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ECONtribute

Discussion Paper No. 291

Explanations

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April 2024

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EXPLANATIONS*

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Abstract

When people exchange ideas, both truths and falsehoods can proliferate. We study the role of explanations for the spread of truths and falsehoods in 15 financial decision tasks. We pay participants to record the reasoning behind each of their answers, 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 their explanation before making their own choice. Listening to explanations strongly improves aggregate accuracy. This effect is asymmetric: 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 exhibit a significantly richer message space and 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, Financial Reasoning.

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1 Introduction

We obtain most ideas, news and knowledge from listening to others (Hirshleifer, 2020). 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*:¹ the truth will emerge and prevail in an environment where thoughts and opinions are freely exchanged. Yet, misbeliefs can spread rapidly, too, whenever individuals systematically fail to identify falsehoods (Lazer et al., 2018; Pennycook and Rand, 2021). 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 exchange of ideas are explanations: people share justifications for and reasoning behind their beliefs and choices, often conveyed by word of mouth from peer to peer (Shiller, 2020). Unlike in canonical models of social learning, people do not only learn from *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; Brown et al., 2008).

We run a series of pre-registered experiments using a design comprising two separate experiments with different sets of respondents. We start with an Orator experiment that characterizes the *supply of explanations*. Respondents complete 15 canonical financial decision problems culled from the existing literature. 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. There is an objectively correct or consensus answer in financial economics for each question, allowing us to characterize mistakes. 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 increases in the accuracy of the listener’s subsequent response to the question.

To study the *interpretation of explanations* and its consequences for social learning, we then conduct a Receiver experiment, in which respondents face the same 15 tasks. They first make their own incentivized choice. Within-person and across tasks, 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

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

choice, which may now differ from their initial choice. 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 from mere observation 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 effects.

We begin by analyzing how explanations shape aggregate optimality rates. Just observing someone else's answer increases the average frequency of optimal choices in the sample from 55.4% to 59.5% (treatment *Choice Only*, $p < 0.01$). Explanations boost the aggregate improvement from exposure to others: across all tasks, explanations raise the accuracy rate from 55.2% to 62.7% (*Explanation*, $p < 0.01$). The treatment effect of *Explanation* is 82% higher than that of *Choice Only* ($p < 0.01$).

To understand the drivers of the aggregate effect on optimality, we focus on receivers who are confronted with an answer that *conflicts* with their own prior answer. First, those with incorrect priors may learn from correct choices, creating learning opportunities. Second, those with correct priors might encounter incorrect choices, leading to unlearning opportunities. We find that the aggregate benefit of explanations over merely observing someone's answer is entirely driven by learning opportunities: in those cases, the imitation rate is 55.8% in *Explanation* but only 42.8% in *Choice Only* ($p < 0.01$). This corresponds to a 30.4% increase in seizing learning opportunities through explanations. 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 the unlearning conditions in *Choice Only* and *Explanations*, respectively ($p = 0.87$). Asymmetric learning emerges in 14 out of 15 tasks, among listeners with weakly and strongly held priors, and is robust to various sample restrictions.

What is the economic interpretation of this treatment effect of explanations? To develop a better understanding, we cast our treatments in a standard belief formation model. The model illustrates that the treatment effect can only arise from how explanations shape the perceived accuracy of the orator's answer. This raises the question of whether the impact of explanations is akin to observing the orator's numerically expressed confidence. To test this hypothesis, 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 stated confidence does not significantly shift imitation in learning and unlearning opportunities. Therefore, an explanation is a signal of accuracy that is different from the orator's subjective, 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' be-

havior. To distinguish between these two channels, we design an additional Receiver study, in which respondents read the transcript of the matched orator’s explanation instead of listening to the corresponding recording. This preserves the exact verbal content conveyed by the explanation while eliminating the role of the speaker’s delivery using their voice. A strongly asymmetric effect of explanations on learning and unlearning persists in the *Transcript* treatment, suggesting that it is primarily driven by the supply and interpretation of the *content* of explanations. While we exactly replicate the average null effect of explanations in unlearning situations of the *Transcript* treatment, there is a 8.1 p.p. increase of the imitation rate in learning opportunities (relative to *Choice Only*), which equals 62% of the effect size induced by the *Explanation* treatment.

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 answer this question, we conduct a mechanism analysis that systematically explores the two margins of variation that could shed light on the asymmetry: first, it may arise from content differences in the supply of explanations. Second, different effects on imitation rates might result from differences in the characteristics of participants in learning versus unlearning situations.

In the first step of our mechanisms analysis, we characterize the content of the more than 6,900 naturally provided 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 the substantive content that rationalizes the answer to a question: specifically, they provide *arguments*. Arguments tend to be domain-specific; they 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 markers of certainty, linguistic and rhetorical features, and can be described by speech and text metrics, among others. We code a large collection of text features culled from the existing literature. These features are domain-general in the sense that they similarly apply to explanations for different questions and answers. We employ a combination of dual human coding, a large language model and machine learning methods to analyze the universe of our explanation transcripts in a robust and replicable manner.

Our argument annotation delivers, for each of the 15 tasks, the collection of all naturally provided arguments, their frequency in explanations for correct versus incorrect choices, and estimates of their idiosyncratic effects on imitation rates. The resulting dataset is comprehensive and can be analyzed both at the level of individual tasks and by aggregating across tasks. To illustrate our results at the task level, consider the question of whether actively managed investment funds systematically outperform passively managed ones in terms of expected net returns. The most frequent argument

is that active funds—unlike passively managed ones—can quickly adapt to changes in the market, which is present in 57.2% of the explanations for incorrect answers but almost absent (2.9%) from explanations for correct answers. The second most common one argues that active funds charge higher fees, which is prominent among explanations for correct answers (22.7%) and nearly absent from those for incorrect answers (3.2%). In total, we identify 11 unique arguments. Among the most effective ones are the one on active funds being able to react to the market—in unlearning situations—and the argument that passive funds target long-term growth—in learning situations—, both of which raise imitation rates by more than 20 p.p. relative to *Choice Only*. We discuss patterns of heterogeneity in the number of arguments, the degree of consensus and variation in the effects on imitation across tasks. This angle on the data delivers unprecedented access to the nature of people’s reasoning about a given topic and its likelihood of influencing others, but does not yet shed light on the drivers of the asymmetric treatment effect, since the substantive content of arguments is naturally difficult to compare across tasks.

To draw broader conclusions about differences between explanations for correct and incorrect choices based on our argument data, we define four classes of arguments with increasing “quality:” (i) the absence of any argument, (ii) irrelevant arguments, i.e., off-topic reasoning, (iii) fallacious arguments in which the premises are false or do not establish the conclusion and (iv) sound arguments, which have true premises and a valid conclusion. We find large differences in the prevalence of the different argument classes between learning and unlearning opportunities. While respondents in unlearning opportunities are more likely to encounter no (21.8% vs. 16.0% in learning), irrelevant (22.6% vs. 17.7%), or fallacious arguments (51.0% vs. 10.5%), respondents in learning opportunities are more likely confronted with sound arguments (55.8% vs. 4.7% in unlearning).

Are these different argument classes associated with different effects on imitation rates? Reassuringly, higher-quality arguments are associated with higher effects on imitation rates. Yet, even conditional on encountering an argument from the same class, the impact on imitation rates remains far higher in learning than in unlearning situations. In fact, we find that the argument gap in explanations at most accounts for 25% of the asymmetric effect.

What content features other than the quality of arguments drive the asymmetry? We turn to an analysis of the second component of our content annotation approach, domain-general speech and text features, such as certainty markers. While this analysis reliably confirms intuitions about the prevalence of specific features, the core insight is that explanations for correct answers reflect a significantly *richer* message space: they contain more occurrences of most features. Indeed, 24 out of 31 features more frequently occur in explanations for learning opportunities. This finding is corroborated by a quantitative, pre-registered measure of richness annotated using a large language model.² The average richness score of explanations for correct choices is 0.76 SD higher than for

²In our annotation with GPT-4, we define rich explanations as detailed, comprehensive, logically structured, nuanced, and tailoring the argument to fit the context, while a sparse explanation is basic, narrow, unclear or disorganized, presenting only surface-level understanding, lacking depth or specific details and

incorrect choices.³

Can these differences in the features and richness of explanation content, then, account for the asymmetric treatment effect? First, we test to which extent different explanation features are predictive of imitation per se, revealing that the richness of a message is by far the strongest predictor in regressions that account for the correlation of features. A one-standard deviation increase in the richness score is associated with a 11.8 p.p. higher imitation rate, relative to not receiving an explanation. The strong benefit of richer explanations suggests an interesting relationship with the principle of *Occam's Razor*, which posits that the simplest explanation is usually the preferred one. While simplicity may be valued, our findings show that comprehensiveness and detail in an explanation can enhance its social influence in the case of financial reasoning. Second, we ask to what extent differences in the richness of message spaces account for the differential effect of explanations in learning and unlearning opportunities. Our analyses suggest that the richness gap explains approximately 60% of the differential treatment effect of explanations. We conclude from our combined content analyses that the richness of explanations is likely a central determinant of imitation in general and the asymmetric effect on learning versus unlearning in particular, with argument types playing a secondary role.

In the final step of our mechanisms analysis, we study the role of participant characteristics. The observed asymmetric effect may, in part, stem from the unique characteristics of participants who make an accurate prior choice. These individuals may either have traits that, as orators, naturally make them more influential or, as listeners, leads them to interpret information in a manner that induces less imitation from explanations. Our analyses show that some orator characteristics are indeed predictive of imitation: for example, male and more educated orators induce more imitation through their explanation, whereas Black speakers are imitated less. These effects may reflect inferences made from both content and voice, but note that receivers were not explicitly informed about the orators' sociodemographics. While orator characteristics are somewhat predictive of imitation in general, they contribute virtually nothing to the asymmetric treatment effect of explanations above and beyond content. Similarly, differences in receiver characteristics do not explain away the asymmetry. If anything, accounting for differences in receiver characteristics somewhat widens the differential treatment effects.

In conclusion, our mechanism evidence suggests that content differences are the key determinant of differential treatment effects in our setting. Leveraging methods that provide direct access to *what* people communicate 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 and persuasion, which has been the

failing to clearly relate to the context.

³Note that we document this pronounced richness-truth correlation in a setting featuring aligned incentives between sender and receiver, and factual questions on which *motivated* beliefs are unlikely. The association between richness and truth may differ—and perhaps even reverse—in domains that involve incentives for persuasion and motivated beliefs. For instance, conspiracist explanations in politics can often be very rich.

focus of much of the previous literature (Cialdini, 2007, 2001; Cialdini and Goldstein, 2004).

Our paper contributes to an emerging literature on learning from qualitative information, e.g., in the form of stories (Graeber et al., 2023; Aina, 2023) and narratives (Andre et al., 2022; Kendall and Charles, 2022; Barron and Fries, 2023; Hüning et al., 2022; Shiller, 2017, 2020; Ambuehl and Thyssen, 2024; Schwartzstein and Sunderam, 2021, 2022; Andre et al., 2023; Bursztyn et al., 2023; Han et al., 2024). Barron and Fries (2023) 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. Graeber et al. (2024) examine how the process of verbal information 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. 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, 2016; Rozenblit and Keil, 2002) and arguments (Sloman et al., 1998; Sloman, 1993; Hahn and Tešić, 2023; Cheng and Holyoak, 1985; Gick and Holyoak, 1980). Our contribution lies in providing a rich characterization of the supply of qualitative explanations and in estimating their consequences for economic decisions in a controlled setting. While early work by Langer et al. (1978) shows that people are more likely to comply with a request if it is justified by a reason, irrespective of whether the reason is good or bad, we document that people are more likely to imitate choices justified by rich and sound arguments.

We further contribute to a literature that studies how social learning affects the prevalence of biases and misinformation (Hirshleifer, 2020).⁴ 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, 2021). 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. (2022) 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. Our paper differs from the previous literature in four main ways: first, we provide evidence on learning from qualitative explanations in natural

⁴Also related is the work on social learning (Mobius et al., 2015; Weizsäcker, 2010; Conlon et al., 2021; Eyster and Rabin, 2014; Mobius and Rosenblat, 2014; Banerjee, 1992; Bikhchandani et al., 1992; Jackson and Yariv, 2007; Galeotti et al., 2010; Vespa and Weizsäcker, 2023), specifically in the context of financial decisions (Ambuehl et al., 2022; Haliassos et al., 2020; Hvide and Östberg, 2015; Bursztyn et al., 2014; Akçay and Hirshleifer, forthcoming; Han et al., forthcoming; Hirshleifer et al., 2023), as well as the literature on advice giving (Schotter and Sopher, 2003; Schotter, 2003; Çelen et al., 2010; Schotter, 2023). This latter literature on advice has not specifically examined the nature and causal effect of verbal explanations on imitation decisions.

language. Second, we provide new stylized facts about the supply of explanations across 15 canonical financial decision tasks.⁵ Third, we provide new evidence that individuals are, on average, able to discern truths from falsehoods, especially when provided with explanations. Fourth, we provide new evidence that imitation decisions strongly depend on the types and richness of arguments contained in explanations.

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 (Russell and Thaler, 1985; Sonnemann et al., 2013; List, 2003; 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 (2023) studies how meta-cognition shapes social learning. Unlike those findings, ours cannot, by design, be due to meta-cognition. Instead, we examine how explanations affect perceptions of others' accuracy and thereby the proliferation of truths and falsehoods.

Our paper proceeds as follows: Section 2 describes the experimental design of our Orator and Receiver experiments. Section 3 presents our main reduced-form findings on improvements in accuracy and imitation rates in learning and unlearning opportunities. Section 4 provides a simple conceptual framework and two additional experiments that study the economic interpretation of our main findings. To dissect mechanisms underlying the main treatment effects, Section 5 examines the supply and interpretation of explanations. Section 6 examines the role of orator and receiver characteristics in explaining treatment effects. Section 7 concludes.

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 the following criteria. First, we aim for a collection that is broadly representative of the universe of reasoning biases studied in the finance literature.

⁵More broadly, our paper contributes to a literature on persuasion in finance (Mullainathan and Shleifer, 2005; Hu and Ma, 2023; Haaland and Næss, 2023).

This spans behavioral phenomena such as exponential growth bias and nominal illusion but also more specific knowledge about different asset classes and investment decisions, such as the expected returns under active versus passive investing. Second, we restrict our attention to questions with an objectively correct answer or ones where a broad consensus exists in the financial economics literature. This means that we exclude questions that rely on tastes, such as risk attitudes. Moreover, participants in our studies are made aware that a “correct” solution exists.⁶ Third, the questions should be reasonably short to describe.

