiment (466 orators, 6,910 obs.) and variants generated with an LLM.

We can characterize the effect of the richness manipulation depending on the accuracy of the orator’s answer. When the orator is correct, original richness is 3.74 on average, against 3.38 for *Sparse version* ($p < 0.01$) and 6.74 for *Rich version* ($p < 0.01$). On the other hand, when he is incorrect, average richness is 2.40, 2.24 ($p < 0.01$) and 4.73 ($p < 0.01$), respectively.

I.3 Features of rich & sparse versions

To shed more light on what is driving this exogenous linguistic richness variation, we analyze the features of the generated versions in more depth. We therefore repeat the feature annotation exercise described in Section 5.2 separately for each version, and display results in Figure I11.

Beginning with certainty markers, we find that both richer and sparse versions contain more low-confidence markers than original explanations, meaning that even in rich versions the LLM communicates more extensively about the uncertainty contained in the initial explanation. Sparse explanations contain fewer high confidence markers

³⁴This well-behavedness is somewhat at odds with our prompt, which instructed the LLM to aim for a richness of 1/10 and 9/10, respectively. Experimentation shows LLMs are not very good at obtaining very specific richness scores, so that these indications were only meant to broadly increase richness differences.

O I4: Effect of original richness on sparse and rich versions’ richness

	Sparse version richness		Rich version richness	
	(1)	(2)	(3)	(4)
Intercept	0.657*** (0.019)	0.649*** (0.027)	2.212*** (0.042)	1.487*** (0.055)
Orator correct		0.157*** (0.041)		1.571*** (0.092)
Original richness	0.705*** (0.006)	0.662*** (0.012)	1.157*** (0.011)	1.353*** (0.020)
Original richness × Orator correct		0.026* (0.015)		-0.370*** (0.025)
Observations	6910	6910	6910	6910
R ²	0.701	0.706	0.650	0.671

Notes: All richness measures are standardized using the mean and standard deviation of original explanations. Sample is the Orator experiment (466 orators, 6,910 obs.) and variants generated with an LLM.

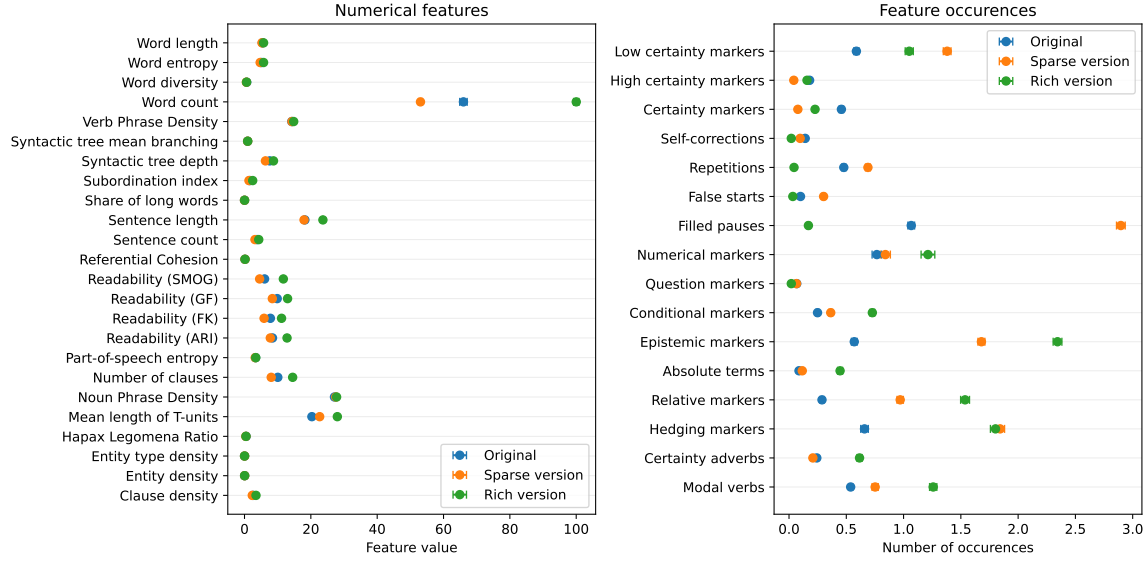
and even rich versions contain slightly fewer than the originals, perhaps because the LLM is slightly overcautious in wanting to preserve informational content.

Disfluencies are more common in sparse versions than in the original and rarer in rich versions, a pattern that applies to self-corrections, repetitions, false starts and especially strongly to filled pauses. Indeed, originals contain 1.06 filled pauses (e.g., “uh” or “uhm”) against only 0.16 in rich versions and 2.89 in sparse versions. Clearly, the LLM identifies these as prominent features of maximally rich or sparse explanations. In most other features, we also obtain that they are less frequent in sparse versions and more frequent in rich ones.

Taken together, these results show that the linguistic richness manipulation affects the presence of numerical correlates of richness and of language markers that contribute to it. We therefore conclude that it achieved its aim in an effective, broad and balanced way.

I.4 Arguments of rich & sparse versions

Finally, we examine how each versions’ richness depends on the original’s richness in Table I4. Column 1 shows that the sparse version dampens original richness but has a slight fixed boost, when one might have expected a negative coefficient, while column 3 shows the rich version amplifies original richness differences and also has a much more sizeable fixed richness boost. Columns 2 and 4 show that there is no strong effect of orator accuracy on this pattern for sparse versions, but that rich versions amplify richness heterogeneity less strongly for correct orators. Perhaps this is because correct explanations are often already comparatively rich, so that there is less room to increase it further.



Online Appendix Figure I11: Features and markers of original, rich & sparse versions. *Notes:* Sample is the Orator experiment (466 orators, 6,910 obs.) and variants generated with an LLM.

To verify that each version indeed preserves the informational content of explanations, as is stressed in the LLM prompt, we repeat the argument-tagging exercise described in Section 5.1.1 independently for each version. More precisely, we use GPT-4 again to tag which of our manually identified arguments are present in each edited version, separately for each version of each explanation.

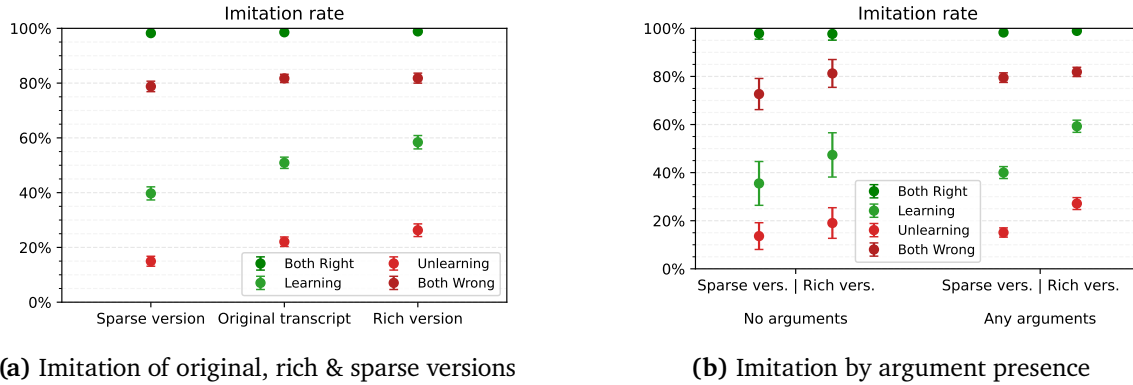
Across all rounds and all arguments (including “Other” and “Irrelevant”), the correlation between arguments identified in the original explanation and in the sparse version is 0.68, with a Cohen’s κ of 0.67 indicating “substantial agreement”. Similarly, the correlation between arguments in the original and the rich version is 0.66, and a Cohen’s κ of 0.66 again reflecting “substantial agreement”. Agreement between the two versions, the condition which ensures the validity of our experimental design, is even higher with a correlation of 0.76, and a Cohen’s κ at 0.76 showing we have “substantial agreement” and are very close to “almost perfect agreement”.

When an argument is not identified in the rich version, it is also not identified in the sparse version in 98% of cases. However, when an argument is identified in the rich version, it is also identified in the sparse version 73% of the time. Indeed, sparse versions contain 1.09 arguments on average, slightly less than the rich versions which contain 1.32, a comparatively small but significant difference ($p < 0.01$).

In conclusion, the richness manipulation appears very effective at preserving the informational content of explanations, though it is not perfect. It should be noted that

assessing the presence of specific arguments is inherently noisy, so that even preserving informational content perfectly is likely to lead to some disagreement in the ex-post argument identification. Moreover, since rich versions contain more words and LLMs work on tokenized words, there is a higher chance that the LLM picks up on an instance of an argument for richer transcripts, so that the small differences we do observe could reflect this algorithmic bias.

Nonetheless, as a conservative robustness check, we repeat our main analysis on the explanations for which there is complete agreement on the informational content of both versions. For 63% of the sample, GPT-4 exactly agrees on the presence or absence of each of the arguments, including “Other” and “Irrelevant”, in both versions. This fraction is quite high given the noisy nature of argument tagging, with another substantial fraction of explanations agreeing on all but one or two arguments. Among this sample with perfect agreement, imitation is 8.1 p.p. higher in *Rich version* than in *Sparse version* ($p < 0.01$). Moreover, it is 20.2 p.p. higher in learning situations ($p < 0.01$), 10.7 p.p. higher in unlearning situations ($p < 0.01$), 1.6 p.p. higher when both are wrong ($p = 0.42$) and 0.7 p.p. higher when both are right ($p = 0.37$). Since these effects are significant and very close to those in the full sample, we conclude that our experimental findings are not driven by changes in the informational content of explanations.



Online Appendix Figure I12: Effect of richness manipulation on imitation, relative to *Transcript* and by presence of arguments. *Notes:* Sample is the Richness receiver survey (972 receivers, 14,580 obs.). Whiskers show 95% CIs.

1.5 Heterogeneity by presence of arguments

Another check we can implement is to test whether the richness manipulation has effects that differ based on the presence of any argument. Large differences in the effect of the treatment between explanations with and without arguments suggest that variation

in informational content plays some role in the results. For explanation without any arguments, imitation is 57.0% and 62.1% in *Sparse version* and *Rich version*, respectively, against 65.0% and 72.8% for explanations with arguments. This 2.7 p.p. difference in effect sizes is not very large and not statistically significant ($p = 0.36$). Figure I12b plots the imitation rates for each condition separately for each configuration, which also all have small and insignificant differences in effect sizes. However, it should be noted that this test is not very powerful because explanations without any arguments are quite rare, making up only 7.9% of the sample.

I.6 Comparison with original *Transcript* treatment

Although results should be interpreted more carefully since they are not part of the same experimental design, it is nonetheless interesting to compare imitation of the edited versions with that of the original explanations in the *Transcript* condition. Overall, it sits between the sparse and rich versions, since its imitation rate is 69.5%, above the 64.3% of *Sparse version* ($p < 0.01$) and below the 71.9% of *Rich version* ($p < 0.01$). Figure I12a documents that, also within each situation, original explanations are in-between the sparse and rich versions. Since the richness of originals also sits in-between that of the versions, these findings further point toward an effect of richness on imitation.

J Additional results from Balls-and-urns experiment

J.1 Logistics

Respondents in both studies received a base reward of \$2 for completing the study. Participants could win a bonus of \$10 following the same incentive structure as in the main experiment, defining an answer as correct if it is within ± 3 p.p. of the Bayesian posterior. Beliefs are elicited as integer percentages between 0% and 100% using a text box. Median completion times were 13 minutes in both experiments. Both experiments were run in April 2025 using a U.S. sample on Prolific. The Orator experiment was run for a total of 554 respondents, of whom 464 gave valid data. The Receiver experiment was run for 1,975 respondents, of whom 1,856 gave valid data.

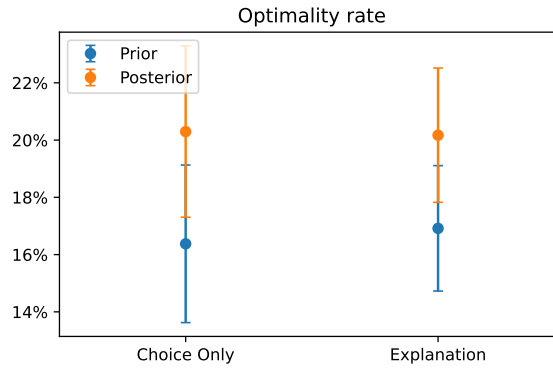
In line with our pre-registration, we drop respondents who self-reported using searching for answers online or using external tools. To curb the use of AI assistants,³⁵ we asked receivers whether the orator used an automatic voice generator or seemed to be reading a script. As specified in our pre-registration, we then exclude all orators for whom a majority of receivers agree: these cases represents 2.2% of valid recordings.

In light of prior research, we expected the share of respondents selecting a correct response to be low (Bordalo et al., 2025). This implies learning and unlearning situations should be very rare in the sample under random matching. To increase power to detect learning effects, we therefore stratify the orator assignment based on the receiver’s prior answer. If a receiver’s prior answer is incorrect, we randomly assign them to a correct or incorrect orator with equal probability. If it is correct, we assigned them an orator without stratification. In our raw sample, receiver and orator are both wrong in 40.4% and both right in 2.9% of observations, while learning and unlearning situations occur 40.4% and 13.4% of the time. We then de-stratify our sample using expected frequencies under random matching with an optimality rate of 16.7%, estimated by pooling orators and receiver priors. All summary statistics, regressions and figures presented in the main body and in the following sections are re-weighted to the population frequency.