To provide an example of a task with an objectively correct answer, consider the following question about the concept of inflation, with the correct answer underlined:

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?

- (i) More than today*
- (ii) Exactly the same as today*
- (iii) Less than today*

Other questions do not have an objectively correct answer but relate to a broad consensus in financial economics, such as the following one on the expected benefit of stock-picking based on public information:

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) False*

Some questions refer to basic technical knowledge on how financial markets work, such as the following one on the determinants of the value of a call option:

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) Higher volatility increases the value of a call.*
- (ii) Higher volatility decreases the value of a call.*
- (iii) Higher volatility has no effect on the value of a call.*

⁶The effect of explanations on imitation choices might be different in settings where people think that no correct answer exists.

Finally, we include questions about recent financial market innovations that are widely discussed in public such as those related to crypto currencies:

Since the blockchain is decentralized, most Bitcoin mining is done by many small miners.

(i) *True*

(ii) *False*

We embrace that the differences across these tasks will likely evoke structurally different explanations. For example, 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 are simply unsure about what is right. This difference captures two separate important features of bias in practice and may be reflected in explanations as we discuss in the following sections. Table 1 outlines the motivation and origin of the different tasks, while Appendix Table A1 shows the exact wording of all questions. Note that the tasks vary in the number of response options: some have two options, such as whether actively or passively invested funds yield higher net returns. Others have three answers, such as the question about the disposition effect. In most of our 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. The full set of instructions is reproduced in Appendix D.1. In the beginning, participants are told the following:

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.*

We ask respondents to not search for answers on the internet.⁸

In practice, people typically have (at least some) time to think about an explanation they are asked to give. Correspondingly, rather than forcing respondents to talk immediately upon reading

⁷Note that due to these differences across questions, one might naturally expect different frequencies of correct responses, because randomizing would create an optimality rate of 50% in a two-option problem but a rate of 33% in a three-option task. However, these features are constant across conditions and thus cannot affect treatment comparisons.

⁸We ask participants at the end of the study whether they searched for any answers. There was no penalty for indicating that they did, but we exclude those observations from our analysis. 7.0% of participants indicated that they searched for answers.

Table 1: Motivation of financial decision questions

Task	Explanation
<i>Understanding of interest rates</i>	
Nominal illusion	Failing to assess purchasing power in real terms. Taken from Lusardi and Mitchell (2007).
Exponential growth bias	Underestimating the exponential effects of compounding. Taken from Lusardi and Mitchell (2007).
Interest rates and bond prices	Assessing the interaction between interest rates and bond prices. Taken from Lusardi and Mitchell (2007).
Interest rates and stock prices	Assessing the interaction between interest rates and stock prices. Adaptation from Lusardi and Mitchell (2007).
<i>Understanding of market efficiency</i>	
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 market participants.
Disposition effect	Failing to account for the random walk movement of stock prices. Investors have a stronger tendency to sell assets at a profit than to sell at a loss.
Actively managed funds*	Overestimating the return (after fees) of actively vs. passively managed funds. Adaptation from Haaland and Næss (2023).
Good company heuristic	Failing to consider that market prices reflect available information, including growth prospects.
Home bias	Believing that firms headquartered close to home outperform better investments.
Herding	Being influenced by the “old news” from others, e.g., stories of friends, when investing.
<i>Other Financial Topics</i>	
Diversification	Assessing how investing in several different asset classes affects risk. Taken from Atkinson and Messy (2012).
Historical stock returns	Estimating average historical returns of the S&P500.
Value of a call option	Inferring how uncertainty affects the value of financial derivatives.
Bid-ask spread	Assessing knowledge about features of financial transactions.
Crypto mining*	Testing knowledge of the structure and operations of the Bitcoin network.

Notes: Questions with a * have an answer space with 2 options, all others have 3 options. See Appendix Table A1 for the complete wording of questions.

the question, we show them the question first and they decide when to start their recording. An example screen is shown in Appendix Figure A12.

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 optimal?*” 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 to 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 main 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. Chafe and Tannen, 1987; Akinnaso, 1982; Berger and Iyengar, 2013). Among other things, written text tends to be more formal, structured, pre-meditated, and requires higher cognitive effort (e.g., Bourdin and Fayol, 2002). Since written text production is exhausting and cognitively more challenging, the transcripts of orally provided explanations are substantially longer. Much of social learning follows from oral conversations, making speech recordings an ideal testing ground for studying the effect 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 the measured explanations compared to the explanations that people give spontaneously in the real world.

Timeline. Respondents (i) read introductory instructions that explain the basic study features including incentives; (ii) are required to pass a comprehension check; (iii) read the first question and record their explanation; (iv) select their answer to the question; (v) state their confidence; then repeat (iii)-(v) for the second task and so on.

2.4 Part 2: Receiver Experiment

To characterize the effect of explanations on social learning and unlearning, we conduct a Receiver experiment that leverages the choices and recordings provided in the Orator experiment. We provide the full set of instructions in Appendix D.2.

As in the Orator experiment, respondents iterate through 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* treatment) or additionally listen to the recording of their explanation (*Explanation* treatment). Fourth, the receiver again has an opportunity to select their preferred choice with incentives for accuracy, providing the posterior belief. 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 the *Choice Only* condition. We oversample the *Explanation* condition to obtain the statistical power needed to examine heterogeneous effects by features of the explanations.

The comparison between *Explanation* and *Choice Only* allows us to identify the specific effect of listening to a recording providing an explanation on learning and unlearning, above and beyond the mere observation of another respondent’s choice. The *Choice Only* condition is critical for controlling for (i) the effects of 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.⁹

Incentives. Respondents have a 10% chance of being eligible for an additional \$10 bonus payment. Whether they receive the bonus or not 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.

⁹We compare the effect of an explanation to simply observing the orator’s choice and confidence score (Section 4.2) and the effect of reading an explanation’s content to hearing it delivered orally (Section 4.3).

Timeline. Respondents (i) read computerized instructions; (ii) are required to pass a comprehension check; (iii) provide their best answer to the first question and state their confidence; (iv) see the answer of a respondent in the Orator experiment in *Choice Only* and listen to their explanation in the *Explanation* condition; (v) provide their best answer and state their confidence again; then repeat steps (iii)-(v) for the second task and so on.

2.5 Logistics

Respondents in both studies received a 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 (Eyal et al., 2021). The Orator experiment was run for a total of 505 U.S. respondents in December 2023, out of which 466 provided valid responses. 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 rely on an Amazon Web Services (AWS) backend to stratify and distribute recordings into our Receiver experiment. The Receiver experiment was run with 1,385 U.S. respondents in December 2023, out of which 1103 provided valid responses.¹⁰ We provide an overview of all data collections and corresponding pre-registrations in Appendix Table A2.

3 The Effects of Explanations on Social Learning

We start by providing basic descriptives about the explanations provided by our respondents. We then turn to the effects of explanations on imitation and optimality rates and break them down by learning and unlearning opportunities. Finally, we conclude this section 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. There is substantial variation in length: the 10th percentile is 11 seconds and the 90th percentile is 55 seconds. Appendix Figure A1 shows a histogram of recording lengths. The audio quality of the recordings obtained through our online experiments is high. Analyses of the audio files show that our online respondents encountered virtually no obstacles with the recording technology. Only 1.1% of recordings are unusable, typically because of a technical microphone problem or because respondents accidentally submitted it too early. Incomprehensible voice messages or high background noise

¹⁰For both experiments we exclude participants who indicated that they looked up answers to the financial decision questions online, in accordance with our pre-registration.

appear very rarely and are therefore no relevant concerns for our study. We then obtain transcripts of the recordings that preserve details and nuances of the spoken text, notably filler words such as “um” or “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 C.1 for details).¹¹ We find that 13.1% of the explanations are pure restatements of the question and/or the answer given, without adding any content matter. These may both be due to people not trying to give 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, a substantial fraction of recordings, 13.7%, contain explicit expressions of the speaker’s confidence, as the following response shows:

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.

This first look at basic descriptives suggests that the Orator experiment succeeded in providing a database of heterogeneous explanations for our set of tasks. These analyses only serve to provide a first indication of the quality and features of explanations. In Section 5, we go much further in examining their characteristics.

3.2 Explanations and Optimality Rates

We start by analyzing the effects of our treatments on the average 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 the *Choice Only* condition 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’ average knowledge about a task before learning from another respondent. The posterior optimality rate captures average accuracy after receivers observe another respondent’s answer only (*Choice Only* condition) or additionally listen to their verbal explanation (*Explanation* condition).

Figure 1 shows these optimality rates pooled across all 15 tasks. Prior to exposure, 55.4% and 55.2% of the respondents provided correct answers in the *Choice Only* and *Explanation* conditions, respectively ($p = 0.85$). We document two main findings on posterior optimality rates. 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 significantly raises the size of the improvement to 7.5 p.p. (0.15 SD, $p < 0.01$). This difference in improvement rates across

¹¹As we explain in more detail in that Appendix, we also replicate the findings with a state-of-the-art large language model, GPT-4.

the *Choice Only* and *Explanation* condition is statistically significant ($p < 0.01$) and quantitatively large: explanations induce a 82% larger improvement than mere observations of another’s choice. The analysis of optimality rates establishes that explanations, on average, have a strongly positive effect on social learning. At the same time, this average effect shrouds variation across initially correct and incorrect listeners, different tasks and explanations.

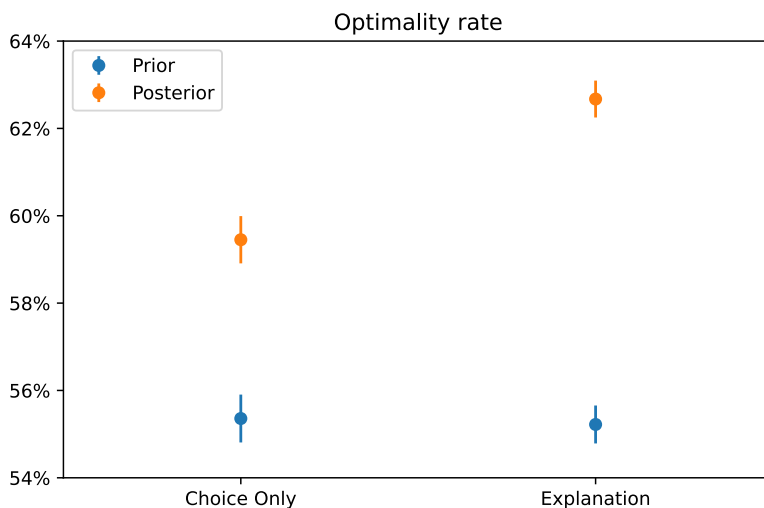


Figure 1: Prior and posterior optimality by treatment. *Notes:* Share of correct receiver choices before and after exposure to the orator’s choice (*Choice Only*) or explanation (*Explanation*). *Explanation* sample is the main Receiver survey (1,103 receivers) with 13,111 observations, *Choice Only* sample is pooled from all collections (2,733 receivers) with 8,232 observations. Whiskers show standard errors.

3.3 Explanations and Imitation Rates

As a first step, note that our sample is composed of structurally very different sets of orator-receiver matches, which are lumped together in the calculation of optimality rates. 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. Intuitively, the two groups of receivers matched with an orator who gave the same answer should not change their initial response and thus have little effect on aggregate improvements. Instead, changes of prior choices should be driven by receivers who are confronted with a conflicting choice. We therefore focus on the two groups that drive treatment effects on social learning: receivers with incorrect prior choices exposed to correct choices on the one hand, and receivers with correct choices exposed to incorrect choices on the other. We refer to these as *learning opportunities* and *unlearning opportuni-*

ties, respectively.¹² These two types of matches are equally frequent in our sample (due to random matching of receivers and orators): there are 21.2% learning opportunities and 20.3% unlearning opportunities.

Figure 2 displays the frequency of imitation in learning and unlearning opportunities. This figure illustrates two key findings. First, the unlearning rate does not differ significantly between *Choice 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 an imitation rate of 42.8% ($p < 0.01$). This 30.4% increase in the learning rate shows that, on average, explanations are highly beneficial for identifying a correct answer.

Both results together suggest a distinctive pattern in how verbal explanations causally shape learning and unlearning, which we will refer to in the following as the *asymmetric benefit of explanations*: explanations increase the spread of truths but do not curb the contagion of falsehoods.

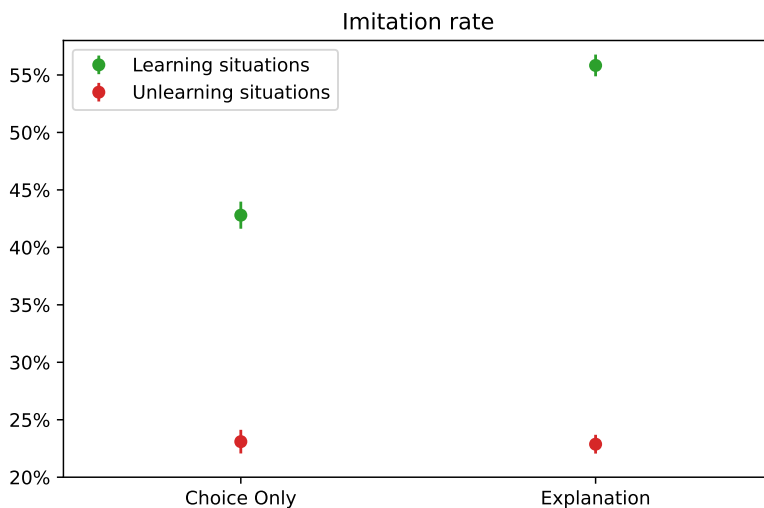


Figure 2: Imitation rate by treatment in learning and unlearning situations. *Notes:* In learning situations, initially incorrect receivers are exposed to a correct orator; in unlearning situations, initially correct receivers are exposed to an incorrect orator. *Explanation* sample is the main Receiver survey (1,103 receivers) with 2,762 learning and 2,645 unlearning observations, *Choice Only* sample is pooled from all collections (2,733 receivers) with 1,764 learning and 1,680 unlearning observations. Whiskers show standard errors.

Result 1. *Listening to another respondent’s explanation strongly increases optimality rates on average, relative to just observing their answer. This benefit of explanations is asymmetric: explanations increase*

¹²We will correspondingly refer to explanations associated with the correct answer to a question as *learning explanations* and to explanations provided for incorrect answers as *unlearning explanations*.

imitation in learning opportunities but do not decrease imitation in unlearning opportunities.

3.4 Heterogeneity and Robustness

Cross-task variation. We examine cross-task variation in our main findings (see Appendix Figure A2). We estimate a positive treatment effect of *Explanation* on optimality rates in 14 out of the 15 tasks. This improvement rate is not significantly correlated with the prior optimality rate in a given task ($r = -0.06$, $p = 0.82$). The asymmetric benefit of explanations, defined as the difference in learning rates between *Explanation* and *Choice Only* subtracted from the corresponding difference in unlearning rates, is similarly pervasive across task: we obtain a positive estimate in 14 tasks. At the same time, there is substantial heterogeneity, with point estimates ranging from a maximum of +25.9 p.p. in the “Exponential growth bias” task to a median value of +12.1 p.p. in the “Interest rates and stock prices” task to a minimum value of -3.1 p.p. in the “Value of call option” task.

Robustness. In Appendix B.5, we find that the asymmetric effects of explanations are robust to various sample restrictions, and we confirm that our main effect on optimality rates is indeed almost entirely driven by receivers confronted with a conflicting response. In additional analyses, we find that asymmetric learning emerges both among listeners with strong and weak priors, and is more pronounced when priors are weak (see Appendix Figure A11).

4 Interpreting the Treatment Effect of Explanations

Having established a treatment effect of explanations, the question arises as to what drives 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 further characterize our treatment effect in light of this framework.

4.1 Conceptual Framework

In Appendix A, we discuss a simple model of imitation based on Bayesian updating from a signal with subjectively perceived signal precision (or diagnosticity). Specifically, imitation is shaped by two forces: first, an individual’s confidence in their prior answer, often referred to as *meta-cognition*; and second, the subjective perception of whether the orator is accurate. The latter element is central: to learn from the “signal” that the decision-maker receives through the treatment—seeing another’s answer or additionally listening to their explanation—, they needs to assign a diagnosticity to it. The subjective diagnosticity is a belief about the likelihood that the observed answer matches the true state. This belief about the accuracy of an answer is the precise channel through which the treatment manipulation creates effects on social learning.

First, this shows that an explanation can theoretically be thought of as conveying a signal of the *reliability* of the orator’s choice. This, in turn, raises the question of whether the verbal explanation an orator provides is equivalent to their self-assessed *confidence*, i.e., their quantitative belief in their accuracy. We examine this issue in the subsection 4.2.

Second, the conceptual framework clarifies the relationship between optimality and imitation rates. Under random matching of orators and receivers, there is an equal share of learning and unlearning opportunities among all matches. As a consequence, under the assumption that receivers confronted with confirming answers do not switch systematically, the sign of the difference between learning and unlearning rates is a sufficient statistic for whether there are aggregate improvements. In our data, we find that this assumption is overwhelmingly borne out, although there is a small but significant difference between *Explanation* and *Choice Only* in situations where the orator and receiver are both wrong. Appendix B.5.2 provides additional details on this finding, explains why its aggregate impacts are small and shows our results are robust to keeping all situations by distinguishing simply by prior accuracy. In particular, Appendix Figure A11 shows that, as expected, the sign of the difference between learning and unlearning rate perfectly predicts whether there is improvement or not in all of our tasks.

Third, the model illustrates that our main reduced-form finding of treatment differences between *Choice Only* and *Explanation* cannot be explained by meta-cognition (unlike in, e.g., Enke et al., 2023), because the distribution of prior answers and confidence is—by virtue of treatment randomization—the same across conditions. The treatment effect has to arise, instead, from the effects of explanations on the perceived accuracy of orators’ explanations. This implication of the model is important because it establishes why our design will allow us to abstract from the role of prior confidence in examining the mechanisms underlying the treatment effect.

In conclusion, a simple but central insight from the model is that, in economic terms, an explanation can be productively thought of as a signal of an answer’s reliability. In the following we will shed light on two central aspects of this signal: (i) does learning about the orator’s stated confidence produce similar effects as does receiving an explanation? (ii) Do explanations mainly convey information through their content or through their oral delivery?

4.2 Are Explanations Equivalent to a Numerical Confidence Statement?

From a reduced-form perspective, verbal explanations are a signal of message reliability generated by the sender of a message. Under that interpretation, explanations might be equivalent to observing a quantitative statement of a the originator’s confidence. To empirically assess this hypothesis, we conduct an additional Receiver experiment that allows us to benchmark the effect of explanations against directly observing the orator’s confidence in their answer.

Design. This additional experiment closely follows the baseline Receiver experiment and is also based on the orator data collected in the baseline Orator experiment. Condition *Choice Only* is identical to the baseline. Condition *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 Appendix B.6. In each task, we randomly assign respondents to the *Choice Only* (20%) treatment or the *Confidence* treatment (80%).

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

Results. We compare the treatment effect of the *Confidence* treatment on optimality and imitation rates to the treatment effect of *Explanation*. The results are visualized in Figure 3. Panel (a) shows that the *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 59.5% in *Confidence* compared to 59.0% in *Choice Only* ($p = 0.51$).¹³ Turning to the imitation patterns, we find that *Confidence* has virtually no treatment effect on both the learning and unlearning rate. At 22.4% and 23.1%, respectively, the unlearning rates of *Confidence* and the control *Choice Only* are virtually identical ($p = 0.61$). Learning rates are similarly close at 43.4% and 42.8% ($p = 0.70$), especially in comparison to the 55.8% learning rate in *Explanation*.

From the absence of any sizable treatment effects in *Confidence* we conclude that explanations operate differently from merely conveying a quantitative signal of the orator’s confidence. There are a multitude of possible reasons. For example, people are not usually presented with others’ numerical confidence statements in practice, but they are exposed to qualitative statements indicating confidence. Also, 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 result motivates our detailed mechanism analyses in Sections 5 and 6.

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 in quantitatively meaningful ways.*

¹³The prior optimality rate in *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 *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 ($p = 0.09$).

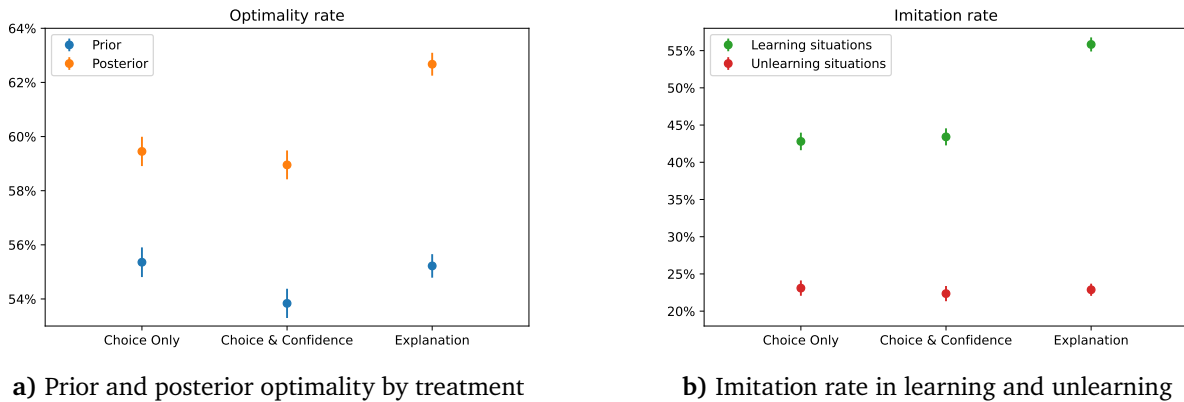


Figure 3: Effect of *Choice & Confidence* on optimality and imitation rates. *Notes:* *Explanation* sample is the main Receiver survey (1,103 receivers), *Choice & Confidence* sample is the corresponding Receiver survey (713 receivers), *Choice Only* sample is pooled from all collections (2,733 receivers). Whiskers show standard errors.

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: the content of the explanation (what is said) and the delivery of the explanation through the speaker’s voice (how it is said). This distinction is important because it allows us to understand whether the benefits of explanations for social learning are likely to be limited to oral conversations or may similarly occur in written exchanges, for example. Ever since Mehrabian et al. (1971), it is clear that non-content features may play a crucial role in the effectiveness of communication.¹⁴ To distinguish between 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 delivery through voice, while keeping constant the content channel.

Design. We transcribe each of the explanations provided in our baseline Orator experiment in a way that preserves the details and nuances of the spoken text, including, for example, filler words such as *um* and *eh*. The design of the additional experiment is identical to our baseline Receiver experiment except that the *Explanation* treatment is replaced with a *Transcript* treatment, in which participants read the transcript of a recording rather than listening to the corresponding voice message. In each task, we randomly assign respondents to the *Choice Only* (20%) treatment or the *Transcript* treatment (80%). To keep the voice message and the transcript treatments as comparable as possible, the text of the transcript is displayed progressively. Example screens from this experiment are provided in Appendix B.6.

¹⁴Recent evidence shows that emotions as revealed by voice features play a central role in the context of monetary policy communication (Gorodnichenko et al., 2023).

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

Results. Panel (a) of Figure 4 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 small across-treatment differences in the prior optimality rate, *Transcript* produces a 2.0 p.p. ($p < 0.01$) increase from prior to posterior compared to *Choice Only*. This corresponds to approximately 58.9% of the size of the improvement in *Explanation* (at 3.4 p.p., $p < 0.01$). Panel (b) of Figure 4 zooms in on the imitation rates in learning and unlearning opportunities. A strong asymmetric effect of explanations also emerges in the transcript treatment. While transcripts have a strong treatment 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 61.9% of the treatment effect in *Explanation*. 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*.¹⁵

We conclude from these results that both substantive content features of explanations and the oral delivery matter for social learning, with content elements driving the majority of the effect. Taking the quantitative estimates at face value suggests that 58.9% of the effect on optimality and 61.9% of the effect on the imitation rate in learning situations are due to the content of explanations rather than the orator's voice. These findings motivate our in-depth analysis of content features of explanations which follows in Section 5.

Result 3. *The treatment effect of explanations on social learning is largely due to their content, with a smaller role played by non-content features conveyed orally.*

5 The Supply and Interpretation of Explanations

All findings about the effects of explanations up to this point were identified through experimental manipulations and did not require any assumptions about or analysis of the actual content of the explanations that were exchanged. The objective of the following two sections is to shed light on the mechanisms underlying our main finding: the asymmetric treatment effect of explanations in learning versus unlearning opportunities. To that end, we go beyond the reduced-form treatment effects and directly study the rich data on explanations.

¹⁵Note 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.

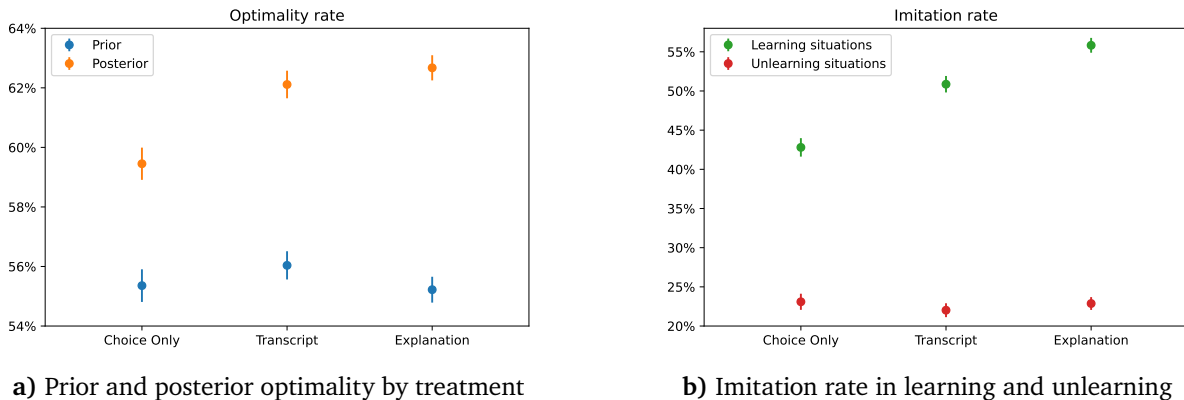


Figure 4: Effect of *Transcript* on optimality and imitation rates. *Notes:* *Explanation* sample is the main Receiver survey (1,103 receivers), *Transcript* sample is the corresponding Receiver survey (917 receivers), *Choice Only* sample is pooled from all collections (2,733 receivers). Whiskers show standard errors.

To structure the mechanism analysis, we systematically explore two margins of empirically measurable variation that could drive the asymmetric treatment effects: first, differences in imitation rates might derive from content differences in the supply of explanations. Intuitively, explanations for correct choices may differ from those for incorrect choices in ways that increase the likelihood of imitation. For example, individuals who know the right answer might give “better,” more compelling explanations, inducing the asymmetric treatment effect. Second, different imitation rates could be the result of differences between the characteristics of participants in learning versus unlearning situations. In particular, recall that learning and unlearning opportunities are determined by the accuracy of a participant’s answer. As a result, participants in learning situations are likely to differ systematically from those in unlearning situations. This sample selection is not a confound or flaw of the design, but a basic feature affecting *any* exchange of ideas: different ideas are shared and explained by people with systematically different characteristics.

In our investigation of mechanisms, we distinguish between channels concerning the content of explanations and its interpretation on the one hand (this section), and the role of orator and receiver characteristics on the other hand (Section 6).

5.1 Dissecting Explanations

To test for the role of the content of explanations, we analyze the language used in the recordings. Such language data, however, is hard to analyze in a comprehensive manner, because language is high-dimensional: each sentence and its oral delivery through voice have innumerable features and interpretations (Batista et al., 2024; Ludwig and Mullainathan, 2024).

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. Specif-

ically, they provide *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 answer. On the other hand, an explanation is characterized by (an infinite number of) text features: it exhibits speech and text metrics, markers of certainty, linguistic and rhetorical features, etc. We think of such features as domain-general, i.e., similarly pertaining 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 speech figures, expressions or structural elements, such as length.

5.1.1 Argument Annotation

Identifying arguments. To identify arguments from the unstructured text data, we develop a coding scheme detailed in Appendix C. First, we provide a state-of-the-art Large Language Model (LLM), OpenAI’s GPT-4-Turbo, 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 annotated 100 responses in each of the different tasks; whenever they encountered arguments not captured by our scheme, we added them to it. This yielded the final list of arguments.