³⁵In all experiments, the question text is not selectable and therefore difficult to copy-and-paste into a search engine or AI assistant. However, between the main experiment in December 2023 and Balls-and-urns experiment in April 2025, multimodal AI assistants that can analyze screenshots have become much more prevalent. We believe this explains the noticeable rise in orators that appear to read a script from an AI assistant.

J.2 Optimality

In line with the instructions and incentives given to survey participants, we define a correct answer a belief within ± 3 p.p. of the Bayesian posterior. Figure J13 displays optimality rates for the balls-and-urns task. Prior optimality stands at 16.4% and 16.9% in *Choice Only* and *Explanation*, respectively ($p = 0.76$), which, as expected, is considerably lower than the optimality rates around 50% seen in the main experiment. As before, both treatments help listeners select correct answers and significantly increase their optimality rates by 3.9 p.p. ($p = 0.03$) and 3.3 p.p. ($p = 0.05$) respectively. However, the difference in posterior optimality between the two conditions is very small, with *Choice Only* 0.1 p.p. higher than *Explanation*, and not significant ($p = 0.95$).



Online Appendix Figure J13: Effect of *Explanation* on optimality in Balls-and-urns experiment. *Notes:* Share of correct receivers before and after exposure to the orator’s choice or explanation. An answer is defined as correct if it is within ± 3 p.p. of the Bayesian posterior. Sample is the Balls-and-urns receiver experiment (1,856 receivers and obs.). Whiskers show 95% CIs.

J.3 Imitation

In this abstract balls-and-urns setting, choices are continuous probabilities between 0% and 100%, so that imitation is harder to define and quantify. For completeness, we have therefore pre-registered four relevant measures of imitation:

1. *No imitation*: the receiver reports the same posterior belief as their prior belief
2. *Full imitation*: the receiver reports the same posterior belief as the orator
3. *Continuous imitation in $[-1, 2]$* : to measure imitation continuously, we leverage a Grether (1980) decomposition to represent beliefs as log-odds in $\mathbb{R}$,³⁶ and then

³⁶Observations with beliefs of 0% or 100% are dropped from all analyses using continuous imitation.

define continuous imitation as the interpolation weight placed on the orator's belief:

$$\text{Continuous imitation} = \frac{\text{logit}(\text{Receiver posterior belief}) - \text{logit}(\text{Receiver prior belief})}{\text{logit}(\text{Orator belief}) - \text{logit}(\text{Receiver prior belief})}$$

No imitation yields a continuous imitation of 0, and full imitation yields 1. It can be negative if the receiver updates in the opposite direction, and larger than 1 if they go beyond the orator's belief. To limit the influence of extreme outliers due to beliefs close to 0% or 100%, we winsorize continuous imitation to $[-1, 2]$.

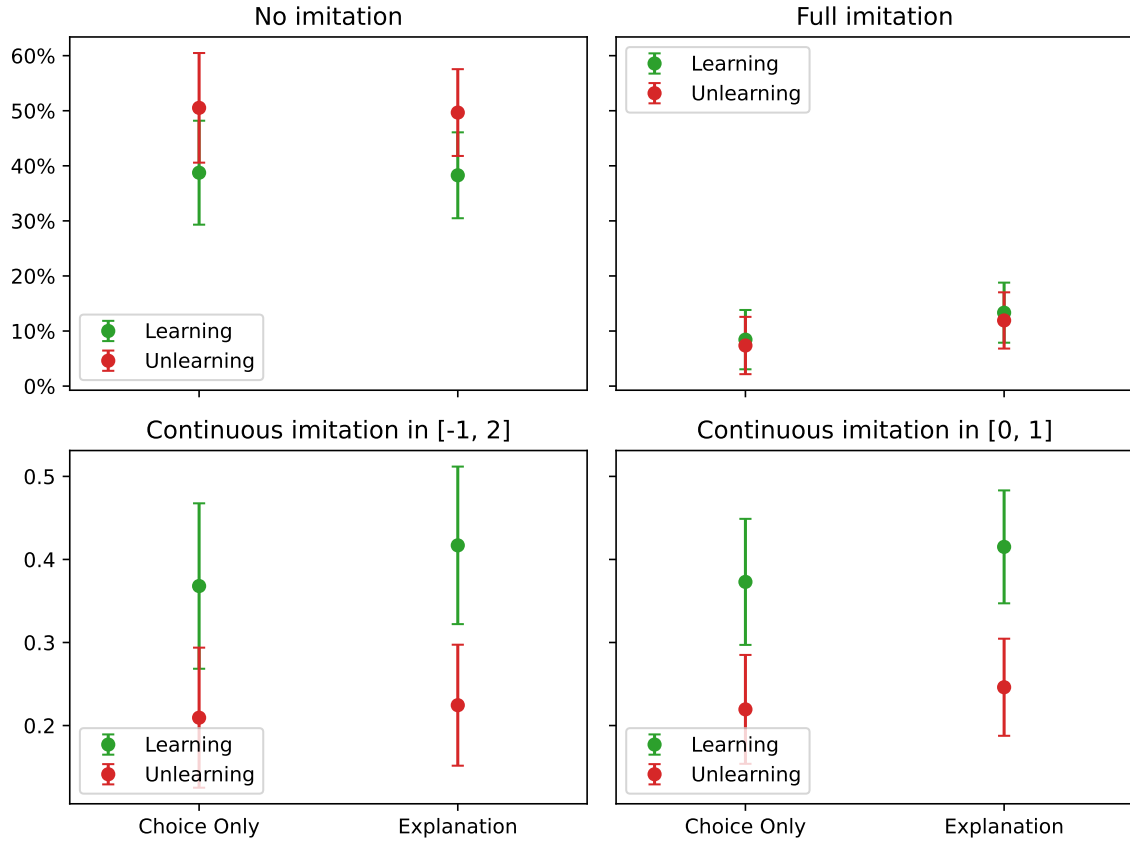
4. *Continuous imitation in $[0, 1]$* : for completeness, we also report results for continuous imitation winsorized to $[0, 1]$.

Across all situations, the share of receivers who do not imitate at all is 50.8%, while 25.3% imitate fully. These two sets have a small overlap, as in 16.4% of cases the receiver has the exact same prior belief as the orator. These confirming signals are typically one of the salient modes of the problem, e.g., the prior or diagnosticity. On the other hand, 38.5% of receivers pick a posterior belief that is neither their own prior belief nor the orator's, with two thirds of these picking answers that are strictly between the two.

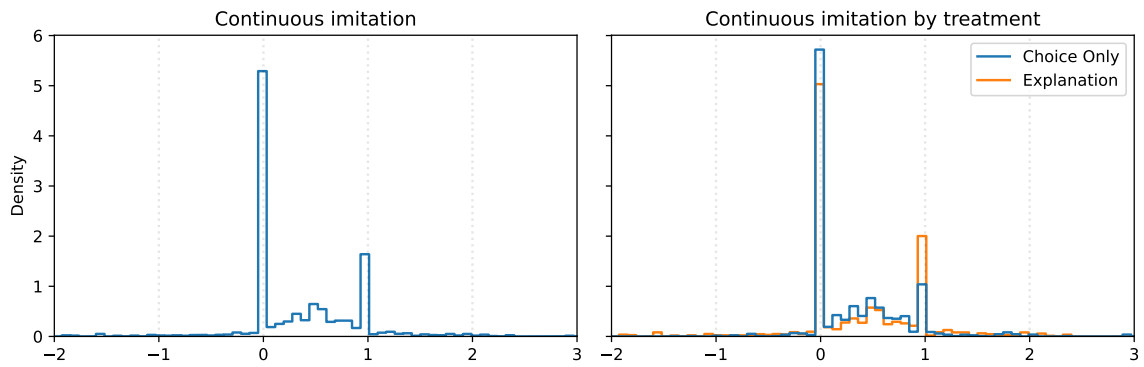
Figure J14 shows imitation in learning and unlearning situations. The share of receivers not imitating is close to 40% in learning situations for both treatments ($p = 0.89$) and closer to 50% for unlearning situations ($p = 0.94$). Full imitation rates are much lower, hovering around 10% for both situations, and again without a significant difference between treatments ($p = 0.21$ in learning and $p = 0.22$ in unlearning). Continuous imitation winsorized to $[-1, 2]$ is about 40% in learning and 20% in unlearning situations, with insignificant differences between treatments ($p = 0.49$, $p = 0.79$). Findings are qualitatively similar for winsorization to $[0, 1]$ ($p = 0.60$, $p = 0.48$).

We further examine the full distribution of continuous imitation, as is done in Figure J15. The left panel shows the distribution pooling treatments, which displays strong modes at 0 and 1, corresponding to no and full imitation. There is a weaker mode around 0.5, suggesting that many receivers update somewhere roughly in the middle of their own prior belief and the receiver's belief.³⁷ Imitation outside of these bounds is rare, as 12.6% of observations are outside of $[0, 1]$, and only 4.5% outside of $[-1, 2]$. Splitting by treatments, the right panel reveals that the difference between *Choice Only* and *Explanation* appears small and unlikely to be statistically meaningful.

³⁷Note that, with integer percentage beliefs, it is impossible to achieve an imitation of exactly 0.5 or a similar round value in log-odds space.



Online Appendix Figure J14: Effect of *Explanation* on imitation in Balls-and-urns experiment. *Notes:* See main text for definitions of imitation measures. Sample is the Balls-and-urns receiver experiment (1,856 receivers and obs.). Whiskers show 95% CIs.

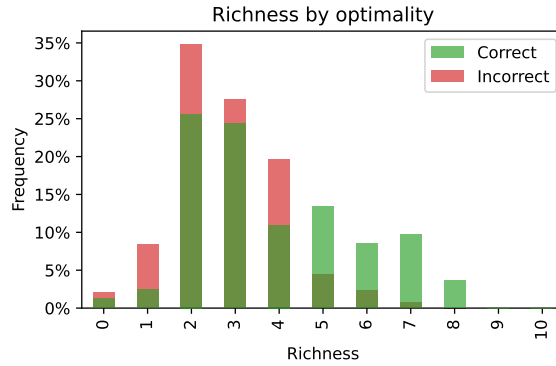


Online Appendix Figure J15: Distribution of continuous imitation in Balls-and-urns experiment. *Notes:* Left panel shows histogram of continuous imitation across treatments. Right panel shows histogram of continuous imitation in *Choice Only* and *Explanation*. The *x*-axis is cut to [-2,3], leaving 2.3% of observations outside of axis limits. Sample is the Balls-and-urns receiver experiment. Whiskers show 95% CIs.

In conclusion, we fail to find a treatment effect of *Explanation* relative to *Choice Only* in the Balls-and-urns task. However, despite our oversampling strategy designed to maximize power, standard errors remain relatively large, so that this is not a very precise null. The difficulty of the task, the complexity of social learning in this context, and the difficulty in defining optimality and imitation make aggregate improvement and learning hard to measure.

J.4 Imitation of richness

We follow the same procedure as in the main experiment to annotate the richness of explanations for the Balls-and-urns experiment. Figure J16 shows the distribution of richness rating by optimality. There is a statistically significant, 0.733 SD difference in richness between correct and incorrect explanations, which is very close to the gap found among financial reasoning tasks.



Online Appendix Figure J16: Richness gap by orator optimality in Balls-and-urns experiment. *Notes:* Sample is the Balls-and-urns orator survey.

We therefore examine whether richness predicts imitation in the Balls-and-urns experiment. Table J5 replicates Column (7) of Table 1, which examines whether richness predicts imitation within learning and unlearning situations. We find that richness has a negative but statistically insignificant effect on no imitation ($p = 0.23$). However, it has a statistically significant effect on full imitation, at $+3.6p.p.$ ($p = 0.05$), and on continuous imitation winsorized to $[-1, 2]$ and $[0, 1]$, at $+0.056$ ($p = 0.06$) and $+0.043$ ($p = 0.05$) respectively.

Although we fail to find effects of *Explanation* on optimality and learning in this ball-and-urns task, we therefore do find evidence that our main hypothesized mechanism, the effect of richness on imitation, holds here. Crucially however, the magnitude of this effect is considerably smaller than for financial reasoning tasks.

O J5: Imitation of richness in Balls-and-urns experiment

	No imitation (1)	Full imitation (2)	Continuous imitation (3)	Cont. in [0,1] (4)
Explanation	-0.013 (0.067)	0.050 (0.039)	0.022 (0.054)	0.032 (0.046)
Learning	-0.110* (0.062)	0.013 (0.033)	0.172*** (0.048)	0.155*** (0.039)
Explanation $\times$ Learning	0.032 (0.078)	-0.024 (0.047)	-0.009 (0.070)	-0.017 (0.054)
Richness	-0.011 (0.023)	-0.003 (0.010)	-0.019 (0.020)	-0.003 (0.014)
Explanation $\times$ Richness	-0.035 (0.028)	0.036* (0.018)	0.056* (0.031)	0.043* (0.023)
Observations	1031	1031	1026	1026
R^2	0.020	0.014	0.036	0.053

Notes: Sample is the Balls-and-urns receiver experiment, restricted to learning and unlearning situations. *Explanation* is a dummy for the *Explanation* treatment, *Learning* is a dummy for learning situations. *Continuous imitation* is winsorized to [-1,2], *Cont. in [0,1]* to [0,1]. See main text for definition of imitation measures.