Annotating explanations. The team of research assistants then annotated the presence of all arguments in the scheme across all 6,910 explanations. To assess the quality of the main annotation, the manual annotation was then performed again, with each task allocated to a new research assistant that was blind to the previous results. Inter-rater reliability is high. If one coder identifies a specific argument, there is a 72% chance that the other coder does so as well. If one coder does not identify an argument, there is a 95% chance that the other coder does not identify it either. Cohen’s κ is 0.67, indicating “substantial agreement” (Cohen, 1960; Landis and Koch, 1977). Inter-rater reliability is even higher for aggregate argument categories, as described in Section 5.2.1. 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. For “any fallacious argument”, these chances are 82% and 89% respectively, and for “any sound argument” they stand at 83% and 89%. As a second test, we performed the argument annotation again using GPT-4. When a human coder identifies a specific argument, there is a 79% chance GPT-4 does so as well. If a human coder does not identify a specific argument, there is a 90% chance GPT-4 does not identify it either. Cohen’s κ between the human annotation and GPT-4 is 0.61, again indicating substantial agreement. Agreement at the level of argument categories is similarly high. We view

these benchmarks as validating our annotation approach, both for the argument-level identification and for aggregate categories.

5.1.2 Feature Annotation

The second part of our approach leverages a collection of 31 text features, all of which are domain-general, i.e., similarly apply to all explanations independent of the different questions and answer options. We first annotate 25 text features using GPT-4. The list of features is culled from the vast literature on text analysis in communications research and previous work that uses natural language data in economics and related fields. It includes explicit markers of uncertainty such as modal verbs (“could”, “might”), epistemic stance markers (“I believe”), hedges (“probably”, “perhaps”), relative language (“almost”, “nearly”), absolute language (“always”) and references to certainty (“definitely”, “certainly”). The list comprises implicit markers of uncertainty, such as disfluencies (“um”, “uh”), filled pauses (“you know”, “like”), repetitions and self-corrections. We further annotate mentions of sources, references to personal experiences or authority as well as directive addresses to the receiver and apologetic phrases. We additionally compute six textual and speech metrics such as the explanation’s word count, speed of talking and the Flesch-Kincaid language complexity score. Appendix Table A5 provides an overview of all features.

Discussion. We see our classifications of substantive arguments and text features as complementary to one another. For example, the substance of an argument may be unrelated to other text features, such as the speed of talking or implicit markers of uncertainty. As such, we start by examining the data on arguments and text features as independent sources of variation in explanations and study their relationship towards the end of this section.

5.2 The Content of Explanations

We discuss the descriptive results from our annotation approach that characterizes the supply side of explanations. 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

Figure 5 displays the results of our final argument annotation across all 15 tasks. For each of the tasks, the left-hand panel shows the frequency of a given argument separately for the sample of explanations for correct versus incorrect answers, ordered by total frequency in our explanations data. The bottom four categories comprise irrelevant arguments, pure restatements of the question or answer, as well as any expressions of the speaker’s level of uncertainty, and any non-argument

reasoning. The right-hand panel displays the estimated effect of a given argument on the likelihood of imitation in learning as well as unlearning situations. To ensure sufficient statistical power, we only show effects for arguments occurring in at least 5% of explanations in the corresponding situation.

Illustration of results: Actively managed funds task. To illustrate these results at the level of an individual task, take the example of the question on actively managed funds (Panel 1).¹⁶ The most frequent argument is that active funds—unlike passively managed ones—can quickly adapt to changes in the market, which is present in 57.2% of the explanations for incorrect answers but almost absent (2.9%) from explanations for correct answers. The second most common one argues that active funds charge higher fees, which is prominent (22.7%) among explanations for correct answers and nearly absent (3.2%) from those for incorrect answers. The third most frequent argument suggests that active funds are managed by experts—more common in the incorrect category—and the fourth most frequent states that it is impossible to predict stock markets—present in just less than 20% of explanations in correct and absent from incorrect. We identified eight additional unique arguments (pertaining to historical performances, differences in levels of diversification and risk levels, among other topics), all of which individually occur in fewer than 5% of the explanations. Irrelevant arguments, defined as those that have premises unrelated to the questions or answer options, are common, and slightly more so in explanations for correct (41.5%) than for incorrect answers (29.5%). Pure restatements are roughly similarly frequent at about 10%. We identify expressions indicating certainty in roughly 20% of all explanations.

Turning to the right-hand panel on the effects of imitation, we find that the two most common arguments have sizable effects on imitation rates, whereas most others do not. The argument that active funds can quickly adapt to changes is associated with an increase of 32.1 p.p. in the imitation rate in unlearning situations, and the argument that active funds charge higher fees increases the imitation rates by 20.7 p.p. in learning situations. We find that irrelevant arguments decrease the likelihood of imitation in both learning and unlearning situations. Pure restatements increase imitation in learning situations but decrease imitation in unlearning. Expressions of uncertainty do not have significant systematic effects in this task, nor does non-argumentative reasoning.

Variation across tasks: Stylized facts. The previous perspective on a single task illustrates the richness of insights on how people reason about a topic of interest emerging from our analysis of the substance of verbal explanations. Synthesizing these findings across tasks, we document the following stylized facts.

First, we see pronounced heterogeneity in the number of distinct arguments circulating for a given topic. It ranges from a maximum of eleven arguments in the case of actively managed funds, as discussed above, to eight arguments on the relationship between interest rates and stock prices

¹⁶The wording of the question and answer options can be found in Appendix Table A1.

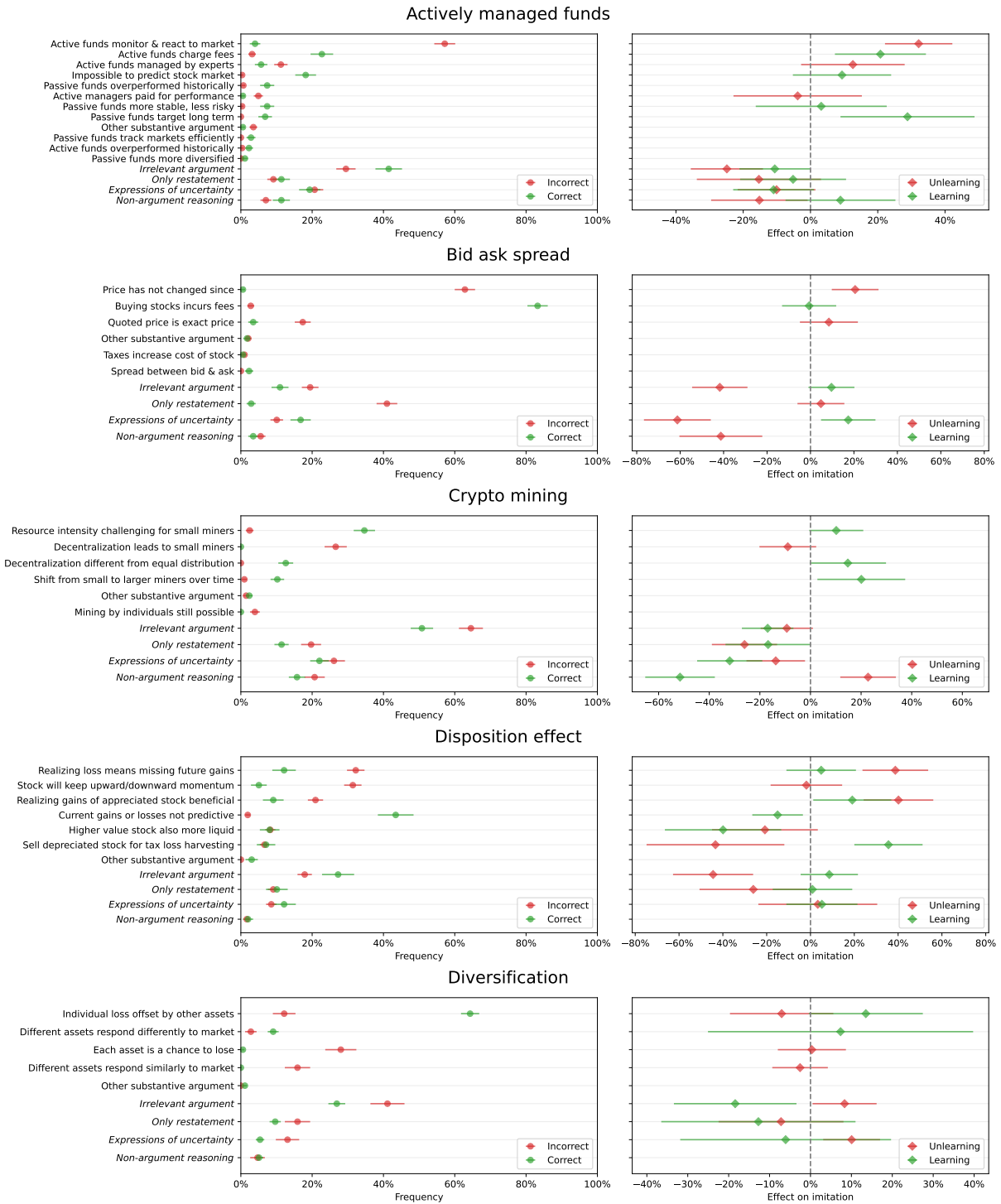


Figure 5: Arguments by task I/III. Notes: Left panel shows the frequency of an argument, shown separately for correct and incorrect explanations. Sample is the Orator survey (466 orators). Right panel shows the difference-in-differences of the imitation rate between *Explanation* and *Choice Only*, between explanations that contain the argument and those that do not, shown separately for learning and unlearning. Only arguments appearing in more than 5% of corresponding explanations are shown in the right panel. Sample is the main Receiver survey (1,103 receivers) for *Explanation*, and all collections (2,733 receivers) for *Choice Only*. Arguments were identified via GPT-4, fine-tuned, and then annotated manually. See below for Parts II and III.

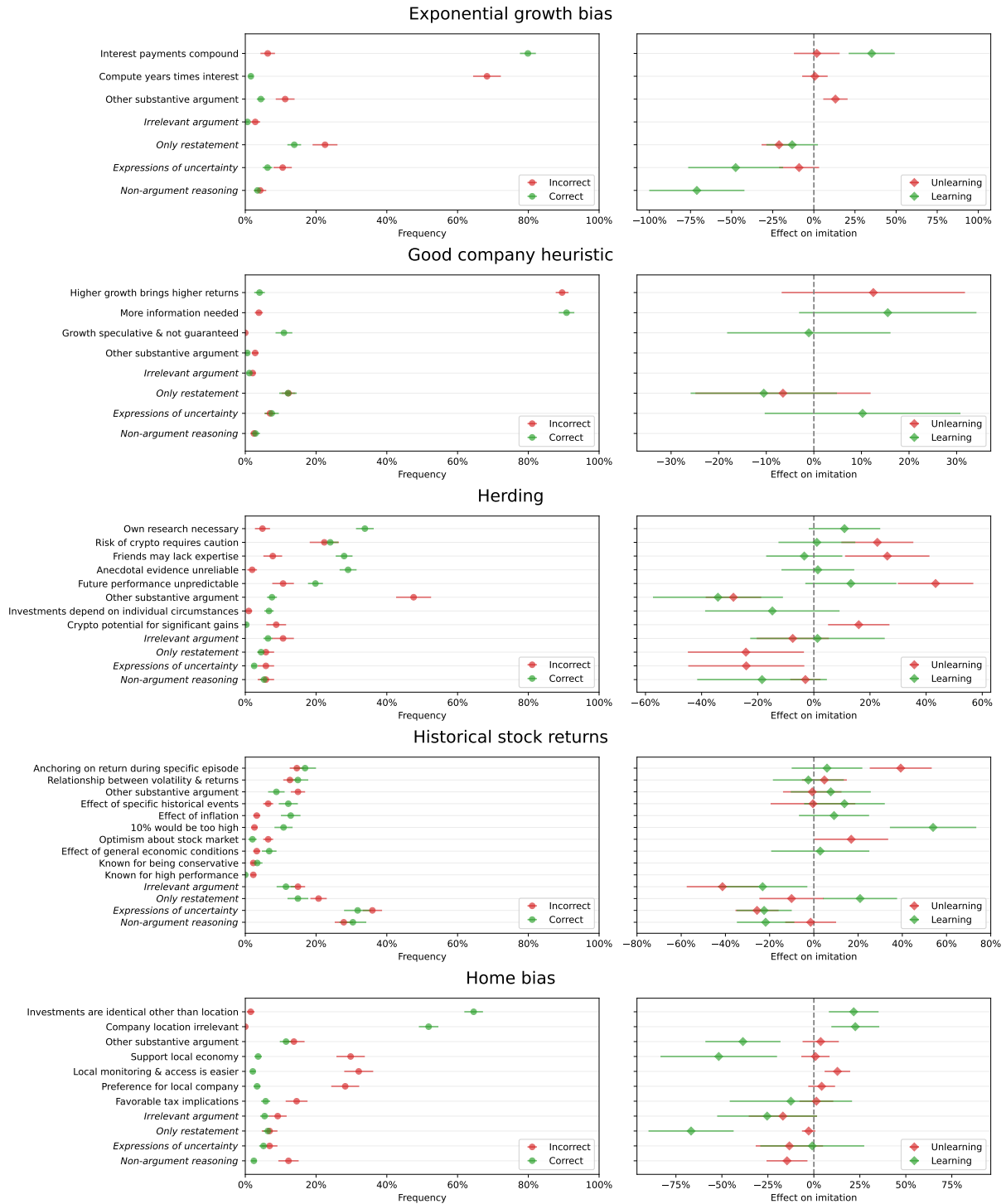


Figure 5: Arguments by task II/III. Notes: See above.

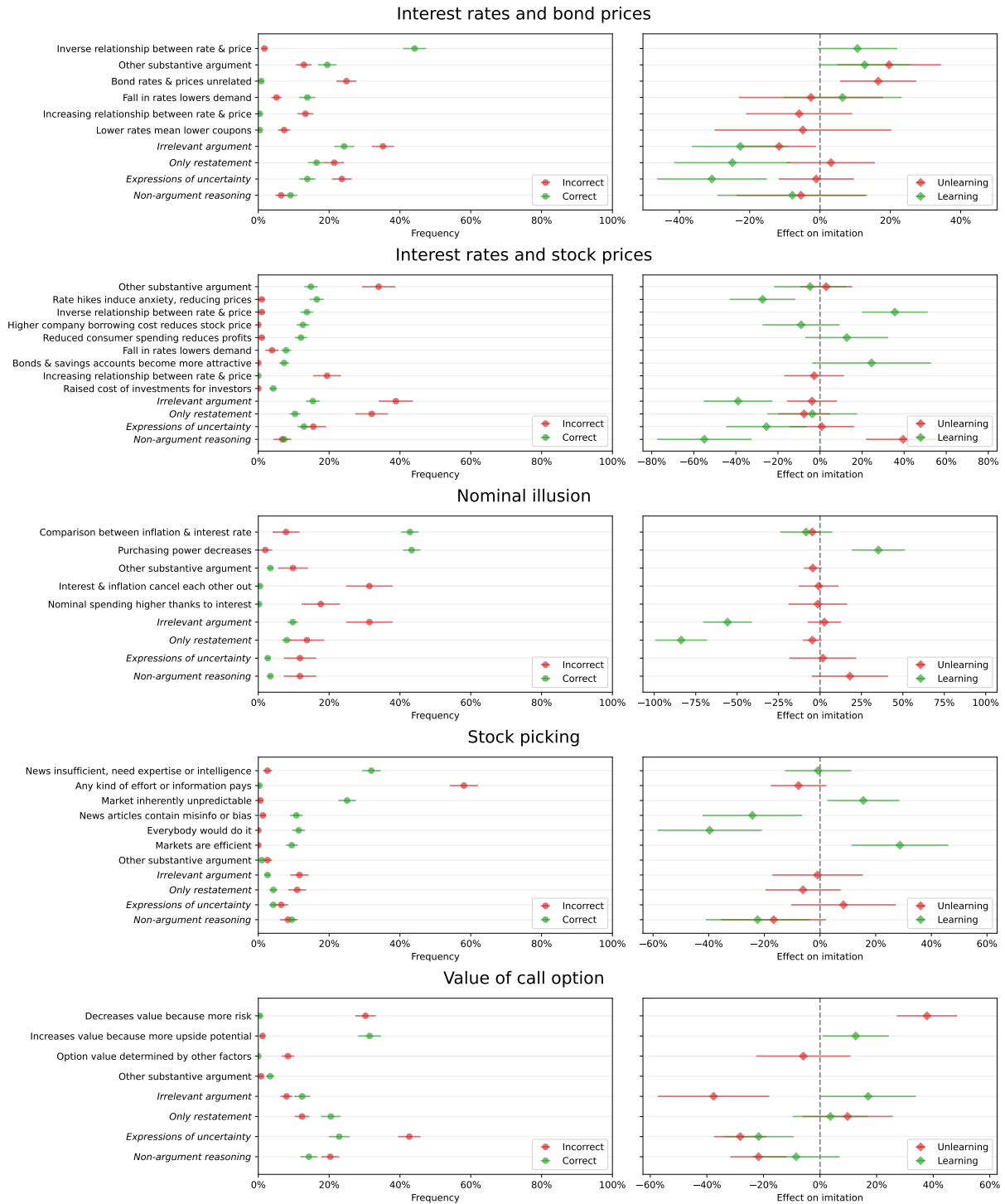


Figure 5: Arguments by task III/III. Notes: See above.

and all the way down to just two distinct arguments in the case of an exponential growth calculation. The median number of arguments across tasks is five.

Second, we see varying degrees of consensus on specific arguments across tasks. For example, none of the nine arguments identified in the task on historical stock returns exceeds a frequency of 20%, whereas we see two arguments occurring with more than 60% and 80% likelihood in the bid-ask spread question. Appendix Figure A3 illustrates the degree of consensus across tasks.

Third, we observe substantial variation in the presence of uncertainty markers and how their prevalence differs for correct and incorrect choices. For some tasks, uncertainty markers are far more frequent among correct than incorrect explanations, e.g., 42.6% vs 22.9% in the value of a call option task, while for other tasks the patterns are reversed, e.g. 10.1% vs 16.8% in the bid ask spread task.

Finally, we document large heterogeneity in the effects of different substantive arguments on imitation rates. In some tasks, arguments for wrong choices increase imitation rates by up to 40 p.p., while other arguments for wrong choices decrease imitation rates by up to 40 p.p. We observe similar heterogeneity for arguments in explanations for correct choices. While some arguments for correct choices increase imitation rates by more than 50 p.p., others decrease the likelihood to imitate by close to 60 p.p..

While this perspective delivers valuable descriptives for each topic as well as on the general nature of financial explanations, it remains difficult to compare substantive content across questions and this perspective does not yet shed light on the drivers of the asymmetric treatment effect. As a next step, we attempt to put more structure on the nature of different arguments that permits an aggregation of the different tasks.

Categorizing arguments across tasks. The insights from the preceding analyses are limited by the fact that the substantive content of arguments is not comparable across tasks. To draw more general conclusions about differences between explanations for correct and incorrect choices, we define four domain-general categories of arguments. First, we code the absence of any argument in an explanation. 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, leveraging standard notions from the discipline of logic, 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 as a sound argument one that has correct premises and where the conclusion follows from the premises. 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. The categorization of the identified arguments in each task into fallacious versus sound is shown in Appendix Table A7.

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.¹⁷

The argument gap. Figure 6 shows our results on 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, respectively. 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%), 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.

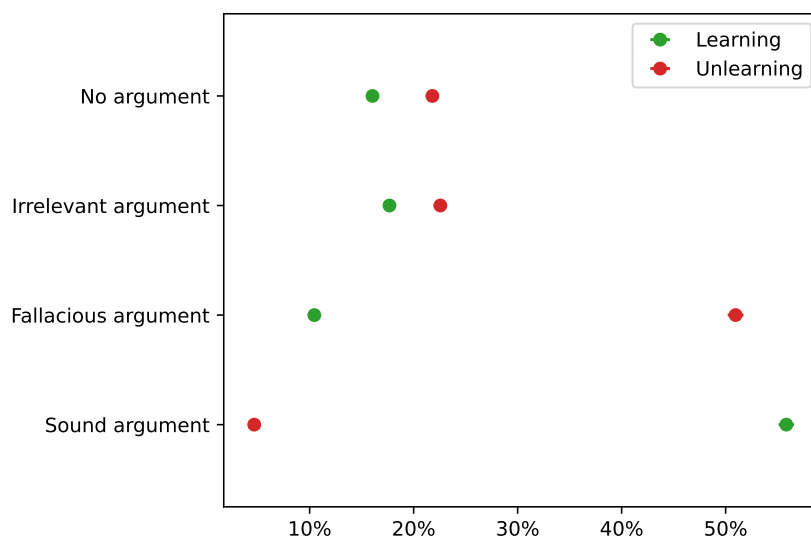


Figure 6: The Argument Gap: argument quality in learning and unlearning opportunities. *Notes:* Argument quality is inferred for each explanation according to the strongest present category. Sample is the main Orator survey (466 orators) matched onto the main Receiver survey for *Explanation* (1,103 receivers) and all collections for *Choice Only* (2,733 receivers). Whiskers show standard errors.

¹⁷In practice, 91.8% of explanations contain at most one of the three argument types and can therefore be classified unambiguously.

Argument types and the asymmetric treatment effect. We next examine whether these different classes of arguments are associated with different effects on imitation rates. 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.

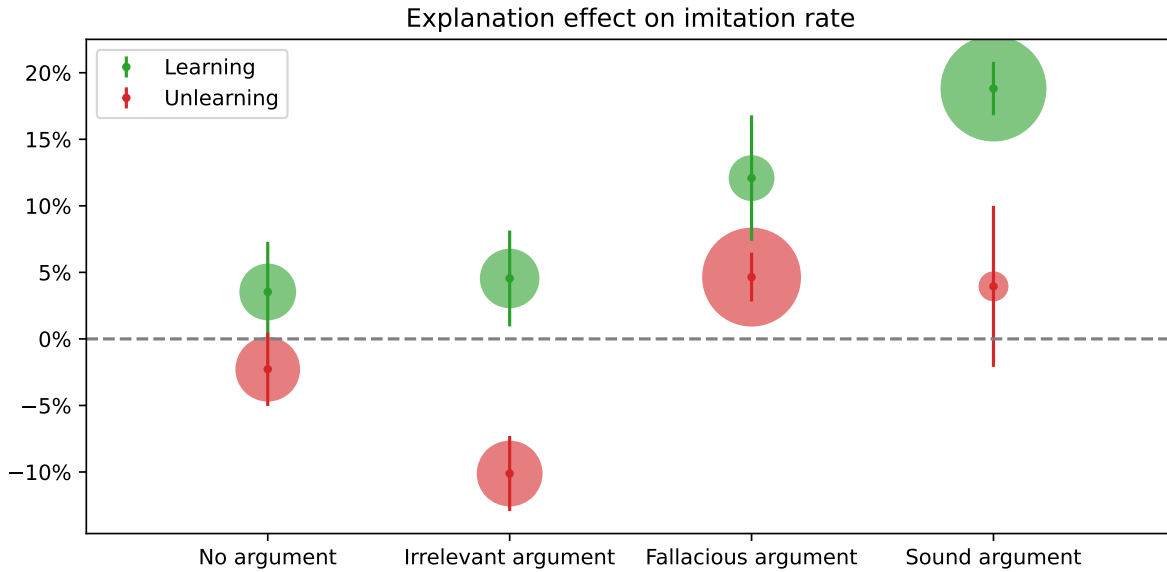


Figure 7: Treatment effect of explanations by argument quality. *Notes:* Differences in imitation rates between *Explanation* and *Choice Only* by explanation’s argument quality. *Explanation* sample is the main Receiver survey (1,103 receivers), *Choice Only* sample is pooled from all collections (2,733 receivers). See Section 5.2.1 for details on the categorization of arguments. Point sizes show frequency of categories. Whiskers show standard errors.

First, consider the treatment effects in unlearning situations. A perhaps striking feature of our original findings in Figure 2 was that there is a precisely estimated null effect of unlearning explanations in the aggregate. This could mean that listeners in unlearning situations in fact tend to not respond to explanations, or that the average null effect simply masks heterogeneity across different types of explanations. Figure 7 shows that the treatment effect in unlearning situations is significantly different from zero in two out of four categories. Most importantly, it is strongly positive at 4.6 p.p. ($p = 0.01$) in the fallacious category, which makes up more than half of the data. This implies that even a fallacious argument makes initially correct listeners significantly more likely to switch to a wrong answer. By contrast, we see a large and significant negative effect of irrelevant arguments: those make initially wrong participants 10.1 p.p. ($p < 0.01$) less likely to imitate. We further see a slightly negative effect of no argument (-2.3 p.p., $p = 0.41$).¹⁸ This provides a clear conclusion:

¹⁸Sound arguments are virtually absent in unlearning situations.

the null effect of explanations in unlearning situations, on average, masks the differential effect of different types of explanations.

Second, turning to learning situations, we find a positive treatment effect on imitation across all four categories. This effect 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 no argument (3.5 p.p., $p = 0.35$) and irrelevant arguments (4.5 p.p., $p = 0.21$). This suggests that if and only if it supports the right answer, *any* explanation tends to help, even if it does not contain an argument or just a bad one. That said, we reassuringly see that good arguments are more persuasive.

Third, we analyze the difference in treatment effects between learning and unlearning situations. We see a significant level shift in the treatment effects of learning versus unlearning in *each* category of arguments. The magnitude of the asymmetric effect varies across categories: it ranges from 14.9 p.p. ($p = 0.02$) for sound and 14.7 p.p. ($p < 0.01$) for irrelevant arguments down to 5.8 p.p. ($p = 0.21$) for none and 7.4 p.p. ($p = 0.14$) in the case of fallacious arguments.

Finally, we can combine the results on the heterogeneity of asymmetric treatment effects with those on the argument gap—i.e., the different frequencies of the argument types between learning and unlearning situations—to ask which fraction of the overall asymmetric effect can be “explained away” by the argument classification. Comparing the coefficient estimates for the asymmetric effect in columns (1) vs. (2) in Table 2, we show that as much as 25% of the asymmetric effect is accounted for by the different composition of argument categories across learning and unlearning opportunities.

Discussion. Explanations induce more imitation in learning than unlearning opportunities across the four different argument classes we examine. Why does an asymmetric effect persist across the whole range of argument types? First, explanations in learning and unlearning opportunities may differ above and beyond the arguments they contain, which we will study in the following. Second, the level shift in imitation rates could be driven by differences in the characteristics of receivers and orators matched in learning and unlearning opportunities (see Section 6).

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. Given the variety of features, a range of distinct insights emerge. First, the results confirm a number of intuitions about how explanations for correct and incorrect explanations 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, although the differences are small. Low certainty markers

Table 2: Decomposition of differential learning effects

	<i>Dependent variable: Imitation</i>								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Explanation	-0.002 (0.014)	0.042** (0.019)	-0.143*** (0.020)	-0.109*** (0.028)	-0.167*** (0.046)	-0.126*** (0.046)	-0.159*** (0.050)	-0.227*** (0.051)	-0.266*** (0.064)
Learning	0.198*** (0.016)	0.197*** (0.020)	0.205*** (0.017)	0.199*** (0.020)	0.199*** (0.016)	0.127*** (0.016)	0.197*** (0.020)	0.118*** (0.020)	0.113*** (0.020)
Explanation × Learning	0.134*** (0.020)	0.101*** (0.025)	0.055** (0.022)	0.056** (0.026)	0.091*** (0.021)	0.153*** (0.020)	0.051** (0.026)	0.075*** (0.025)	0.071*** (0.025)
Argument controls		✓		✓			✓	✓	✓
Richness controls			✓	✓			✓	✓	✓
Orator controls					✓		✓		✓
Receiver controls						✓		✓	✓
Observations	8800	8800	8800	8800	8800	8800	8800	8800	8800
R ²	0.092	0.099	0.112	0.113	0.107	0.166	0.118	0.190	0.195

Notes: *Explanation* sample is the main Receiver survey (1,103 receivers), *Choice Only* sample is pooled from all collections (2,733 receivers), both restricted to Learning and Unlearning situations. *Explanation* is a dummy for the *Explanation* Treatment, and *Learning* a dummy for learning situations. All controls contain the variable itself and an interaction with *Explanation*. *Argument controls* denotes dummies for *No argument*, *Irrelevant argument*, *Fallacious argument* and *Sound argument*. *Richness* denotes richness, cf. Section C.3. Orator and receiver controls are: *Republican*, *Higher education*, *Black*, *Working*, *Age above 35*, *Male*, *(Prior) Confidence*, *Optimality on all others tasks*. Note that the coefficient for *Explanation* is not directly interpretable in regressions with controls, because it is also interacted with non-centered variables. We drop the 0.5% of observations with missing receiver prior confidence from all regressions.