This finding can help us shed light on our failure to find aggregate effects due to explanations in our Balls-and-urns experiment. In learning and unlearning situations, a one-standard deviation increase in richness raises full imitation, the margin that matters for optimality, by 3.6 p.p. In turn, since the optimality rate stands at 16.7%, learning and unlearning situations occur in $2 \times 0.167 \times (1 - 0.167) = 27.8\%$ of matches. A back-of-the-envelope calculation then shows that the effect of explanations on optimality via richness is $0.73 \times 0.036 \times 0.278 = 0.7$ p.p.. This is considerably smaller than the ± 2.4 p.p. confidence interval for posterior optimality in Figure J13, suggesting that despite our large sample this abstract task would have made it difficult to detect any effect of explanations on optimality via richness.

To understand why this potential effect is considerably smaller than for financial reasoning tasks, we perform the same calculation for our main experiment. There, the richness gap between correct and incorrect explanations is very similar at 0.77 SD. However, the effect of richness on imitation is three times larger at 10.7 p.p. (cf. Table 1, Column (7)). Moreover, since the optimality rate across orators and receiver priors is 55.4%, learning or unlearning occurs in $2 \times 0.554 \times (1 - 0.554) = 49.4\%$ of matches, approximately two times more often. The total predicted effect of explanations on optimality via richness is then $0.77 \times 0.107 \times 0.494 = 4.1$ p.p.,³⁸ six times larger than for the

³⁸This is not far from the 3.2 p.p. effect observed in the data, with the difference being due to error in

balls-and-urns. On the other hand, because we can pool the 15 financial reasoning tasks and because optimality rates are higher, the confidence interval for posterior optimality in Figure 1 is ± 0.7 p.p., considerably smaller than the richness effect.

In conclusion, we find some evidence that receivers are more likely to imitate rich explanations in the balls-and-urns task, though the effect is substantially weaker than for financial reasoning tasks. Combined with the difficulty of the task, which makes learning situations rare, this shows the potential effect of explanations is small, and well below our detection threshold. While the rarity of learning situations has an obvious effect, it is less certain why respondents are less likely to imitate richness here. Since the task is very difficult, one could expect more confused respondents to focus more strongly on richness over content. One possible explanation could therefore be that, given the complexity of the task, respondents could have very diffuse priors for the richness of explanations about it, and therefore only use it very weakly to update.

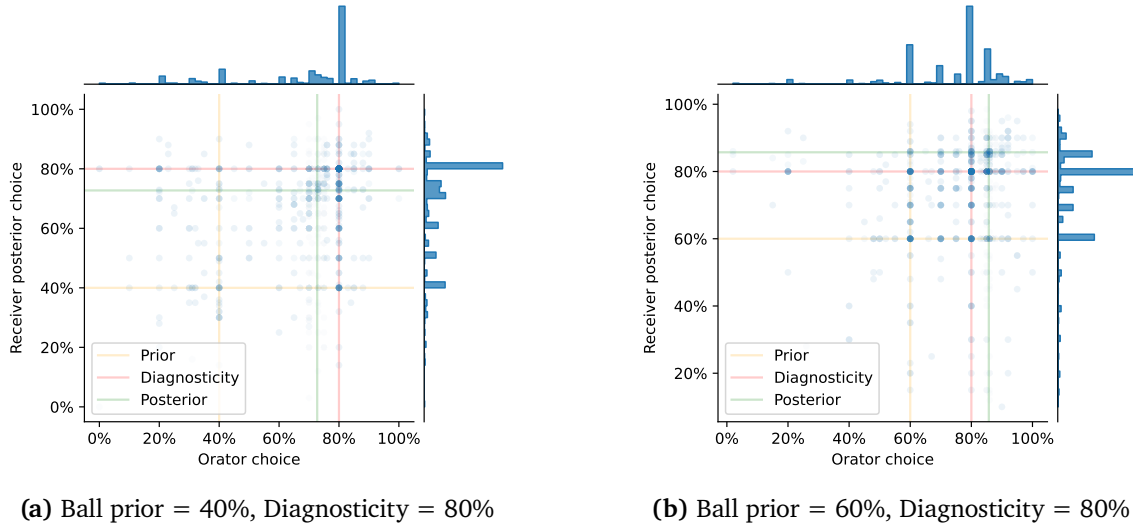
J.5 Imitation of salient modes

Previous research has shown that, when faced with abstract numerical problems like the balls-and-urns task, respondents rely on salient features to form an answer (Bordalo et al., 2025). In particular, experiments show that salience causes neglect of other relevant features, leading to biased answers that cluster around specific modes. For a balls-and-urns inference task similar to ours, Bordalo et al. (2025) find that respondents very often answer the prior or 100%-prior, the diagnosticity or 100%-diagnosticity, or fall back to an ignorance default of 50%-50%. We obtain very similar modes in our data.

Our experiment allows us to study whether social learning about numerical problems also relies on salient features. We can examine whether other modes, besides the posterior, are more likely to be imitated. We confirm this approach is sensible by plotting orator beliefs and receiver posterior beliefs in Figure J17. To increase power, we have grouped symmetric configurations based on the color of the ball draw, so that there are only two groups: configurations with a prior of 40% on the color of the ball draw, and configurations with a prior of 60%. The left panel shows the first case, where the posterior of 72.73% is below the diagnosticity of 80%, and the right panel shows the second case, where the posterior of 85.71% is above. The marginal distributions of beliefs exhibit strong modes at the prior and the diagnosticity, and a weaker, more diffuse mode around the Bayesian posterior. The modes around 100%-prior, 100%-diagnosticity and 50%-50% are comparatively weaker.

The scatter plots, where the opacity of a dot reflects the number of overlapping the estimates used for this calculation.

observations, make clear that receiver posterior beliefs also strongly cluster on modes. Social learning is therefore largely based on switching from one mode to another, rather than smooth updating between likelihoods. For example, the dark blue dots along the “Diagnosticity” vertical line indicate a tendency by receivers to switch to this mode when faced with an orator that supports it. Salient features of a numerical problem therefore determine how subjects form responses to it, but also how they learn about it from others.



Online Appendix Figure J17: Effect of *Explanation* on imitation in Balls-and-urns experiment. *Notes:* Symmetric configurations are grouped based on the color of the ball draw. Left panel shows configurations with a corresponding prior of 40%, right panel shows configurations with a corresponding prior of 60%. Histograms show marginal distribution, scatter plots show joint distribution, with opacity reflecting the number of observations. Sample is the Balls-and-urns receiver experiment, pooling *Choice Only* and *Explanation* treatments.

In line with our pre-registration, we identify orator’s and receiver’s reasoning errors directly from their estimated likelihood. Among orators, 12.5% respond with the prior, 36.7% answer the diagnosticity inverted according to the signal (e.g., if the diagnosticity is 80% and the ball draw is blue, the belief that the ball is red would be 20%), 16.7% give an answer within ± 3 p.p. of the Bayesian posterior, and 34.1% state some other belief. Orators responding 50%, the non-signal-flipped diagnosticity or the flipped prior are relatively rare in our data. Due to our oversampling scheme designed to increase the frequency of learning situations, we have limited power to study these rarer modes, and therefore group them into the “Other” category.

Receiver prior belief modes are very similar. Importantly, receiver posterior belief modes are also very similar. In particular, the share of answers not falling in one of the

O J6: Imitation of modes in Balls-and-urns experiment

	No imitation (1)	Full imitation (2)	Continuous imitation (3)	Cont. in [0,1] (4)
Intercept	0.450*** (0.038)	0.205*** (0.036)	0.410*** (0.041)	0.382*** (0.032)
Diagnosticity · Signal	0.151*** (0.045)	0.264*** (0.043)	-0.047 (0.052)	-0.006 (0.041)
Posterior $\pm 3p.p.$	-0.043 (0.042)	-0.055 (0.039)	-0.006 (0.047)	0.012 (0.036)
Other	0.027 (0.046)	-0.119*** (0.039)	-0.136*** (0.050)	-0.096** (0.038)
Observations	1822	1822	1619	1619
R^2	0.023	0.152	0.011	0.014

Notes: Variables indicate orator belief mode: *Diagnosticity · Signal* is the diagnosticity inverted according to the signal draw, *Posterior $\pm 3p.p.$* are belief within $\pm 3p.p.$ of the Bayesian posterior, *Other* are other answers. *Prior* is left-out. *Continuous imitation* is winsorized to [-1,2], *Cont. in [0,1]* to [0,1]. See main text for definition of imitation measures. Sample is the Balls-and-urns receiver experiment, pooling *Choice Only* and *Explanation* treatments.

three modes is 35.3% and 35.1% respectively ($p = 0.89$), confirming that social learning heavily relies on modes.

Table J6 regresses imitation on the orator’s choice mode, with “Prior” being the held out mode as it represents the simplest heuristic. It shows that “Diagnosticity · Signal” is significantly more likely to be fully imitated, with a 26.4p.p. increase in full imitation, but also that it is more likely not to be imitated at all, with a somewhat smaller 15.1p.p. increase in no imitation. Correspondingly, there is no effect on continuous imitation. Presumably, this is because this mode reflects an (erroneous) mathematical understanding of the problem, and therefore calls for complete agreement or (slightly more rarely) disagreement, but not smooth updating somewhere in-between, so that the full- and no-imitation effects cancel out.

We can further observe that “Posterior $\pm 3p.p.$ ” has no significant effect on imitation, indicating it is not much more or much less convincing than “Prior”, which is an interesting finding. Finally, “Other” has a strong negative effect on full and continuous imitation, indicating receivers are less prone to update fully or even partially based on orators that are not clearly on one of the dominant modes.

So far, we have pooled *Choice Only* and *Explanation* to maximize power. For completeness, Table J7 repeats the same analysis but distinguishes between *Choice Only* and *Explanation* by adding an interaction term for the latter. It fails to find significant effects

of *Explanation* on the imitation of modes, in line with our previous findings for correct answer. However, it should be noted that our experiment is not very well-powered to study imitation of modes other than “Posterior $\pm 3p.p.$ ” because of our stratification strategy, so that we can only detect relatively large effects.

O J7: Effect of *Explanation* on imitation of salient modes in Balls-and-urns experiment

	No imitation (1)	Full imitation (2)	Continuous imitation (3)	Cont. in [0,1] (4)
Intercept	0.571*** (0.070)	0.231*** (0.057)	0.336*** (0.071)	0.313*** (0.059)
Explanation	-0.193** (0.094)	-0.040 (0.072)	0.114 (0.102)	0.106 (0.083)
Diagnosticity · Signal	0.047 (0.080)	0.217*** (0.069)	0.002 (0.083)	0.017 (0.071)
Explanation × Diagnosticity · Signal	0.165 (0.106)	0.077 (0.089)	-0.072 (0.118)	-0.033 (0.097)
Posterior $\pm 3p.p.$	-0.141* (0.075)	-0.087 (0.062)	0.024 (0.076)	0.052 (0.063)
Explanation × Posterior $\pm 3p.p.$	0.154 (0.101)	0.050 (0.080)	-0.040 (0.112)	-0.057 (0.089)
Other	-0.054 (0.081)	-0.204*** (0.058)	-0.075 (0.081)	-0.069 (0.066)
Explanation × Other	0.128 (0.108)	0.136* (0.077)	-0.092 (0.118)	-0.038 (0.093)
Observations	1822	1822	1619	1619
R^2	0.029	0.157	0.013	0.021

Notes: See notes for Table J6. *Explanation* is a dummy for the *Explanation* treatment. Sample is the Balls-and-urns receiver experiment.

Finally, we can examine the effect of the receiver’s prior mode on imitation. Figure J18 plots the full and no-imitation rate by orator and receiver prior belief modes. Recall that two thirds of receivers either imitate fully or not at all, so that this Figure reflects transitions for an important fraction of the sample. Receivers who answered the prior and saw an orator who answered the prior maintained their answer in 69% of cases, a figure that goes up to 94% for diagnosticity signal, indicating that these are socially stable modes. On the other hand only 33% of receivers who gave a correct answer fully imitate the orator, though this effect is partly mechanical because this mode covers a range of $\pm 3p.p.$. Indeed, a receiver who holds their belief while matched with an orator whose belief also falls within this range—but differs numerically—will not be classified as fully imitating, even if no belief updating occurs. The corresponding no-imitation rate is relatively high at 53%.