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 higher quality of explanations, such as empirical statements or indications of sources, are indeed more common in learning explanations. Second, we find 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. The central insight coming out of our feature analysis is, therefore, that explanations for correct answers reflect *richer* message space. We will explore this insight more systematically in the following.

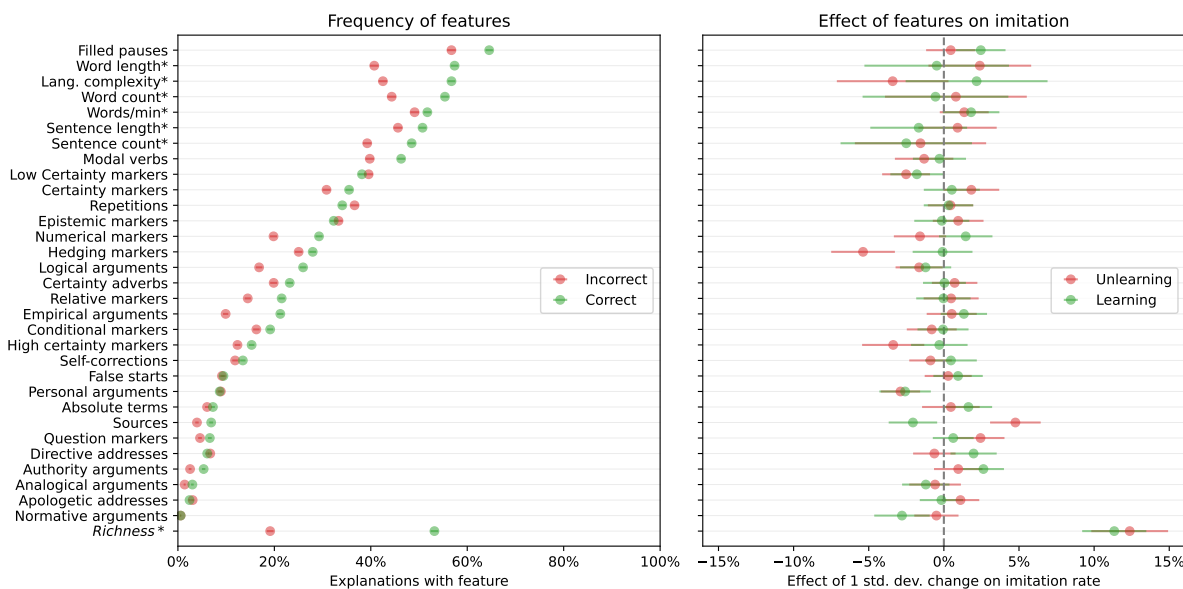


Figure 8: Frequency of explanation features and effects on imitation. *Notes:* Left panel shows share of explanations with features, split by orator optimality. Sample is the Orator survey (466 orators). Continuous features, labeled with a *, show the fraction of speeches with a value above the median. 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 situations. Sample is the main Receiver survey (1,103 receivers) for *Explanation*, and all collections (2,733 receivers) for *Choice Only*. Whiskers show standard errors.

The richness gap. We now explore the richness of explanations in learning versus unlearning situations in a more systematic way. The motivation is that (i) if explanations in learning opportunities are indeed richer and (ii) richness is associated with imitation, the richness gap may account for the asymmetric treatment effect of explanations.

To characterize the richness of a message from natural language, we apply the following pre-registered definition in our coding instructions: “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.”¹⁹ Our coding approach relies on both human and machine coding, and follows similar procedures as our main annotation exercise (Section 5.1).²⁰ We obtain richness scores on an 11-point Likert scale, ranging from 0 to 10 (both inclusive).

We document a richness gap in explanations: the average richness score is 0.76 SD ($p < 0.01$) higher in learning than in unlearning explanations. Appendix Figure A4 shows the distribution of richness scores in each situation as well as the richness gap separately for each of the four categories of arguments. We document a pronounced richness gap across the board: we find magnitudes of 0.28 SD ($p < 0.01$) for none, 0.46 SD ($p < 0.01$) for irrelevant, 0.73 SD ($p < 0.01$) for fallacious and 0.28 SD ($p < 0.01$) for sound arguments.²¹

The effect of text features and richness on imitation. Are the differences in the features of explanations we document predictive of imitation? The right-hand Panel of Figure 8 estimates the effect of each feature on the imitation rates in learning and unlearning situations, respectively. These estimates are obtained from multiple regressions for learning and unlearning situations that include all features, relative to choice only. Similar to our analysis of the effects of arguments, we only report estimates for features present in at least 5% of the corresponding sample of explanations.

We document the following three key findings. We begin by analyzing the effects of the features annotated in our original coding approach, i.e., excluding the richness score. First, we find substantial heterogeneity in the degree to which specific features are associated with increases or decreases in imitation rates. A higher speaking pace (measured by words per minute) and markers for questions are consistently associated with stronger imitation. Conversely, low certainty markers reliably lead to less imitation. Indicating sources has a strongly positive effect on imitation in unlearning but not learning situations. Mentioning numerical markers leads to more imitation in learning but less imitation in unlearning situations. A substantial number of features do not significantly shift imitation.

Second, again abstracting from the richness score, we do not find that the raw features we extract are jointly associated with systematically 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 learning versus unlearning situations in 1 of the 32 variables. This

¹⁹Richness is also a theoretical concept used in different fields of economics, most commonly to characterize the richness of the space of numerical messages in models of communication. While the theory literature uses various definitions of richness, they are all intuitively related to the cardinality and/or granularity of the message space. Here, we attempt to transfer a heuristic notion of richness to the case of messages in natural language.

²⁰Specifically, we score richness using a large language model. While the score constructed based on the verbal prompt is somewhat of a blackbox, it is reassuring that it is strongly correlated with individual text features contained in the explanations in reasonable ways.

²¹Recall that sound arguments are virtually absent in unlearning situations.

suggests that differences in the degree to which these specific features lead to differential imitation are rather marginal and may not contribute significantly to the asymmetric effect in the aggregate.

Third, by far the most potent predictor of imitation is the richness score of an explanation. A 1SD increase in richness is associated with 11.4 p.p. ($p < 0.01$) and 9.5 p.p. ($p < 0.01$) increases in imitation in learning and unlearning situations, respectively.

Does the richness gap explain the asymmetric treatment effect of explanations? Intuitively, 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.

Regression analyses reported in Table 2 show that across various specifications, a very significant portion of up to 65% of the asymmetric effect is explained 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 accounting for richness the estimate of the asymmetric treatment effect does not change when further controlling for argument types. Taken together, we find strong evidence that content differences in the supply encountered in learning and unlearning opportunities play an important part in explaining the asymmetric effects of explanations.

Result 4. *We document pronounced differences in the content of learning and unlearning explanations: First, irrelevant and fallacious arguments are more prevalent in unlearning opportunities, while sound arguments are more common in learning situations. “Better” argument types are associated with higher imitation rates. Second, the most striking difference is that learning explanations are richer, which holds irrespective of the argument type. Richness is the strongest predictor of imitation. The richness gap accounts for approximately 60% of the asymmetric treatment effect of explanations in learning versus unlearning situations, while argument types play no role after accounting for richness.*

6 The Role of Orator and Receiver Characteristics

In this final step of our mechanism analysis, we turn to examining how the variation in orator and receiver characteristics across learning and unlearning situations may contribute to the asymmetric treatment effect of explanations.

This analysis is motivated once again by the fact that the asymmetric treatment effect reflects heterogeneity across an endogenous variable, because orators in learning and receivers in unlearning situations are those with a correct prior answer, while orators in unlearning and receivers in learning situations have an incorrect prior. Intuitively, the asymmetric effect might arise from characteristics of those with correct priors that, as orators, makes them more likely to be imitated or, as receivers, makes them infer systematically less from explanations.

We begin by documenting the heterogeneity of participants on observable characteristics (Section 6.1). In Section 6.2 we study which *orator* characteristics predict imitation, and whether this helps explain the asymmetric effect above and beyond the content differences associated with different groups of orators. In Section 6.3 we then test whether the characteristics of *receivers* are predictive of the responsiveness to explanations, and to what extent this contributes to the asymmetric effect in the aggregate.

6.1 Participant Characteristics in Learning and Unlearning Situations

Note that because the receiver and orator samples are drawn from the same population and because the learning and unlearning samples are determined by the same endogenous variable—prior accuracy—, the orators in learning and the receivers in unlearning situations *should* have the same characteristics on average; similarly, the orators in unlearning and the receivers in learning situations should be similar. Figure 9 shows the full set of observable characteristics we elicit in the study. The left-hand panel summarizes the features of the orator sample, separately for learning and unlearning situations. The right-hand panel presents the characteristics of the receiver sample, again separately for learning and unlearning situations.

Among orators, we indeed find significant and pronounced differences across seven of the eight characteristics we examine between those with incorrect and correct answers. The first six characteristics capture participant sociodemographics. Orators with a correct prior 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 their answers in our study: orators with correct answers have a substantially higher prior accuracy rate in the 14 remaining tasks (60.1% vs. 51.7%) and a higher confidence on the present task (71.8% vs. 62.4%). Among receivers, we find very similar patterns for those with correct and incorrect priors.

The marked differences reflect that the learning and unlearning samples are indeed subject to strong selection. It is worth noting that these samples may also strongly differ across a number of unobservable characteristics.

6.2 The Role of Orator Characteristics

Heterogeneous treatment effects by orator characteristics. We begin by examining the raw relationship between orator characteristics and the treatment effect of explanations based on data from the *Choice Only* and *Explanation* conditions. In the left-hand panel of Figure 10, we report results from regressions that examine to what extent different observables moderate the treatment effect of explanations on imitation, controlling for the accuracy of the orator’s answer. We docu-

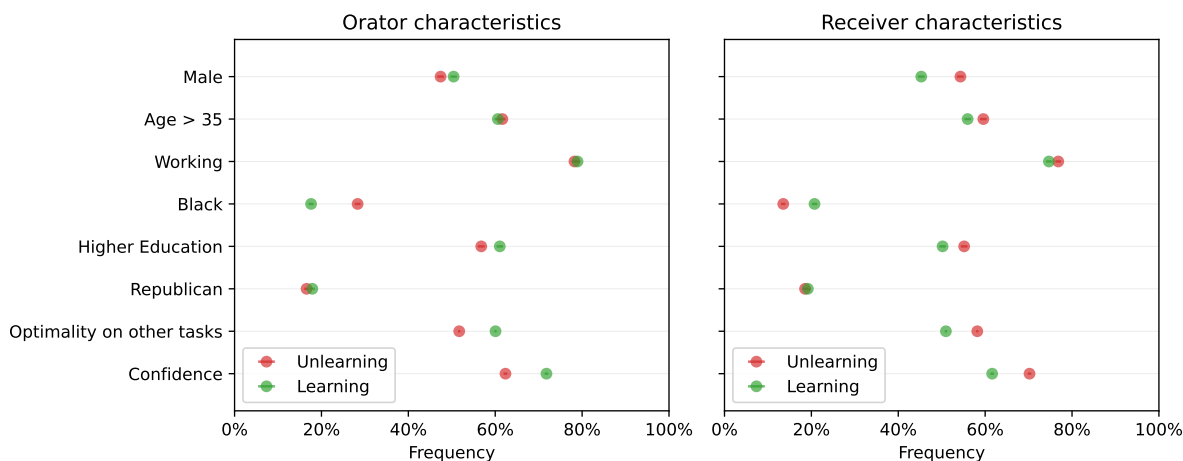


Figure 9: Characteristics of orators and receivers in Learning and Unlearning Situations. *Notes:* Sample is the main Receiver survey (1,103 receivers) for *Explanation*, and all collections (2,733 receivers) for *Choice Only*. *Optimality on other tasks* is the average optimality rate across the 14 other tasks after excluding the current one. Confidence is rescaled from [0, 100] to [0, 1]. 35 is the approximate median age in our dataset. Whiskers show standard errors.

ment that male and more educated speakers induce more imitation through their explanations—marginally so in the case of gender—, whereas Black or older speakers are imitated less.

The right-hand panel examines how the similarity between the orator and the receiver in terms of observable characteristics affects imitation rates. It shows that there are no significant effects of similarity. As such, our data lend no support to *homophily* playing an important role in our setting.

In Appendix Figure A7, we report a complete breakdown of the effect of orators’ and receivers’ in- and out-group memberships on imitation. We find similar heterogeneous treatment effects of orator characteristics in the Transcript treatment, shown in Appendix Figures A6 and A8, suggesting an important role of content variation associated with demographic groups.

Do orator characteristics explain away the asymmetric effect? We now turn to the question of whether differences between orators in learning and unlearning situations contribute to the asymmetric treatment effect of explanations. Intuitively, orators in learning situations may signal specific characteristics through their voice that make them more likely to be imitated, but they also deliver different explanatory content. The preceding estimates should be interpreted as encapsulating *every* feature in the experiment that is correlated with orator characteristics, both those conveyed through transcript differences and differences in the oral delivery.

To decompose the combined effect, we examine whether observable orator characteristics account for some of the asymmetric effect above and beyond the most predictive content features identified in Section 5, richness and argument types. Column 4 of Table 2 shows that orator charac-

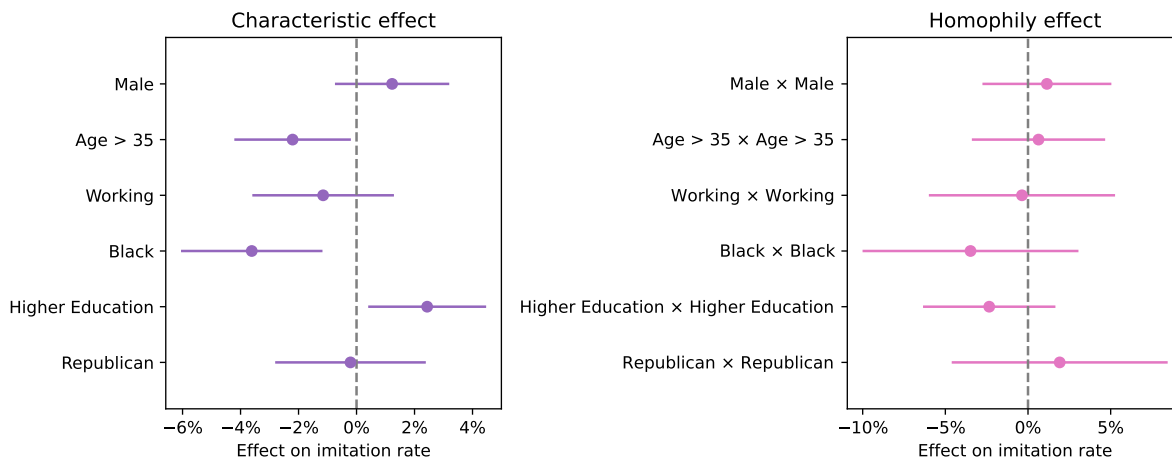


Figure 10: Effect of orator and orator-receiver characteristics on imitation in *Explanation Speech* treatment. *Notes:* Left panel shows coefficients on *Explanation* interacted with orator characteristics, in a linear regression of the imitation rate on orator and receiver optimality, *Explanation*, orator characteristics and *Explanation* interacted with orator characteristics. *Explanation* sample is the main Receiver survey (1,103 receivers), *Choice Only* sample is pooled from all collections (2,733 receivers). Right panel shows coefficient on *Explanation* interacted with orator-receiver characteristics, in a regression like the left panel with additional controls for receiver characteristics, orator-receiver characteristics and *Explanation* interacted with *orator-receiver* characteristics. Here, orator-receiver characteristics are a dummy equal to 1 if the characteristic is shared and 0 otherwise, e.g., *Male* × *Male* is the effect of male receiver listening to a male orator. Whiskers show 95% confidence intervals.

teristics explain away 30% of the differential effects.²² Yet, Column 7 of Table 2 reveals that these characteristics account for barely any of the differential effects once we account for the role of content differences in learning and unlearning situations.

6.3 The Role of Receiver Characteristics

We continue with the receiver side and ask how much of the asymmetric treatment effect is explained by differences in their observable characteristics. To illustrate, consider the following thought experiment. Given that the listener samples in learning and unlearning situations are determined endogenously, the difference in the responsiveness to explanations may be due to the many factors that are correlated with being in either situation, as shown in Figure 9. For example, listeners in learning situations have lower prior confidence, which may not only make them more likely to imitate in *Choice Only*—which it does—but additionally may make them more responsive to explanations. Our analysis takes out these observable differences and compares two hypothetical listeners, one in a learning and one in an unlearning situation, with otherwise identical characteristics. Do we still

²²Appendix Figure A9 examines which orator characteristics explain away the differential effect. It shows that prior confidence and accuracy in the other tasks are most predictive. This is consistent with our finding that the effects of orator characteristics primarily operate through the content of explanations.

observe an asymmetric treatment effect in that case? Table 2 studies whether the observable sample differences between listeners documented above can account for the differential effect. If anything, we find that these observable differences *increase* the differential treatment effect. 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.²³

These quantities should be thought of as potentially underestimating the true role of sample differences between receivers in learning and unlearning situations, both due to measurement error in our characteristics and the unobservable features that our analysis does not account for.

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 and, conditional on a learning or unlearning situation, randomly assigned to receivers.

Result 5. *Differences in observable orator characteristics in learning and unlearning situations account for as much as 30% of the asymmetric treatment effect, though these differences almost exclusively operate through differences in content supplied by different groups of orators. Corresponding differences in receiver characteristics, if anything, somewhat widen the differential treatment effect.*

7 Discussion and Conclusion

We examine how explanations influence the contagion of truths and falsehoods in the context of 15 financial decision problems. In our first experiment, one group of participants provides verbal explanations for their decisions. In a second experiment, a separate set of respondents either only observes an orator's selected answer to a question or also hears one of the over 6,900 verbal explanations before potentially updating their own decisions. Our main finding on the effect of explanations on aggregate optimality rates is an optimistic one: when people talk to each other instead of just observing each other's choices, they tend to behave more optimally. Notably, however, this improvement is entirely driven by the greater spread of truths, as falsehoods do not become less contagious. In an extensive analysis of the underlying mechanisms, we document that explanations for truths contain fewer fallacious and more sound arguments, and are systematically richer than explanations for falsehoods. These content differences, in turn, account for approximately 60% of the differential treatment effects. We find that the characteristics of orators and receivers, which have been the subject of much previous research on imitation dynamics and social learning, are largely unrelated to the asymmetric treatment effect after accounting for content differences.

The central determinant for an explanation's persuasiveness is its richness. This finding is striking in light of the principle of *Occam's Razor*: the simplest explanation is most likely the correct one.

²³Appendix Figure A9 studies the effect of controlling for each individual characteristic separately. It shows that accounting for prior confidence and accuracy in the other tasks somewhat increases the gap.

While simplicity may be valued, our findings show that comprehensiveness and detail in an explanation strongly enhance its social influence in the case of financial reasoning. Future work may study further why richness trumps simplicity.

Limitations and future directions. The evidence in this paper may be extended in various directions. In many contexts, the exposure to others is not determined through random matching. This implies that learning and unlearning opportunities will not be equally frequent, and hence the sign of the difference between learning and unlearning rates does not serve anymore as a sufficient statistic for whether there is aggregate improvement. Moreover, in many situations, people not only listen to but also see each other. This broadens the scope of potential cues that can be used to infer the accuracy of another's choice. Furthermore, interactions are often repeated rather than one-shot, both in the dyadic back-and-forth within a conversation, and across different contexts. All of these considerations are specifically associated with interactions that occur with people that are not strangers, unlike in our experiments. This suggests that a productive extension of our work is to study the contagion of truths and falsehoods in real social networks.

Finally, our study focuses on the spread of truths and falsehoods in financial decision-making. While this domain is highly relevant for economists, ecologically valid for studying social learning and often involves large stakes, it is possible that our results do not carry over to other domains, such as political contexts. Future research should examine whether and how the supply and interpretation of explanations differ in settings where political identity and motivated cognition are additional mechanisms at play.

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A Conceptual Framework

The purpose of this framework is to cast our experimental setup in terms of a standard belief formation setting that speaks to the existing economics literature. It serves to conceptualize our reduced-form findings and to provide a guiding structure for 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 interpretations.

A.1 Setup

Consider a binary question with a correct answer $\omega = 1$ and an incorrect answer $\omega = 0$.²⁴ A decision-maker (DM) i enters with a prior belief p_i that the correct answer is 1 and chooses 1 if and only if that belief exceeds 0.5. The DM's prior answer is $x \in \{0, 1\}$. For simplicity, we assume that the agent's prior belief can be described by the functional form

$$p_i = \alpha_0 + \alpha_1 \mathbb{1}_{(x=1)} + \epsilon_i, \quad (1)$$

where $\mathbb{1}_{(x=1)}$ is the indicator function that the agent chooses the correct answer, and ϵ_i is a zero-mean noise term. We assume that this functional form is a probability, i.e., for all realizations of ϵ_i , $0.5 \leq \alpha_0 + \alpha_1 + \epsilon_i \leq 1$ and $0 \leq \alpha_0 + \epsilon_i \leq 0.5$. To build intuition, suppose that $\alpha_0 = 0$ and $\alpha_1 = 1$. In that case, correct and incorrect receivers would be perfectly confident in their respective answers and could never be convinced to change their mind. Consider instead a situation where $\alpha_0 = \alpha_1 = 0.5$. This corresponds to a situation where a DM taking the correct decision is perfectly confident, whereas an incorrect DM is not confident at all but is, at $p_i = 0.5$, perfectly indifferent between both actions.

The DM then observes a signal $s \in \{0, 1\}$, which is the realized answer of another respondent. To learn from the signal the DM needs to assign a *diagnosticity* to it, i.e., a belief about the likelihood that the observed answer matches the true state. We refer to agent i 's perceived diagnosticity with $d_i = \mathbb{P}(\omega = s|s)$ and again assume that it can be represented by the functional form

$$d_i = \beta_0 \mathbb{1}_{ChoiceOnly} + \beta_1 \mathbb{1}_{(s=1)} \mathbb{1}_{ChoiceOnly} + \gamma_0 \mathbb{1}_{Explanation} + \gamma_1 \mathbb{1}_{(s=1)} \mathbb{1}_{Explanation} + \delta_i. \quad (2)$$

Here, $\mathbb{1}_{(s=1)}$ is the indicator function that the observed signal is answer 1 (i.e., the correct

²⁴The binary setup is without loss of generality: the coding of correct vs. incorrect permits a binary classification of choices that applies to questions with multiple possible responses or a continuous scale.

answer), $\mathbb{1}_{Explanation}$ and $\mathbb{1}_{ChoiceOnly}$ are treatment indicators, and δ_i a noise term. We assume that $d_i \in [0, 1]$ holds for all realizations of δ_i . Moreover, we assume that the DM never interprets an answer as evidence for its counterpart.

Assumption 1. *For all realizations of δ_i , the perceived diagnosticity d_i is greater or equal to 0.5.*

An intuitive interpretation of d_i is as receivers' perceived precision of the answer or explanation they are exposed to. Crucially, the drivers of these perceptions as captured by the treatment indicators are entirely different between *Choice Only* and *Explanation*. In *Choice Only*, perceived diagnosticity is only affected by the very fact that this means that another respondent's best answer was such. The *Explanation* treatment nests this source of learning, but additionally provides a host of additional ways to infer the perceived precision. The richness of verbal expressions in natural language, as well as features of paralanguage such as prosody or tonal emphasis, may provide insights into the accuracy of the orator, all of which will be reflected in the parameters of equation 2.

Given a prior belief p_i , a signal s , and a perceived diagnosticity d_i , the DM updates their belief according to Bayes' rule, which yields their posterior belief π_i that action 1 is correct:

$$\pi_i(s = 1) = \frac{p_i \cdot d_i}{p \cdot d_i + (1 - p_i) \cdot (1 - d_i)} \quad (3)$$

$$\pi_i(s = 0) = \frac{p_i \cdot (1 - d_i)}{p \cdot (1 - d_i) + (1 - p_i) \cdot d_i} \quad (4)$$

As before, the DM chooses action 1 if and only if $\pi_i > 0.5$. We refer to the posterior answer using $y \in \{0, 1\}$.

Our baseline setup puts structure on two central objects of interest in our experiment: people's prior confidence (or meta-cognition), p_i , and the perception of others' behavior's diagnosticity, d_i . The framework pins down the calibration of these objects, i.e., how they are related to the true state. First, the calibration of confidence is determined by α_1 , which is the difference in prior confidence between initially correct and incorrect DMs. Second, the calibration of perceived diagnosticity is governed by the parameters β_1 and γ_1 , which determine differences in the perceived accuracy of correct and incorrect observed answers in the context of the *Choice Only* and *Explanation* treatments, respectively.

A.2 Analysis

We characterize the effect of the different treatments on learning, unlearning and optimality rates. A first observation is that due to Assumption 1, signals that coincide with the receiver's prior choice do not lead to a change from prior to posterior choice.

Proposition 1. *If the prior action coincides with the signal, $s = x_i$, then behavior does not change, $x_i = y_i$.*

Note that while Proposition 1 establishes no switching away from one's already preferred action when receiving a supportive signal, a DM will in this case indeed become more confident, i.e., form a more extreme belief, $|\pi_i - 0.5| > |p_i - 0.5|$.

Learning and unlearning rates. Therefore, the two cases of interest occur when the DM initially chooses the wrong answer and is presented with a correct signal, or when they initially choose the incorrect answer and are presented with an incorrect signal. In the first scenario, the signal can drive the agent from an incorrect to a correct answer. This is what we refer to as *learning*. In the second scenario, the opposite can happen and the agent can switch from a correct to an incorrect answer. We call this *unlearning*. The quantities of interest are the rates of learning and unlearning, which are given by

$$l = \mathbb{E}[\mathbb{1}(\pi_i(s = 1) > 0.5) \mid p_i < 0.5]$$

$$u = \mathbb{E}[\mathbb{1}(\pi_i(s = 0) < 0.5) \mid p_i > 0.5].$$

The following result establishes how these rates depend on the parameters of the functional forms.

Proposition 2. *The learning rate l always rises in α_0 , and further rises β_0 and β_1 (γ_0 and γ_1) in the Choice Only condition (Explanation condition). The unlearning rate u always falls in α_0 and α_1 , and rises in β_0 (γ_0) in the Choice Only condition (Explanation condition).*

To build intuition about the drivers of the learning rate, note that a higher α_0 means that an initially incorrect DM is less confident, i.e., has a belief closer to 0.5, and it therefore takes a (perceived) less precise signal to move them over the behavioral threshold of 0.5. β_0 and γ_0 capture the baseline of perceived diagnosticity in *Choice Only* and *Explanation*, respectively; an increase in these parameters will make *all* observed signals be perceived as more convincing and make it more likely that the DM's belief is moved enough to change

actions. A higher β_1 specifically makes seeing a correct signal more convincing, which is the relevant signal in learning opportunities, and similarly for γ_1 in *Explanation*.

Similarly, for unlearning opportunities, lower a_0 and a_1 mean that the initially correct receiver is less confident in their choice, i.e., has a prior belief closer to 0.5, which implies that a (perceived) less precise signal is needed to move them below 0.5 and thus convince them to switch actions. The perceived persuasiveness of an incorrect signal increases in β_0 in *Choice Only* and in γ_0 in *Explanation*.

Optimality rates. Next, we turn to the expected rate of correct choices across the subject population. We denote the optimality rate prior to signal observations by θ^{pre} , defined as $\mathbb{E}[\mathbb{1}_{p_i \geq 0.5}] = \mathbb{P}[p_i \geq 0.5] \in [0, 1]$. In correspondence to the random matching mechanism of our experimental design, we assume that each DM's signal is uniformly drawn from the pool of choices in the population. Therefore, the expected fraction of participants with a correct answer observing an incorrect signal equals $\theta^{pre} \cdot (1 - \theta^{pre})$, which is, at the same time, the expected fraction of participants with an incorrect answer observing a correct signal. This is a simple but crucial insight that may be counterintuitive at first. Compare two tasks, with the second exhibiting a higher baseline optimality rate before exposure to others. Two forces are simultaneously at play once interaction occurs: first, on the receiver side, a higher baseline rate means there are more correct and fewer incorrect receivers, implying more capacity for potential unlearning by initially correct and less unlearning by initially incorrect receivers. Second, on the orator's side, a higher baseline rate means that there are more correct and fewer incorrect orators, so random matching implies less capacity for potential unlearning and more for learning. In terms of the resulting frequency of learning and unlearning opportunities, these forces exactly offset each other, so that there will always be an identical fraction of learning and unlearning opportunities, in expectation. Formalizing this observation, note that the expected fraction of receivers with a correct posterior answer, denoted by θ^{post} , equals $\theta^{pre} + [\theta^{pre} \cdot (1 - \theta^{pre})] \cdot (l - u)$. This yields the following result.