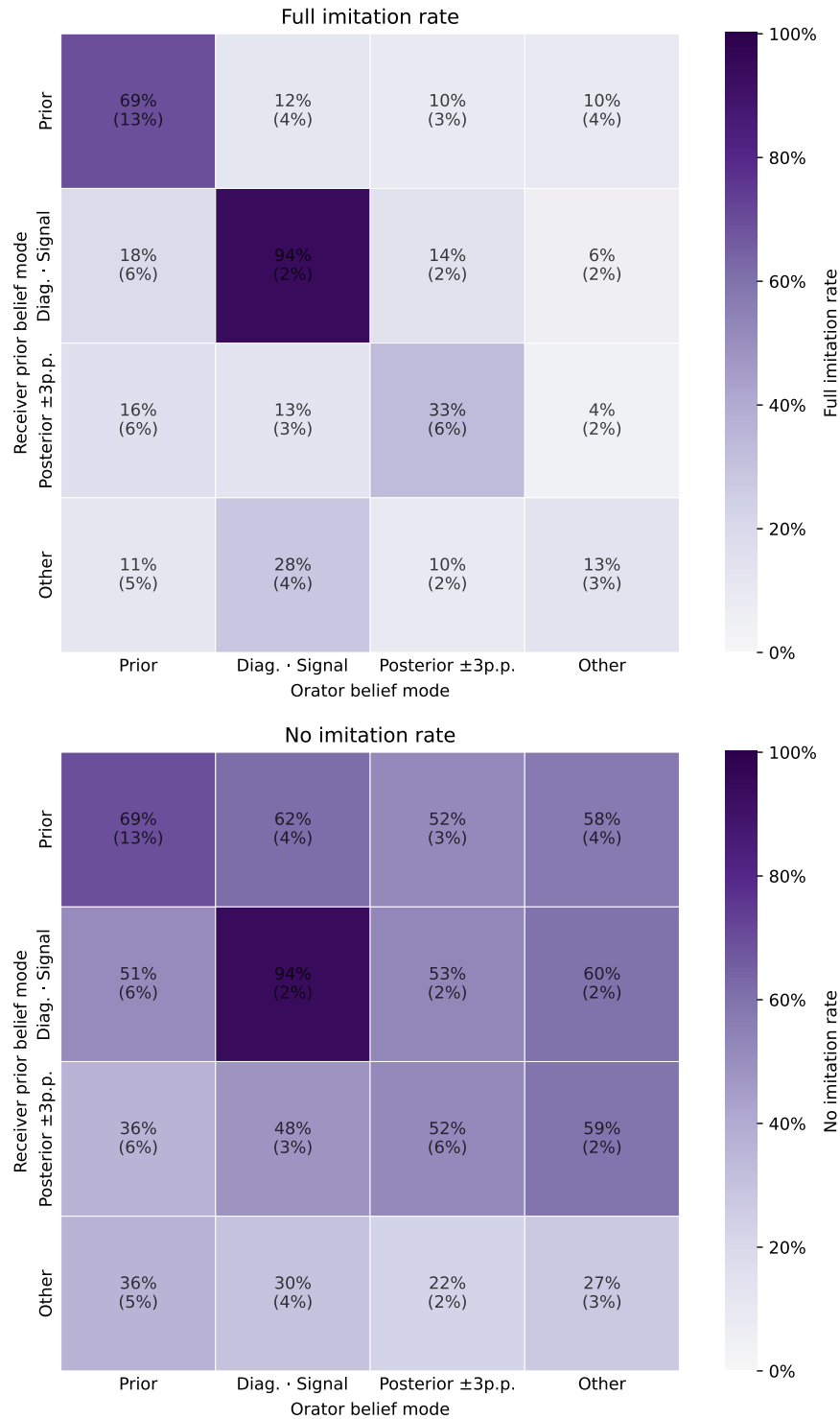
Transitions between modes are lower but still relatively high, typically around 10%-

15%, and these smaller differences are unlikely to be significant. No-imitation rates for these tasks are correspondingly lower, around 50%.

On the other hand, orators giving an answer in the “Other” category see full-imitation rates closer to 5-10%, lower than the other modes, and no-imitation rates around 60%, much higher than the others. Moreover, receivers whose prior belief was “Other” have no-imitation rates around 20%-30%, again considerably lower than for the other modes. They also appear more likely to imitate fully, in particular they fully imitate the “Diagnosticity · Signal” mode in 28% of cases. In conclusion, non-modal answers are more likely to be deviated from, and less likely to be imitated.

Our experimental setting therefore empowers us to study social learning for abstract numerical tasks. We find that salient numerical features, which are important in explaining respondents’ beliefs, also play an important role in the diffusion of beliefs. However, we do not find that social learning, and explanations in particular, attenuate modes that reflect errors in reasoning.

This suggests that, at least for complex, abstract problems like this balls-and-urns inference task, explanations may only lead to weak aggregate improvements in optimality. Bordalo et al. (2025) find that manipulating the framing of tasks, for example adopting the more naturalistic taxicab hit-and-run format (Kahneman and Tversky, 1972), changes the distribution of modes. It is therefore an open question, which we leave to further research, whether more natural tasks also lead to more beneficial social learning.



Online Appendix Figure J18: Imitation by receiver prior belief mode and orator belief mode in Balls-and-urns experiment. *Notes:* Top panel shows share of receivers stating the same belief as the orator, bottom panel shows share of receivers maintaining the same belief as their prior belief. Sample is the Balls-and-urns receiver experiment.

K Survey screens

Read the question, then record your explanation!

Do actively managed investment funds systematically outperform passively managed investment funds in terms of expected net returns, i.e. after accounting for investment fees?

1. Actively managed funds outperform passively managed ones.
2. Actively managed funds do not outperform passively managed ones.

Record an explanation that helps the other participant select the correct answer.

Start Recording

Online Appendix Figure K19: Recording screen from the Orator experiment.

Read the other respondent's answer

Do actively managed investment funds systematically outperform passively managed investment funds in terms of expected net returns, i.e. after accounting for investment fees?

1. Actively managed funds outperform passively managed ones.
2. Actively managed funds do not outperform passively managed ones.

Other person's answer:

Actively managed funds do not outperform passively managed ones.

Other person's confidence:

50%

Online Appendix Figure K20: *Choice & Confidence* treatment screen from the Receiver experiment in Section 4.2.

Do actively managed investment funds systematically outperform passively managed investment funds in terms of expected net returns, i.e. after accounting for investment fees?

1. Actively managed funds outperform passively managed ones.
2. Actively managed funds do not outperform passively managed ones.

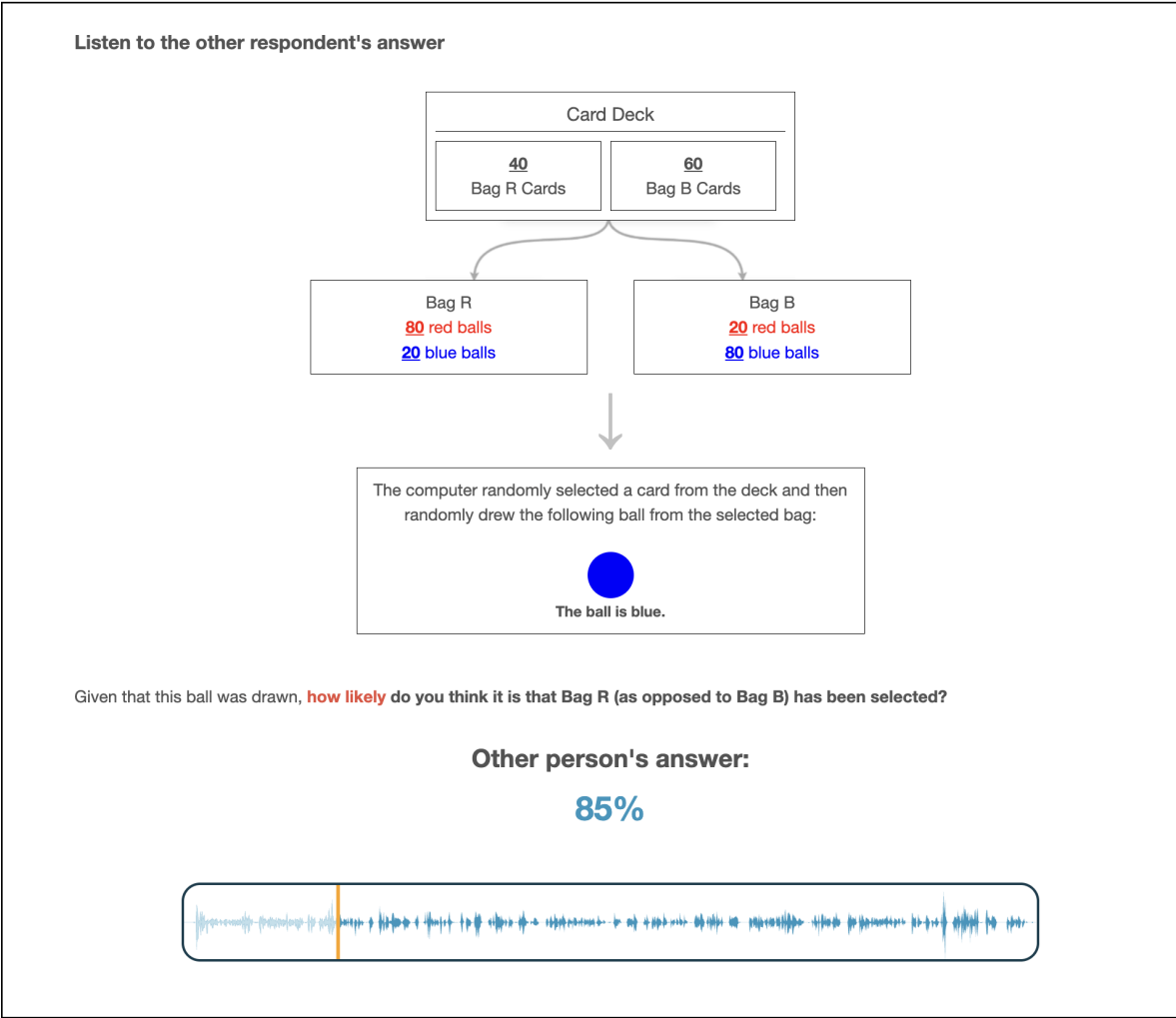
Other person's answer:

Actively managed funds outperform passively managed ones.

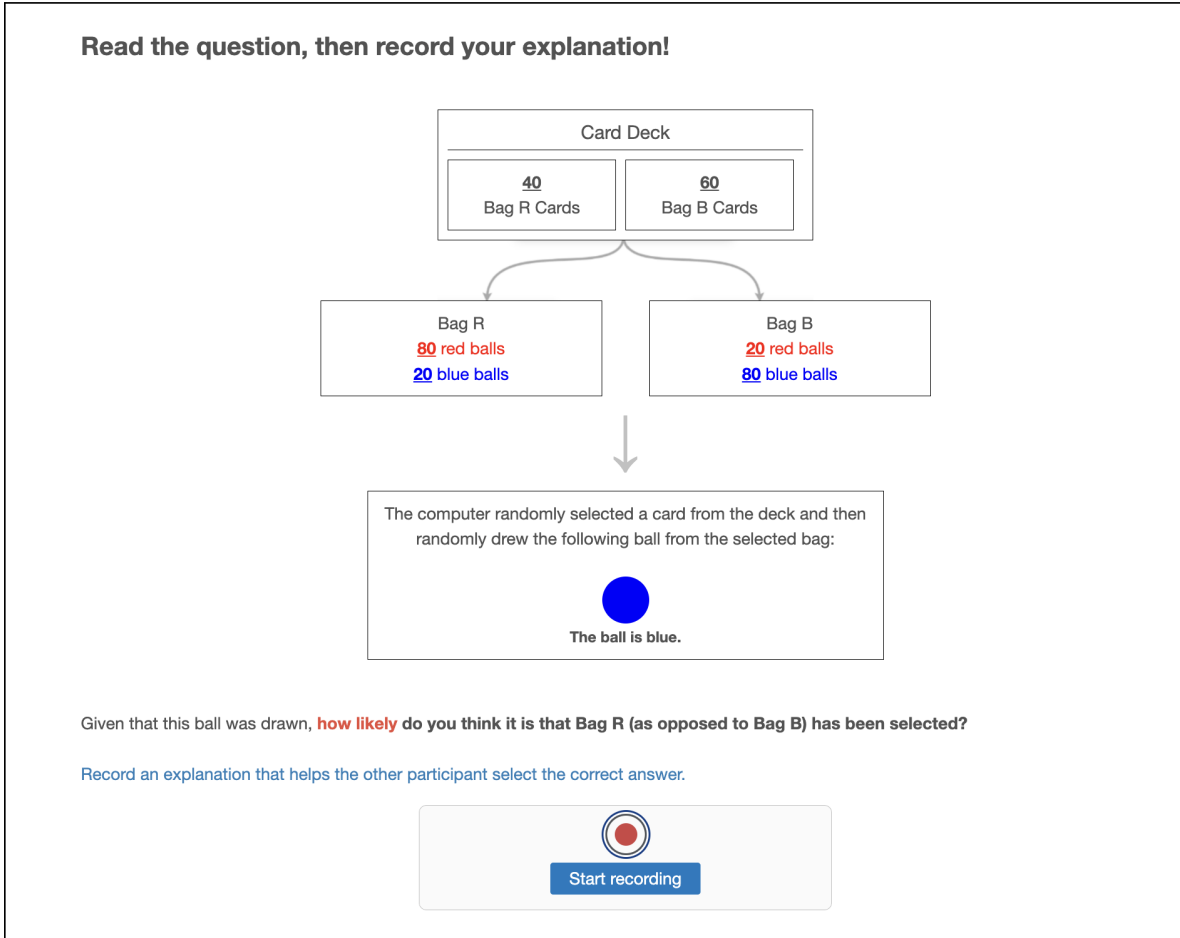
Other person's explanation:

All right. So I'm going to say that actively managed funds, um, actively managed funds do outperform, passively managed funds. And I'm going to say that which is an answer number one because I'm factoring in the level of risk management. So if there's risk management being actively applied to a, you know, to a, a fund then a lot of that risk that would just go on, you know, uncontrolled gets mitigated.

Online Appendix Figure K21: *Transcript* treatment screen from the Receiver experiment in Section 4.3.



Online Appendix Figure K22: Recording screen from the Balls-and-urns orator experiment.



Online Appendix Figure K23: *Explanation* screen from the Balls-and-urns receiver experiment.

L Survey: Orator experiment

Welcome

In this survey, we will ask you to record voice messages to answer different questions. The study is designed for computer (PC or Mac) users only (desktop, laptop, etc.).

Please make sure you are in a quiet environment. You will only receive your completion payment if your voice is clearly recorded.

You are eligible for a bonus of \$10 for one of your recordings! The details of how you might receive a bonus will be explained on the following pages.

For each question, your recording will actually be played to another respondent. The other respondent will have to answer the same question as you after listening to your recording.

Privacy & Anonymity

All voice messages are treated strictly anonymously. They will never be linked to your person and will never be published anywhere. This data will be used solely for academic research. You can therefore talk freely and informally in each voice message. The other respondent who will listen to your voice recording will not be given any more information about you: your anonymity will be preserved.

Test Your Microphone

Use the recorder below to test your microphone. Click “Record”, say the sentence “The dog runs in the park.”, then click “Stop Recording & Submit”. You may have to give your browser permission to access the microphone after you click “Record”. After a recording, it might take the website a few seconds to upload your recording: please be patient.

Trial Question

This trial question is an attention check. To be eligible to participate in this study, we simply ask you to record a voice message that lasts at least 20 seconds on your thoughts about this topic. There is no correct answer, and it does not matter what you say, as long as you record a message that lasts at least 20 seconds.

On how many days in 2024 will the average temperature recorded across all of the U.S. be below 65°F?

[Recording box, activated manually]

General Instructions

Thanks for recording your first voice message! This study will take approximately 30 minutes to complete. You will earn a reward of \$6.00 for completing the survey. To complete the study, you will need to read all instructions carefully and correctly answer the comprehension questions.

Survey Structure

In this study, you will be asked to answer 15 questions on various topics. Questions will have two or three possible options. Exactly one of the options is the correct answer. For each question, you will be asked to record yourself once to give advice on the question and explain your reasoning.

We are interested in how you would give advice in an informal conversation:

- You should share an explanation behind your response.
- Your recording will be played to a few other participants who will have to respond to the same question.
- Other participants can win a bonus for selecting the correct answer.

Importantly:

- You should first read the question, think about your response, and then record your answer.
- The recording begins once you click “Start Recording”.
- After you click to submit a recording, it can take a little while to upload. We kindly ask you to be patient.

We ask you not to search the answers on the internet:

- We are interested in the explanations behind your answer.
- To confirm that you do not search for answers, the survey will monitor whether the survey window remains active.
- If you leave the browser tab of this survey, you will not be eligible for the \$6.00 reward.
- You should remain focused on the survey window and answer questions as best you can using your previous knowledge.

Bonus Payment

At the end of the survey, one out of every ten participants is randomly selected to be eligible for an additional bonus of up to \$10. If you are selected for the bonus payment:

- One of the 15 questions you have answered will be randomly chosen.
- You will receive the bonus of \$10 if the participant selected the correct answer.

One of the participants who listened to your answer will be randomly chosen. You should therefore give your explanation in a way that makes the other respondent most likely to select the correct answer!

Much like you, participants listening to your recordings will have a chance to win a bonus of \$10 if they select the right question in a randomly selected round. Moreover, participants listening to your recordings will be informed that you will receive a bonus if they select the correct answer.

This study will take approximately 30 minutes to complete. You will earn a reward of \$6.00 for completing the survey. To complete the study, you will need to read all instructions carefully and correctly answer the comprehension questions.

Comprehension Questions

Please answer the comprehension questions below. Note that if you fail them twice in a row, you will not be eligible for the completion payment.

In this study, you will record a number of voice messages on different questions. Which one of the following statements is true?

- I should answer as if I'm talking to myself because the recording will never be played to another person.
- I should give a well-rehearsed response as if I'm giving a speech to a large audience of people that I don't know.
- I should share an explanation behind my response as if I were to give advice in an informal conversation. My response will be shared with other participants who later have to respond to the same question.

Which one of the following statements is true?

- On questions where I will be recorded, each recording only starts once I click “Start Recording” on a page.
- On questions where I will be recorded, each recording starts as soon as I enter a page.

Which one of the following statements is true?

- I can leave the tab of the experiment to search for answers online without consequences on my payment.
- If I leave the tab of the experiment, I will not be paid.

Remember!

Your chances of receiving the bonus payment are highest if the other participant chooses the correct answer.

Main Part: Example Task (Inflation)

On the next page, a question will be displayed. You should first read the question, think about your response, and then record your answer. The recording begins once you click “Start Recording”. After recording your advice, you will select your own answer to the question.

Read the question, then record your explanation!

Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, would you be able to buy:

1. More than today
2. Exactly the same as today
3. Less than today

Record an explanation that helps the other participant select the correct answer.

[Recording box, activated manually]

Provide your best answer

Please answer what you think is the correct answer to the question.

[Question with multiple choice response]

How certain are you that your above answer is correct?

[Slider from 0% (Not at all certain) to 100% (Fully certain)]

Additional Questions

Your answer to the following question will not affect your reward or bonus payment for this study, so please answer honestly. Did you search the answer to any of the 15 questions before providing your advice or your own answer?

- Yes
- No

[Followed, on a separate page, by elicitation of sex, age, ethnicity, education, employment and political affiliation.]

M Survey: Explanation receiver experiment

Welcome

In this survey, you will be asked questions on various topics. Besides giving your answer to a question, you will sometimes listen to a voice message of someone else's thoughts on the question. The study is designed for computer (PC or Mac) users only (desktop, laptop, etc.) and only works on Firefox and Chrome.

Voice Messages from Previous Participants

For some of the questions, you will first listen to a voice message from another participant. In a previous survey, we asked respondents to record their thoughts on the same questions that you will be asked.

Test Your Speaker

Use the play button below to test your speaker. Click "Play" to play back a voice message and select the sentence that you heard in the text box below.

[Player of a recording of someone saying "The dog runs in the park."]

Attention Check

Please select the sentence that you listened to in the voice message above:

- The koala climbs up the tree.
- The dog runs in the park.
- The lion looks at the gazelle.
- The cat waits for the mouse to come back.
- The fox sneaks through the garden.
- The turtle swims in the sea.

General Instructions

This study will take approximately 30 minutes to complete. You will earn a reward of \$6.00 for completing the survey. To complete the study, you will need to read all instructions carefully and correctly answer the comprehension questions.

Survey Structure

In this study, you will be asked to answer 15 questions on various topics. Questions will have two or three possible options. Exactly one of the options is the correct answer. In each round, there are four steps:

1. You provide your best answer to the question.
2. You get information about a previous respondent's answer:
 - For some questions, you will listen to a voice message of another person once.
 - For other questions, you will see the answer of another participant to the question.
3. You have a second chance to provide your best answer to the question. Your answer may or may not be different from your response in (1), given what you learned about the other participant's answer in (2).

When you enter a page with a recording, the recording will play automatically. You will only be able to listen to it once.

Bonus Payment

At the end of the survey, one out of every ten participants is randomly selected to be eligible for an additional bonus of up to \$10. If you are selected for the bonus payment:

- One of the 15 rounds you have answered will be randomly chosen.
- Either your answer from step (1) or your answer from step (3) will be randomly chosen.
- You will receive the bonus of \$10 if you selected the correct answer.

Participants who made the recordings were informed they had a chance to win a bonus of \$10 if you selected the correct answer. They were also informed that you had a chance to win a bonus of \$10 if you selected the correct answer.

Comprehension Questions

Please answer the comprehension questions below. Note that if you fail them twice in a row, you will not be eligible for the completion payment.

In this study, you will listen to a number of voice messages on different questions. Which one of the following statements is true?

- Before each of the 15 questions I'll be asked, I will listen to a voice message from another respondent.
- Before each of the 15 questions I'll be asked, I will see what another respondent answered.
- On some of the 15 questions I'll be asked, I might listen to a voice message from another respondent. On other questions, I will see what the respondent answered.

Which one of the following statements is true?

- On questions with a voice recording, each recording only starts playing once I click "Play" on a page.
- On questions with a voice recording, each recording starts playing automatically when I enter a page, so I should read the question and pay attention to the recording.

Which one of the following statements is true?

- The answers I chose have no effect on my expected bonus.
- I maximize my expected bonus by selecting my best answer to each question.

Main Part: Example Question (Inflation)

[Prior Choice:] Provide Your Best Answer

Please answer what you think is the correct answer to the question.

Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, would you be able to buy:

1. More than today
2. Exactly the same as today
3. Less than today

How certain are you that your above answer is correct?

[Slider from 0% (Not at all certain) to 100% (Fully certain)]

[Explanation Treatment:]

Now, you will listen to a recording of a voice message from a previous respondent who shares the explanation behind their answer to the exact same question that you just answered. The voice message will automatically start playing.

Please listen closely to the recording.

You will be able to proceed to the next page once the recording has finished playing.

[PAGEBREAK]

Listen to the other respondent's answer

[Box with question text]

Other person's answer:

[Answer of other respondent]

[Recording of other respondent, on auto-play]

[Choice Only Treatment:]

Now, you will observe the answer from a previous respondent.

Please pay close attention to the other person's answer.

[PAGEBREAK]

Read the other respondent's answer

[Box with question text]

Other person's answer:

[Answer of other respondent]

[Posterior Choice:] Provide Your Best Answer

Your answers on this page may or may not be different from your previous response, given what you learned about the other participant's answer.

Please answer what you think is the correct answer to the question.

[Question with multiple choice answer]

Your answer is correct if you selected the right answer.

How certain are you that your above answer is correct?

[Slider from 0% (Not at all certain) to 100% (Fully certain)]

Additional Questions

Did you look up any answers on the internet? Your response to this question will not affect your payment. Please answer truthfully.

- Yes
- No

Additional Information

The explanations you just listened to likely differed systematically in how rich or sparse they were. Rich explanations include substantial details on the reasoning and tend to be elaborate, while sparse explanations provide limited details.

Which statement do you most agree with? Over the course of this experiment, I learned about whether a given answer is correct...

- ...more from sparse explanations than from rich explanations.
- ...more from rich explanations than from sparse explanations.
- ...equally much from rich and sparse explanations.

Why do you think this is the case?

[Open text box]

[Followed, on a separate page, by elicitation of sex, age, ethnicity, education, employment and political affiliation.]

N Survey: Transcript receiver experiment

Welcome

In this survey, you will be asked questions on various topics. This study is designed for computer (PC or Mac) users only (desktop, laptop, etc.). If you are accessing this study on a smartphone, a tablet or any other non-PC devices, please switch to PC and enter the study again, or return the submission on Prolific.

Please write at least 15 words describing your opinion about daylight savings in the United States. Whether you are in favor or against daylight savings does not affect your eligibility to participate in this study. However, we ask that you write at least 15 words on your thoughts about this topic.

[Text box]

General Instructions

This study will take approximately 30 minutes to complete. You will earn a reward of \$6.00 for completing the survey. To complete the study, you will need to read all instructions carefully and correctly answer the comprehension questions.

Survey Structure

In this study, you will be asked to answer 15 questions on various topics. Questions will have two or three possible options. Exactly one of the options is the correct answer. In each round, there are four steps:

1. You provide your best answer to the question.
2. You get information about a previous respondent's answer:
 - For some questions, you will see another participant's answer to the question and additionally read the transcript of the explanation they recorded.
 - For other questions, you will only see the participant's answer.
3. You have a second chance to provide your best answer to the question. Your answer may or may not be different from your response in (1), given what you learned about the other participant's answer in (2).

When you enter a page with a recording, the recording will play automatically. You will only be able to listen to it once.

Bonus Payment

At the end of the survey, one out of every ten participants is randomly selected to be eligible for an additional bonus of up to \$10. If you are selected for the bonus payment:

- One of the 15 rounds you have answered will be randomly chosen.
- Either your answer from step (1) or your answer from step (3) will be randomly chosen.
- You will receive the bonus of \$10 if you selected the correct answer.

Participants who made the recordings were informed they had a chance to win a bonus of \$10 if you selected the correct answer. They were also informed that you had a chance to win a bonus of \$10 if you selected the correct answer.

Comprehension Questions

Please answer the comprehension questions below. Note that if you fail them twice in a row, you will not be eligible for the completion payment.

In this study, you will read a number of explanations on different questions. Which one of the following statements is true?

- Before each of the 15 questions I'll be asked, I will read the transcript of an explanation recorded by a previous respondent.
- Before each of the 15 questions I'll be asked, I will see what a previous respondent answered.
- On some of the 15 questions I'll be asked, I might read the transcript of an explanation recorded by a previous respondent. On other questions, I will see what the previous respondent answered.

Which one of the following statements is true?

- Previous respondents typed their explanations into a text box.
- Previous respondents recorded their explanations as voice messages which were then automatically transcribed into text.

Which one of the following statements is true?

- The answers I chose have no effect on my expected bonus.
- I maximize my expected bonus by selecting my best answer to each question.

Main Part: Example Question (Inflation)

[Prior Choice:] Provide Your Best Answer

Please answer what you think is the correct answer to the question.

Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, would you be able to buy:

1. More than today
2. Exactly the same as today
3. Less than today

How certain are you that your above answer is correct?

[Slider from 0% (Not at all certain) to 100% (Fully certain)]

[Transcript Treatment:]

Read the other respondent's explanation

[Box with question text]

Other person's answer:

[Answer of other respondent]

Other person's explanation:

[Transcript of explanation, displayed progressively]

[Choice Only Treatment:]

Read the other respondent's answer

[Box with question text]

Other person's answer:

[Answer of other respondent]

[Posterior Choice:] Provide Your Best Answer

Your answers on this page may or may not be different from your previous response, given what you learned about the other participant's answer.

Please answer what you think is the correct answer to the question.

[Question with multiple choice answer]

Your answer is correct if you selected the right answer.

How certain are you that your above answer is correct?

[Slider from 0% (Not at all certain) to 100% (Fully certain)]

Additional Questions

Did you look up any answers on the internet? Your response to this question will not affect your payment. Please answer truthfully.

- Yes
- No

Additional Information

The explanations you just read likely differed systematically in how rich or sparse they were. Rich explanations include substantial details on the reasoning and tend to be elaborate, while sparse explanations provide limited details.

Which statement do you most agree with? Over the course of this experiment, I learned about whether a given answer is correct...

- ...more from sparse explanations than from rich explanations.
- ...more from rich explanations than from sparse explanations.
- ...equally much from rich and sparse explanations.

Why do you think this is the case?

[Open text box]

[Followed, on a separate page, by elicitation of sex, age, ethnicity, education, employment and political affiliation.]

O Survey: Choice & Confidence receiver experiment

Welcome

In this survey, you will be asked questions on various topics. This study is designed for computer (PC or Mac) users only (desktop, laptop, etc.). If you are accessing this study on a smartphone, a tablet or any other non-PC devices, please switch to PC and enter the study again, or return the submission on Prolific.

Please write at least 15 words describing your opinion about daylight savings in the United States. Whether you are in favor or against daylight savings does not affect your eligibility to participate in this study. However, we ask that you write at least 15 words on your thoughts about this topic.

[Text box]

General Instructions

This study will take approximately 15 minutes to complete. You will earn a reward of \$3.00 for completing the survey. To complete the study, you will need to read all instructions carefully and correctly answer the comprehension questions.

Survey Structure

In this study, you will be asked to answer 15 questions on various topics. Questions will have two or three possible options. Exactly one of the options is the correct answer. In each round, there are three steps:

1. You provide your best answer to the question.
2. You get information about a previous respondent's answer:
 - For some questions, you will see another participant's answer to the question and the participant's confidence in their answer, on a scale from 0% to 100%. 0% means the respondent was not at all certain, 100% means the respondent was fully certain.
 - For other questions, you will only see the participant's answer.
3. You have a second chance to provide your best answer to the question. Your answer may or may not be different from your response in (1), given what you learned about the other participant's answer in (2).

The confidence question previous respondents were asked was exactly like the confidence question you will be asked after giving your answers in each round.

Bonus Payment

At the end of the survey, one out of every ten participants is randomly selected to be eligible for an additional bonus of up to \$10. If you are selected for the bonus payment:

- One of the 15 rounds you have answered will be randomly chosen.
- Either your answer from step (1) or your answer from step (3) will be randomly chosen.
- You will receive the bonus of \$10 if you selected the correct answer.

Participants who gave the previous answers were informed they had a chance to win a bonus of \$10 if you selected the correct answer. They were also informed that you had a chance to win a bonus of \$10 if you selected the correct answer.

Comprehension Questions

Please answer the comprehension questions below. Note that if you fail them twice in a row, you will not be eligible for the completion payment.

In this study, you will read a number of explanations on different questions. Which one of the following statements is true?

- Before each of the 15 questions I'll be asked, I will see what a previous respondent answered and how confident they were.
- Before each of the 15 questions I'll be asked, I will see what a previous respondent answered.
- On some of the 15 questions I'll be asked, I might see what a previous respondent answered and how confident they were. On other questions, I will see what the previous respondent answered.

Which one of the following statements is true?

- Confidence is expressed as a sentence such as "I am not very confident" or "I'm extremely confident."
- Confidence is expressed as a percentage from 0% to 100%.

Which one of the following statements is true?

- The answers I choose have no effect on my expected bonus.
- I maximize my expected bonus by selecting my best answer to each question.

Main Part: Example Question (Inflation)

[Prior Choice:] Provide Your Best Answer

Please answer what you think is the correct answer to the question.

Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, would you be able to buy:

1. More than today
2. Exactly the same as today
3. Less than today

How certain are you that your above answer is correct?

[Slider from 0% (Not at all certain) to 100% (Fully certain)]

[Choice & Confidence Treatment:]

Read the other respondent's answer

[Box with question text]

Other person's answer:

[Answer of other respondent]

Other person's confidence:

[Confidence of other respondent, from 0% to 100%]

[Choice Only Treatment:]

Read the other respondent's answer

[Box with question text]

Other person's answer:

[Answer of other respondent]

[Posterior Choice:] Provide Your Best Answer

Your answers on this page may or may not be different from your previous response, given what you learned about the other participant's answer.

Please answer what you think is the correct answer to the question.

[Question with multiple choice answer]

Your answer is correct if you selected the right answer.

How certain are you that your above answer is correct?

[Slider from 0% (Not at all certain) to 100% (Fully certain)]

Additional Questions

Did you look up any answers on the internet? Your response to this question will not affect your payment. Please answer truthfully.

- Yes
- No

[Followed, on a separate page, by elicitation of sex, age, ethnicity, education, employment and political affiliation.]

P Survey: Richness manipulation receiver experiment

Welcome

In this survey, you will be asked questions on various topics. This study is designed for computer (PC or Mac) users only (desktop, laptop, etc.). If you are accessing this study on a smartphone, a tablet or any other non-PC devices, please switch to PC and enter the study again, or return the submission on Prolific.

Please write at least 15 words describing your opinion about daylight savings in the United States. Whether you are in favor or against daylight savings does not affect your eligibility to participate in this study. However, we ask that you write at least 15 words on your thoughts about this topic.

[Text box]

Please also complete the captcha below.

[Captcha]

Attention Check

This question is an attention check. To be eligible to participate in this study, we simply ask you to record a voice message that lasts at least 20 seconds on your opinion about daylight savings in the United States. Whether you are in favor or against daylight savings does not affect your eligibility to participate in this study. However, we ask that you record a message that lasts at least 20 seconds.

[Recording box, activated manually]

General Instructions

This study will take approximately 25 minutes to complete. You will earn a reward of \$4.50 for completing the survey. To complete the study, you will need to read all instructions carefully and correctly answer the comprehension questions.

Survey Structure

In this study, you will be asked to answer 15 questions on various topics. Questions will have two or three possible options. Exactly one of the options is the correct answer. In each round, there are three steps:

1. You provide your best answer to the question.
2. You will see another participant's answer to the question and additionally read an edited version of the explanation they recorded.
3. You have a second chance to provide your best answer to the question. Your answer may or may not be different from your response in (1), given what you learned about the other participant's answer in (2).

When you enter a page with an explanation, the explanation will be displayed automatically. You will only be able to read it once.

We ask you not to search the answers on the internet or to use external tools:

- To confirm that you do not search for answers, the survey will monitor whether the survey window remains active.
- If you use the internet or external tools, you will not be eligible for the \$4.50 reward.
- You should remain focused on the survey window and answer questions as best you can using your previous knowledge.

Bonus Payment

At the end of the survey, one out of every ten participants is randomly selected to be eligible for an additional bonus of up to \$10. If you are selected for the bonus payment:

- One of the 15 rounds you have answered will be randomly chosen.
- Either your answer from step (1) or your answer from step (3) will be randomly chosen.
- You will receive the bonus of \$10 if you selected the correct answer.

Participants who made the recordings were informed they had a chance to win a bonus of \$10 if you selected the correct answer. They were also informed that you had a chance to win a bonus of \$10 if you selected the correct answer.

Comprehension Questions

Please answer the comprehension questions below. Note that if you fail them twice in a row, you will not be eligible for the completion payment.

In this study, you will read a number of explanations on different questions. Which one of the following statements is true?

- Before each of the 15 questions I'll be asked, I will read an explanation written by the researchers behind this survey.
- Before each of the 15 questions I'll be asked, I will only see what a previous respondent answered.
- Before each of the 15 questions I'll be asked, I will read an edited version of an explanation recorded by a previous respondent.

Which one of the following statements is true?

- Previous respondents typed their explanations into a text box.
- Previous respondents recorded their explanations as voice messages which were then automatically transcribed and edited.

Which one of the following statements is true?

- The answers I choose have no effect on my expected bonus.
- I maximize my expected bonus by selecting my best answer to each question.

Main Part: Example Question (Inflation)

[Prior Choice:] Provide Your Best Answer

Please answer what you think is the correct answer to the question.

Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, would you be able to buy:

1. More than today
2. Exactly the same as today
3. Less than today

How certain are you that your above answer is correct?

[Slider from 0% (Not at all certain) to 100% (Fully certain)]

[Rich or Sparse Version Treatment:]

Read the other respondent's explanation

[Box with question text]

Other person's answer:

[Answer of other respondent]

Other person's explanation:

[Transcript of explanation, displayed progressively]

[Posterior Choice:] Provide Your Best Answer

Your answers on this page may or may not be different from your previous response, given what you learned about the other participant's answer.

Please answer what you think is the correct answer to the question.

[Question with multiple choice answer]

Your answer is correct if you selected the right answer.

How certain are you that your above answer is correct?

[Slider from 0% (Not at all certain) to 100% (Fully certain)]

Additional Questions

Did you look up any answers on the internet? Your response to this question will not affect your payment. Please answer truthfully.

- Yes
- No

[Followed, on a separate page, by elicitation of sex, age, ethnicity, education, employment and political affiliation.]

Q Survey: Balls-and-urns orator experiment

Welcome

In this survey, we will ask you to record voice messages to answer different questions. The study is designed for computer (PC or Mac) users only (desktop, laptop, etc.). Please make sure you are in a quiet environment. You will only receive your completion payment if your voice is clearly recorded.

You are eligible for a bonus of \$10 for one of your recordings! The details of how you might receive a bonus will be explained on the following pages.

For each question, your recording will actually be played to another respondent. The other respondent will have to answer the same question as you after listening to your recording.

Privacy & Anonymity

All voice messages are treated strictly anonymously. They will never be linked to your person and will never be published anywhere. This data will be used solely for academic research. You can therefore talk freely and informally in each voice message. The other respondent who will listen to your voice recording will not be given any more information about you: your anonymity will be preserved.

Test Your Microphone

Use the recorder below to test your microphone. Click “Record”, say the sentence “The dog runs in the park.”, then click “Stop Recording & Submit”. You may have to give your browser permission to access the microphone after you click “Record”. After a recording, it might take the website a few seconds to upload your recording: please be patient.

Trial Question

This trial question is an attention check. To be eligible to participate in this study, we simply ask you to record a voice message that lasts at least 20 seconds on your thoughts about this topic. There is no correct answer, and it does not matter what you say, as long as you record a message that lasts at least 20 seconds.

On how many days in 2025 will the average temperature recorded across all of the

U.S. be below 65°F?

[Recording box, activated manually]

General Instructions

Thanks for recording your first voice message! This study will take approximately 10 minutes to complete. You will earn a reward of \$2.00 for completing the survey. To complete the study, you will need to read all instructions carefully and correctly answer the comprehension questions.

Survey Structure

We are interested in how you would give advice in an informal conversation:

- You should share an explanation behind your response.
- Your recording will be played to a few other participants who will have to respond to the same question.
- Other participants can win a bonus for selecting the correct answer.

Importantly:

- You should first read the question, think about your response, and then record your answer.
- The recording begins once you click “Start Recording”.
- After you click to submit a recording, it can take a little while to upload. We kindly ask you to be patient.

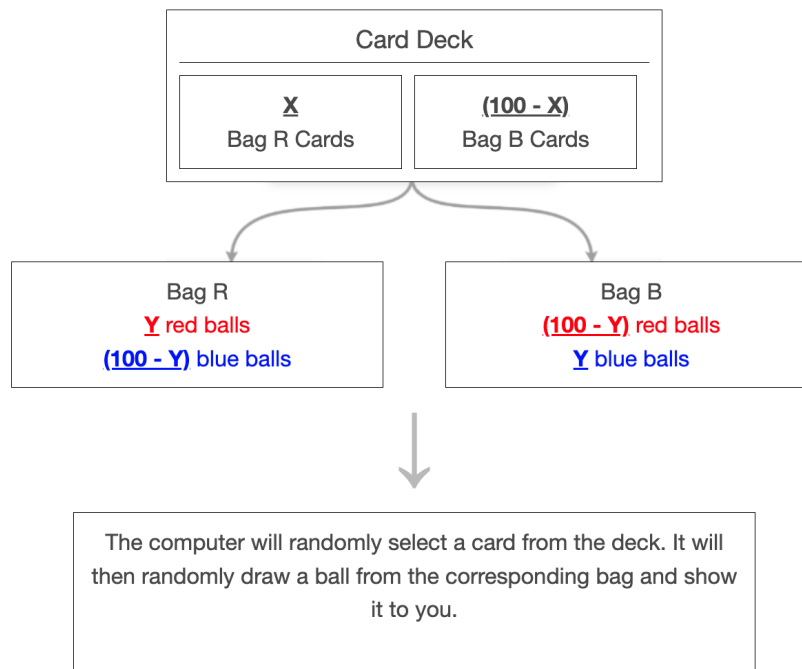
We ask you not to search the answers on the internet:

- We are interested in the explanations behind your answer.
- To confirm that you do not search for answers, the survey will monitor whether the survey window remains active.
- If you leave the browser tab of this survey, you will not be eligible for the \$2.00 reward.
- You should remain focused on the survey window and answer questions as best you can using your previous knowledge.

The Task

In this study, your task is to guess which of two bags was secretly selected by a computer. As a hint, you will see a colored ball that was drawn from the secretly-selected bag.

The setup is as follows:



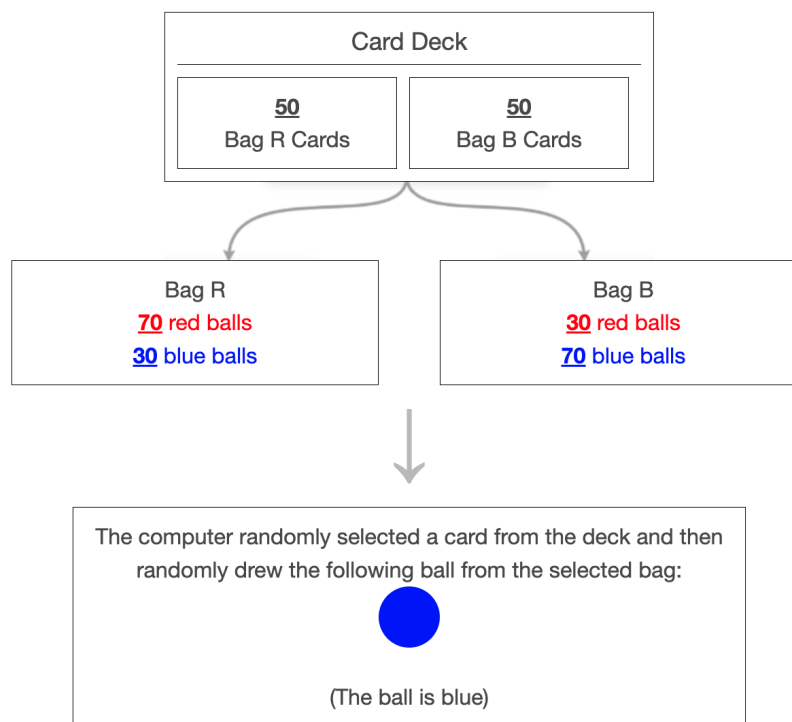
- There is a deck of 100 cards, some of which have “Bag R” written on them and some of which have “Bag B” written on them. We denote the number of cards with Bag R on them by “ X ” (the number of cards with Bag B is $100 - X$).
- There are two bags, Bag R and Bag B. Both bags contain 100 balls each, some of which are red and some of which are blue. Bag R always contains at least as many red balls as blue balls and Bag B always contains at least as many blue balls as red balls. It is always the case that the number of red balls in Bag R is equal to the number of blue balls in Bag B. We denote this number by “ Y ”.
- For example, Bag R might contain 95 red balls and 5 blue balls, and so Bag B would contain 5 red balls and 95 blue balls.

The task proceeds as follows:

1. You will be told how many cards have "Bag R" vs. "Bag B" written on them.

2. You will be told how many balls in Bag R and Bag B are red or blue.
3. The computer will randomly select one of the 100 cards. If the card has "Bag R" written on it, the computer selects Bag R. If the card has "Bag B" written on it, the computer selects Bag B. You will not observe which card was drawn, so you will not know for sure which bag was selected.
4. The computer will then randomly draw one ball from the selected bag and show it to you.
5. You will then be asked to provide a percentage chance to indicate how likely you think it is that the computer selected Bag R or B.

Example



- In the example above, there are 50 cards labeled "Bag R" and 50 cards labeled "Bag B". Bag R contains 70 red and 30 blue balls and bag B contains 30 red and 70 blue balls.
- A blue ball was drawn.

- You would then tell us the percentage chance you think the computer selected Bag R, based on the information provided.

Your certainty

During the task:

- You will tell us the percentage chance you think the computer selected Bag R.
- We will ask you how certain you are about your answer. Specifically, we are interested in how likely you think it is (in percentage terms) that your answer is within ± 3 percentage points of the statistically correct answer.

Bonus payment

At the end of the survey, one out of every ten participants is randomly selected to be eligible for an additional bonus of up to \$10. If you are selected for the bonus payment:

- One of the participants who listened to your answer will be randomly chosen.
- You will receive \$10 if the participant's answer is within ± 3 percentage points of the statistically correct answer.
- You should therefore give your explanation in a way that makes the other respondent most likely to select the correct answer!

Much like you, participants listening to your recordings will have a chance to win a bonus of \$10 if their answer is within ± 3 percentage points of the statistically correct answer. Moreover, participants listening to your recordings will be informed that you will receive a bonus if they select an answer within ± 3 percentage points of the statistically correct answer.

Comprehension Questions

Please answer the comprehension questions below. Note that if you fail them twice in a row, you will not be eligible for the completion payment.

In this study, you will record a voice message on a question. Which one of the following statements is true?

- I should answer as if I'm talking to myself because the recording will never be played to another person.
- I should give a well-rehearsed response as I'm giving a speech to a large audience of people that I don't know.

- I should share an explanation behind my response as if I were to give advice in an informal conversation. My response will be shared with other participants who later have to respond to the same question.

Which one of the following statements is true?

- On questions where I will be recorded, each recording only starts once I click “Start Recording” on a page.
- On questions where I will be recorded, each recording starts as soon as I enter a page.

Which one of the following statements is true?

- I can leave the tab of the experiment to search for answers online without consequences on my payment.
- If I leave the tab of the experiment, I will not be paid.

Which one of the following statements is true?

- When I’m asked to indicate my certainty about my decision, the people running this study are interested in how certain I am that my estimate of the percentage chance that Bag R was selected is statistically correct.
- When I’m asked to indicate my certainty about my decision, the people running this study are interested in how certain I am that Bag R was selected.

Which one of the following statements is true?

- If the computer draws a card with “R” on it from the deck of cards, it will draw a ball from Bag R and show it to me.
- If the computer draws a card with “R” on it from the deck of cards, it will draw a ball from a randomly selected bag and show it to me.

Which one of the following statements is NOT true?

- Bags R and B always have the same proportion of red and blue balls.
- Bag R always has at least as many red balls as blue balls.
- Bag B always has at least as many blue balls as red balls.

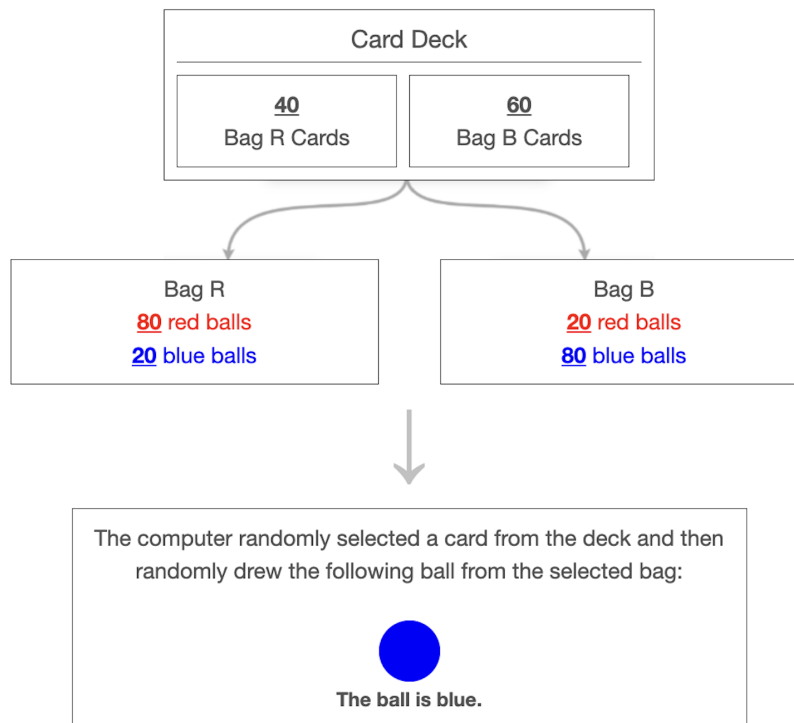
Remember!

Your chances of receiving the bonus payment are highest if the other participant chooses the correct answer.

Main Part

On the next page, the main task will be displayed. You should first read the question, think about your response and then record your answer. The recording begins once you click "Start Recording". After recording your explanation, you will select your own answer to the question.

Read the question, then record your explanation!



Given that this ball was drawn, how likely do you think it is that Bag R (as opposed to Bag B) has been selected?

Record an explanation that helps the other participant select the correct answer.

[Recording box, activated manually]

Provide your best answer

Please answer what you think is the correct answer to the question.

Given that this ball was drawn, how likely do you think it is that Bag R (as opposed to Bag B) has been selected?

[Input X] % likely that Bag R was selected.

[$100 - X$] % likely that Bag B was selected.

How certain are you that your above answer is within ± 3 percentage points of the statistically correct answer?

[Slider from 0% (Not at all certain) to 100% (Fully certain)]

Additional Questions

Your answer to the following question will not affect your reward or bonus payment for this study, so please answer honestly. Did you search the answer to the question or use external tools, like an AI assistant, before providing your advice or your own answer?

- Yes
- No

[Followed, on a separate page, by elicitation of sex, age, ethnicity, education, employment and political affiliation.]

R Survey: Balls-and-urns receiver experiment

Welcome

In this survey, you will be asked to make an estimate. Besides providing your estimate, you might listen to a voice message of someone else's thoughts on the correct estimate. The study is designed for computer (PC or Mac) users only (desktop, laptop, etc.) and only works on Firefox and Chrome.

Voice messages from previous participants

Before providing your estimate, you may be asked to first listen to a voice message from another participant. In a previous survey, we asked respondents to record their thoughts on the same estimation task.

Test your speaker

Use the play button below to test your speaker. Click “Play” to play back a voice message and select the sentence that you heard in the text box below.

[Play button screenshot here]

Please select the sentence that you listened to in the voice message above:

- The koala climbs up the tree.
- The dog runs in the park.
- The lion looks at the gazelle.
- The cat waits for the mouse to come back.
- The fox sneaks through the garden.
- The turtle swims in the sea.

General Instructions

This study will take approximately 10 minutes to complete. You will earn a reward of \$2 for completing the survey. To complete the study, you will need to read all instructions carefully and correctly answer the comprehension questions.

Survey Structure

In this study, you will be asked to complete an estimation task. In each round, there are four steps:

1. You provide your best answer to the task.
2. You get information about a previous respondent’s answer:
 - You might listen to a voice message of another participant once.
 - You might see the answer of another participant.
3. You have a second chance to provide your best answer to the task. Your answer may or may not be different from your response in (1), given what you learned about the other participant’s answer in (2).

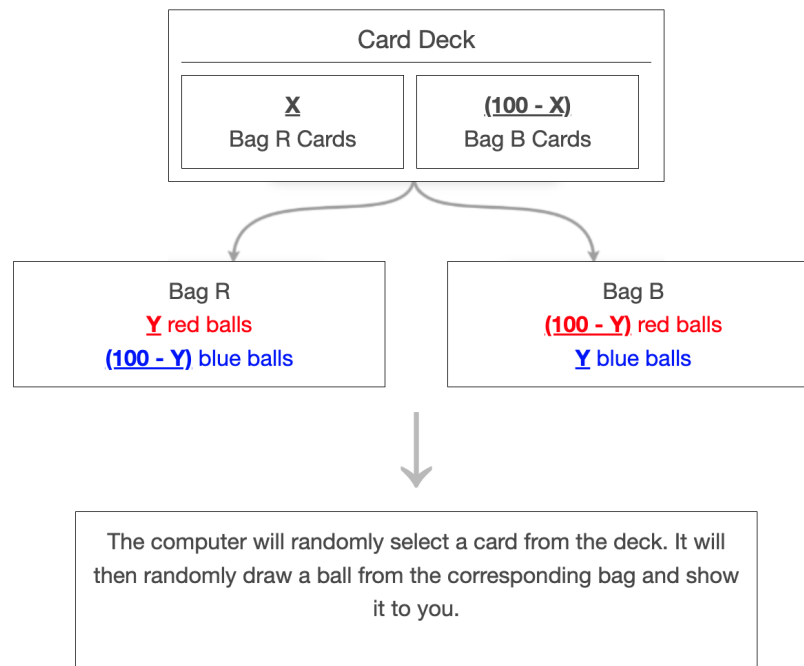
When you enter a page with a recording, the recording will play automatically. You will only be able to listen to it once.

We ask you not to search the answers on the internet or to use external tools:

- To confirm that you do not search for answers, the survey will monitor whether the survey window remains active.
- If you leave the browser tab of this survey, you will not be eligible for the \$2 reward.
- You should remain focused on the survey window and answer questions as best you can using your previous knowledge.

The Task

In this study, your task is to guess which of two bags was secretly selected by a computer. As a hint, you will see a colored ball that was drawn from the secretly-selected bag.



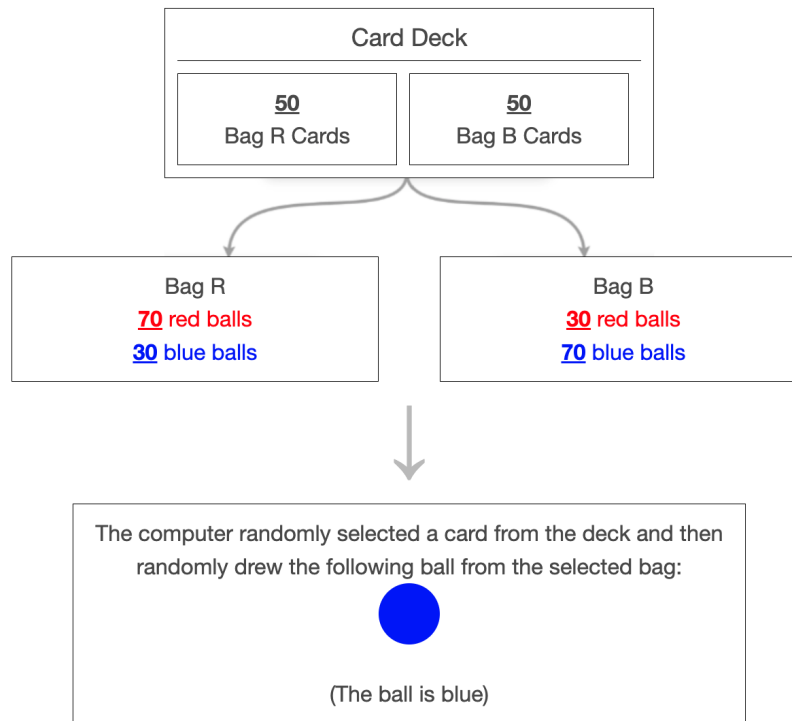
- There is a deck of 100 cards, some of which have “Bag R” written on them and some of which have “Bag B” written on them. We denote the number of cards with Bag R on them by “ X ” (the number of cards with Bag B on them is $100 - X$).
- There are two bags, Bag R and Bag B. Both bags contain 100 balls each, some of which are red and some of which are blue. Bag R always contains at least as many red balls as blue balls, and Bag B always contains at least as many blue balls as red balls. It is always the case that the number of red balls in Bag R is equal to the number of blue balls in Bag B. We denote this number by “ Y ”.

- For example, Bag R might contain 95 red balls and 5 blue balls, and so Bag B would contain 5 red balls and 95 blue balls.

The task proceeds as follows:

1. You will be told how many cards have "Bag R" vs. "Bag B" written on them.
2. You will be told how many balls in Bag R and Bag B are red or blue.
3. The computer will randomly select one of the 100 cards. If the card has "Bag R" written on it, the computer selects Bag R. If the card has "Bag B" written on it, the computer selects Bag B. You will not observe which card was drawn, so you will not know for sure which bag was selected.
4. The computer will then randomly draw one ball from the selected bag and show it to you.
5. You will then be asked to provide a percentage chance to indicate how likely you think it is that the computer selected Bag R or B.

Example



- In the example above, there are 50 cards labeled "Bag R" and 50 cards labeled "Bag B". Bag R contains 70 red and 30 blue balls and Bag B contains 30 red and 70 blue balls.
- A blue ball was drawn.
- Step 1: You enter the percentage chance you think the computer selected Bag R, based on the information provided.
- Step 2: You see a randomly drawn other participant's answer, and you may listen to their explanation. Note: that participant saw exactly the same problem, including the same draw of the ball.
- Step 3: You enter the percentage chance you think the computer selected Bag R, based on the information provided and the other participant's answer.

Your certainty

During the task:

- You will tell us the percentage chance you think the computer selected Bag R.

- We will ask you how certain you are about your answer. Specifically, we are interested in how likely you think it is (in percentage terms) that your answer is within ± 3 percentage points of the statistically correct answer.

Bonus payment

At the end of the survey, one out of every ten participants is randomly selected to be eligible for an additional bonus of up to \$10. If you are selected for the bonus payment:

- Either your answer from step (1) or your answer from step (3) will be randomly chosen.
- You will receive \$10 if your answer is within ± 3 percentage points of the statistically correct answer.

Participants who made the recordings were informed they had a chance to win a bonus of \$10 if you selected an answer within ± 3 percentage points of the statistically correct answer. They were also informed that you had a chance to win a bonus of \$10 if you selected an answer within ± 3 percentage points of the statistically correct answer.

Comprehension Questions

Please answer the comprehension questions below. Note that if you fail them twice in a row, you will not be eligible for the completion payment.

1. In this study, you will listen to a number of voice messages on different questions. Which one of the following statements is true?
 - I will listen to a voice message from another respondent about the task.
 - I will see what another respondent answered on the task.
 - I might listen to a voice message from another respondent about the task, or see what another respondent answered on the task.
2. Which one of the following statements is true?
 - On a page with a voice recording, the recording only starts playing once I click "Play".
 - On a page with a voice recording, the recording starts playing automatically when I enter, so I should read the question and pay attention to the recording.
3. Which one of the following statements is true?

- The answers I choose have no effect on my expected bonus.
- I maximize my expected bonus by selecting my best answer to each question.

4. Which one of the following statements is true?

- When I'm asked to indicate my certainty about my decision, the people running this study are interested in how certain I am that my estimate of the percentage chance that Bag R was selected is statistically correct.
- When I'm asked to indicate my certainty about my decision, the people running this study are interested in how certain I am that Bag R was selected.

5. Which one of the following statements is true?

- If the computer draws a card with "R" on it from the deck of cards, it will draw a ball from Bag R and show it to me.
- If the computer draws a card with "R" on it from the deck of cards, it will draw a ball from a randomly selected bag and show it to me.

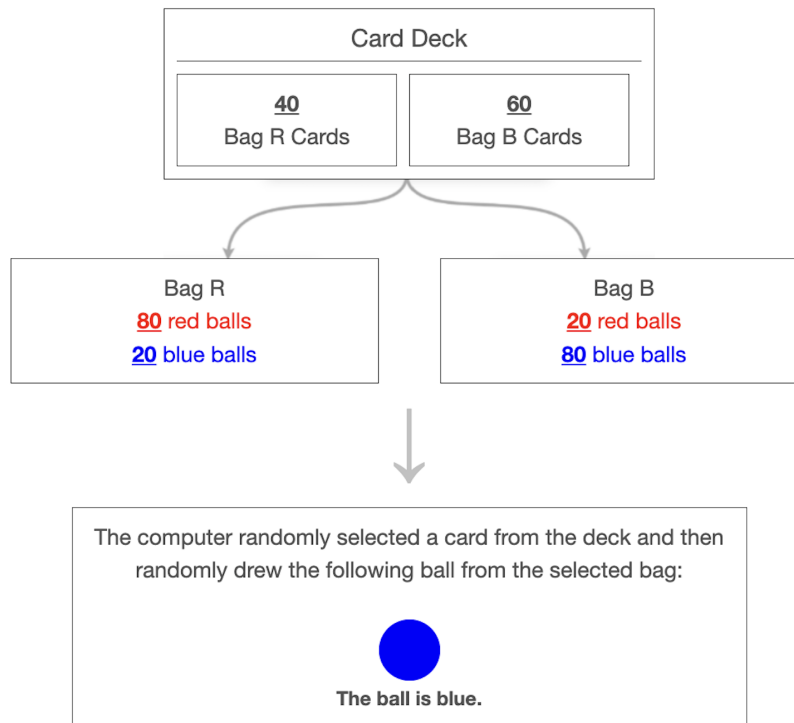
6. Which one of the following statements is NOT true?

- Bags R and B always have the same proportion of red and blue balls.
- Bag R always has at least as many red balls as blue balls.
- Bag B always has at least as many blue balls as red balls.

Main Part

On the next page, the main task will be displayed.

[Prior Choice:] Provide your best answer



Given that this ball was drawn, how likely do you think it is that Bag R (as opposed to Bag B) has been selected?

[Input X]% likely that Bag R was selected.

[100 – X]% likely that Bag B was selected.

How certain are you that your above answer is within +/- 3 percentage points of the statistically correct answer?

[Slider from 0% (Not at all certain) to 100% (Fully certain)]

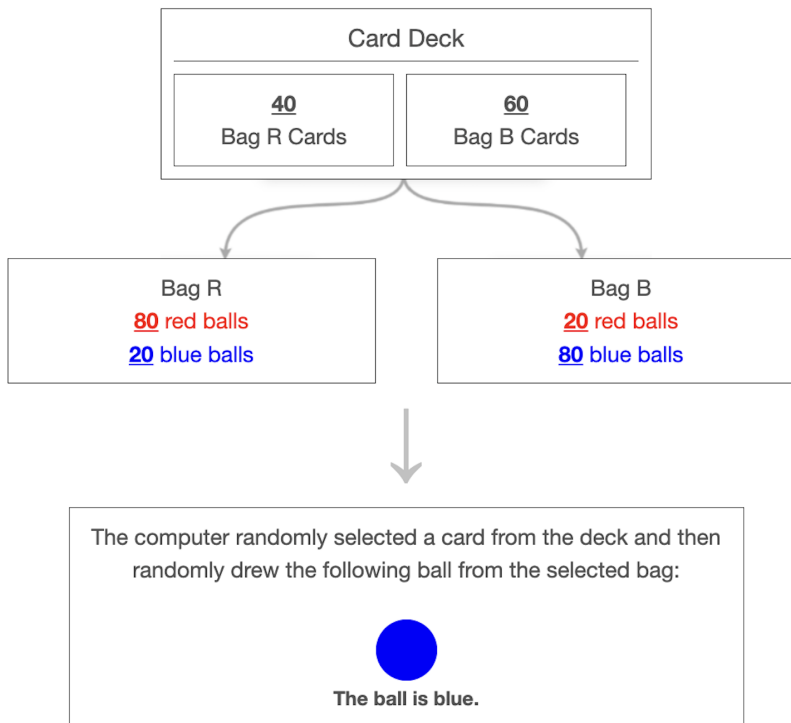
[Explanation Treatment:]

Now, you will listen to a recording of a voice message from a previous respondent who shares the explanation behind their answer to the exact same question that you just answered. The voice message will automatically start playing.

Please listen closely to the recording.

You will be able to proceed to the next page once the recording has finished playing.

[PAGEBREAK]



Listen to the other respondent's answer

Other person's answer:

[Answer of other respondent]

[Recording of other respondent, on auto-play]

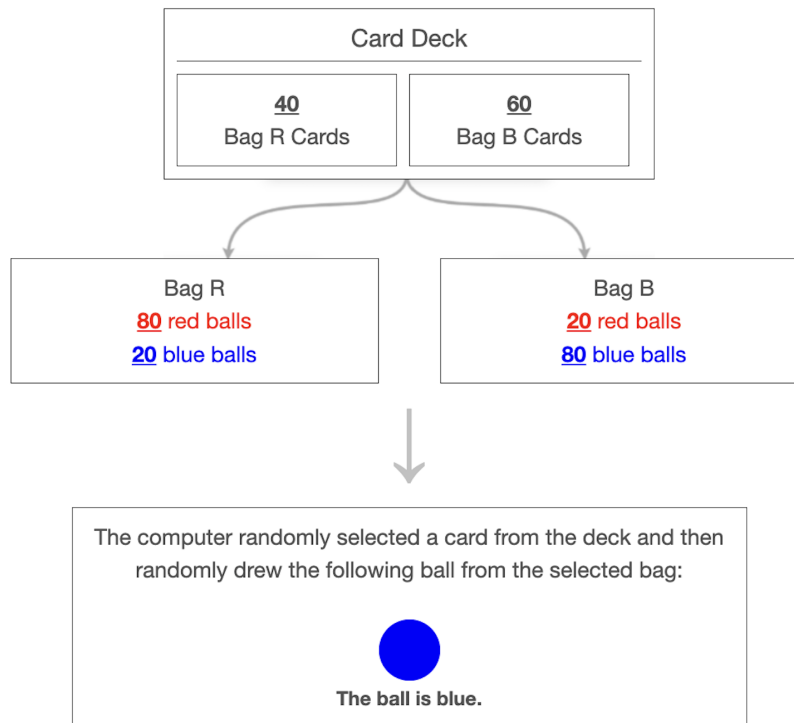
[Choice Only Treatment:]

Now, you will observe the answer from a previous respondent.

Please pay close attention to the other person's answer.

[PAGEBREAK]

Read the other respondent's answer



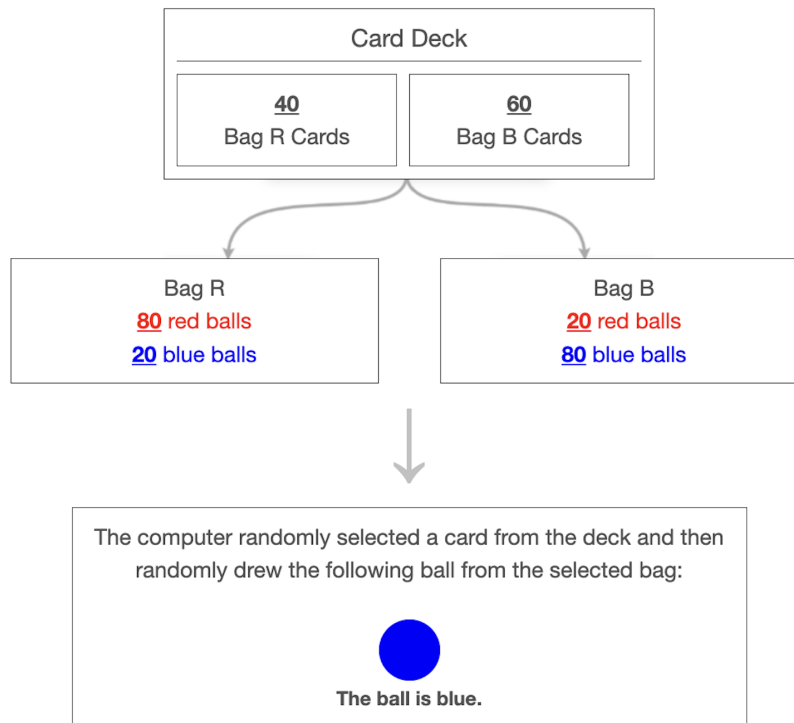
Other person's answer:

[Answer of other respondent]

[Posterior Choice:] Provide Your Best Answer

Your answers on this page may or may not be different from your previous response, given what you learned about the other participant's answer.

Please answer what you think is the correct answer to the question.



Given that this ball was drawn, how likely do you think it is that Bag R (as opposed to Bag B) has been selected?

[Input X]% likely that Bag R was selected.

[100 – X]% likely that Bag B was selected.

How certain are you that your above answer is within +/- 3 percentage points of the statistically correct answer?

[Slider from 0% (Not at all certain) to 100% (Fully certain)]

Additional Questions

Your answer to the following question will not affect your reward or bonus payment for this study, so please answer honestly.

Did you search the answer to the question or use external tools, like an AI assistant, before providing your advice or your own answer?

- Yes
- No

[Followed, on a separate page, by elicitation of sex, age, ethnicity, education, employment and political affiliation.]