Proposition 3. *The posterior optimality rate exceeds the prior optimality rate if and only if the learning rate exceeds the unlearning rate. The posterior optimality rate rises with the learning rate and falls with the unlearning rate.*

The implication of Proposition 3 is that the analysis of the learning and unlearning rates directly extends to the analysis of optimality rates. The first part highlights a critical reduced-form relationship between learning, unlearning and optimality rates: the sign of

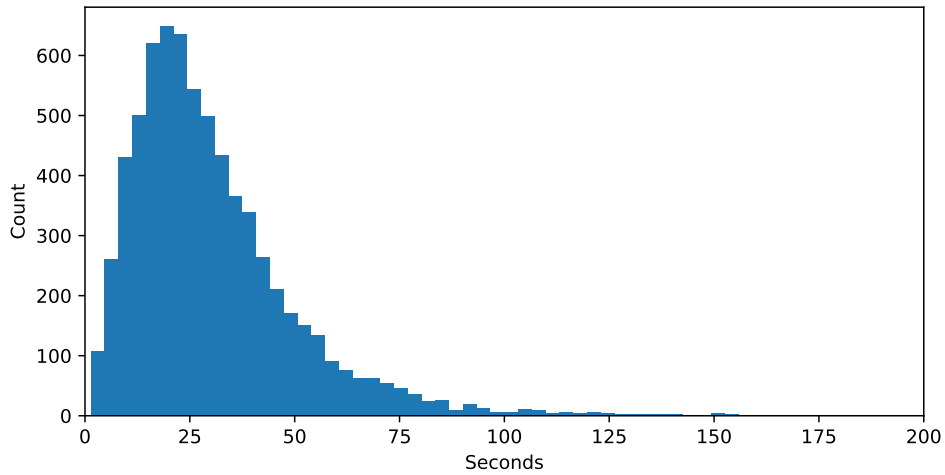
the difference between learning and unlearning rate determines whether there is an aggregate improvement or not, i.e., whether the posterior exceeds the prior optimality rate. This provides a simple formal justification to study learning and unlearning rates as the drivers of aggregate improvements, as we did in Section 3. Crucially, this result is entirely independent of the prior optimality rate in a given task.

The second part establishes that, conditional on the sign of $(l - u)$, the importance of learning and unlearning rates is governed by $\theta^{pre} \cdot (1 - \theta^{pre})$, which expresses the frequency of both of learning and unlearning opportunities as a function of the prior optimality rate. Intuitively, when the prior optimality rate is closer to $\frac{1}{2}$, opportunities for learning and unlearning become more frequent, and the impact of the imitation rates in these situations on the posterior optimality rate becomes greater.

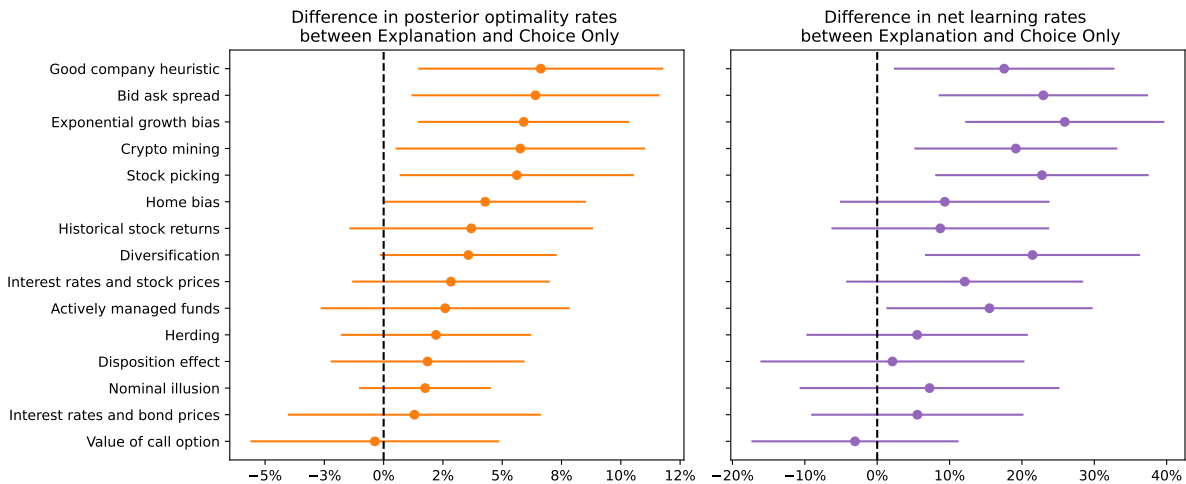
Linking model to data. Before delving into an empirical exercise motivated by this framework, we point out what our reduced-form findings imply in terms of the model. Our main pattern as stated in Result 1 is a differential effect of explanations (relative to mere observation) on learning versus unlearning. First, it implies that $\gamma_0 \approx \beta_0$. This means that the perceived diagnosticity of incorrect answers is similar irrespective of whether the receiver just learned about the orator's choice or also listened to their explanation. Intuitively, explanations associated with incorrect answers do not provide receivers with any additional insight that the corresponding answer is incorrect, on average. Second, our finding implies that $\gamma_1 > \beta_1$. This means that relative to the perceived diagnosticity of incorrect answers, correct answers are associated with a higher increase in perceived diagnosticity under explanations than mere observation. Put differently, explanations associated with correct answers boost perceived diagnosticity.

B Additional figures and tables

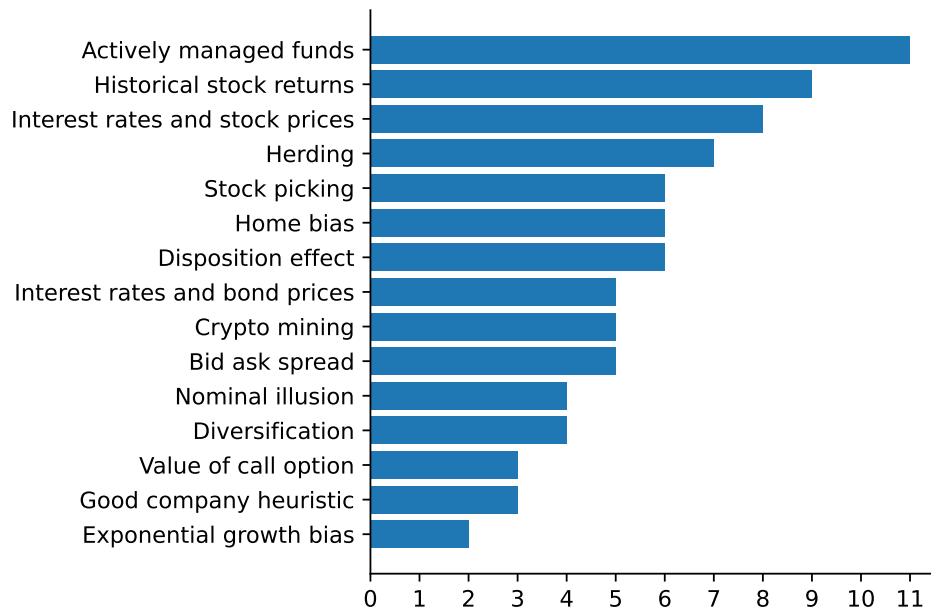
B.1 Additional figures



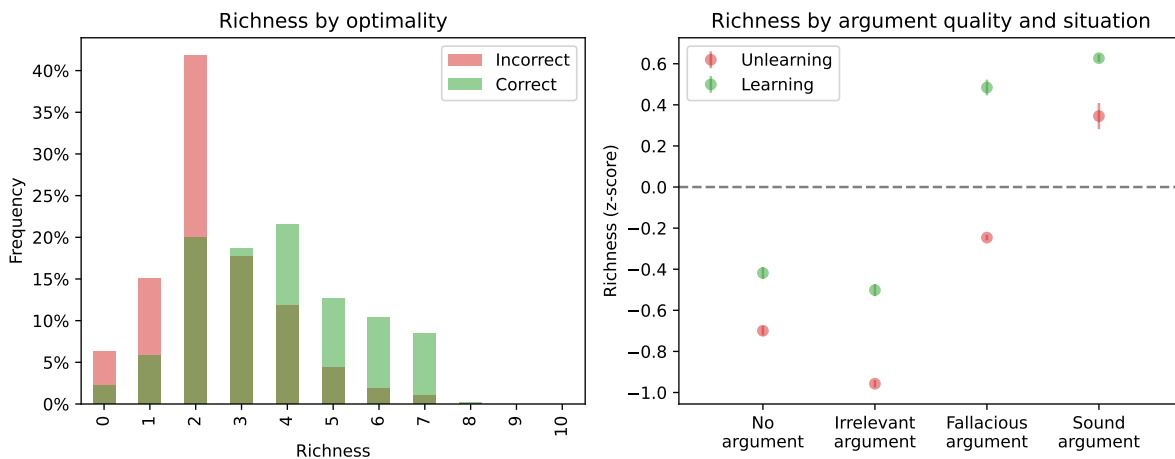
Appendix Figure A1: Histogram of recording lengths. *Notes:* Sample is the Orator survey with 466 orators and 6,910 valid explanations.



Appendix Figure A2: 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. *Explanation* sample is the main Receiver survey (1,103 receivers), *Choice Only* sample is pooled from all collections (2,733 receivers). Whiskers show 95% confidence intervals.



Appendix Figure A3: Number of identified arguments by task. *Notes:* See Section 5.1.1 and Appendix C.4 for details on argument identification.



Appendix Figure A4: Richness gap by orator optimality, and by argument quality and situation. *Notes:* *Explanation* sample is the main Receiver survey (1,103 receivers), *Choice Only* sample is pooled from all collections (2,733 receivers). See Appendix C.3 for details on richness ratings. Whiskers show standard errors.

B.2 Additional tables

Appendix Table A1: Overview of financial decision questions

Task	Question
Actively managed funds	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) <i>Actively managed funds do not outperform passively managed ones.</i>
Bid ask spread	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) <i>More than \$30</i>
Crypto mining	Since the blockchain is decentralized, most Bitcoin mining is done by many small miners. (i) True (ii) <i>False</i>
Disposition effect	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) <i>This does not make a difference</i>
Diversification	When an investor spreads his money among different assets, does the risk of losing money: (i) Increase (ii) <i>Decrease</i> (iii) Stay the same
Exponential growth bias	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) <i>More than \$110</i> (ii) Exactly \$110 (iii) Less than \$110
Good company heuristic	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) <i>Need to know more information</i>
Herding	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) <i>Should invest less</i> (iii) Should not affect my decision
Historical stock returns	What is the average annual return of the S&P 500 stock market index over the past 20 years? (i) <i>Less than 10%</i> (ii) Between 10% and 15% (iii) More than 15%
Home bias	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) <i>Given the assumptions, both are equally good investments.</i>
Interest rates & bond prices	If the interest rate falls, what should generally happen to bond prices? (i) <i>Rise</i> (ii) Fall (iii) Bond prices are not affected
Interest rates & stock prices	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) <i>Stock prices will fall</i> (iii) Stock prices will stay the same
Nominal illusion	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) <i>Less than today</i>
Stock picking	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) <i>False</i>
Value of a call option	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) <i>Higher volatility increases the value of a call.</i> (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 marked by italics.

Appendix Table A2: 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/56V_NLR.pdf
Explanation Speech Receiver Experiment	Prolific	1,103	<i>Choice Only Explanation</i>	Choices in 15 financial decision tasks	https://aspredicted.org/56V_NLR.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/RH4_375.pdf
Transcript Receiver Experiment	Prolific	917	<i>Choice Only Transcript</i>	Choices in 15 financial decision tasks	https://aspredicted.org/VPC_5NH.pdf

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

Appendix Table A3: Decomposition of differential learning effect in *Transcript* treatment

	<i>Dependent variable: Imitation</i>								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Explanation	-0.009 (0.015)	0.022 (0.019)	-0.134*** (0.021)	-0.109*** (0.028)	-0.096** (0.048)	-0.032 (0.048)	-0.093* (0.053)	-0.124** (0.053)	-0.115* (0.067)
Learning	0.198*** (0.016)	0.197*** (0.020)	0.205*** (0.017)	0.199*** (0.020)	0.199*** (0.016)	0.127*** (0.015)	0.197*** (0.020)	0.118*** (0.019)	0.113*** (0.020)
Explanation × Learning	0.091*** (0.021)	0.045* (0.026)	0.024 (0.022)	0.056** (0.026)	0.068*** (0.022)	0.092*** (0.021)	0.011 (0.027)	0.016 (0.026)	0.018 (0.026)
Argument controls		✓		✓			✓	✓	✓
Richness controls			✓	✓			✓	✓	✓
Orator controls					✓		✓		✓
Receiver controls						✓		✓	✓
Observations	7871	7871	7871	8800	7871	7871	7871	7871	7871
R ²	0.072	0.079	0.086	0.113	0.078	0.161	0.089	0.178	0.180

Notes: See notes for Table 2. *Explanation* sample is the main Transcript survey (917 receivers), *Choice Only* sample is pooled from all collections (2,733 receivers). We drop the 0.1% of observations with missing receiver prior confidence from all regressions.

B.3 Additional results on confidence

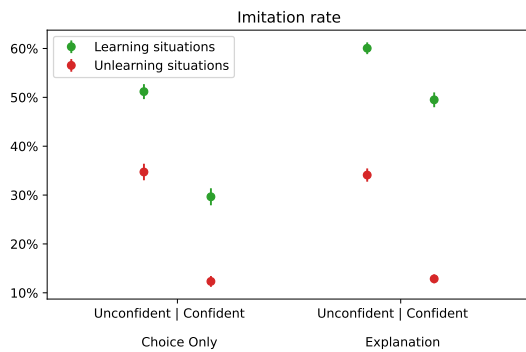
We study how learning from explanations interacts with the confidence of receivers. On average, receivers report a prior confidence of 67.79%, with a median of 71.00%. Incorrect receivers report a prior confidence of 61.33% against 72.78% for correct ones (a 0.4 SD difference, $p < 0.01$). As expected, orator confidence follows a very similar pattern.²⁵

To study the effect of receiver confidence on imitation, Figure A5a reports the results from Figure 2 by distinguishing between confident and unconfident receivers. These are receivers who reported a prior confidence above or below the sample median, respectively. Confident respondents are less likely to imitate in all configurations. Beyond that, in Choice Only, the difference between confident and unconfident receivers appears small. On the other hand, there is a sizable gap between confident and unconfident receivers in the Explanation treatment.

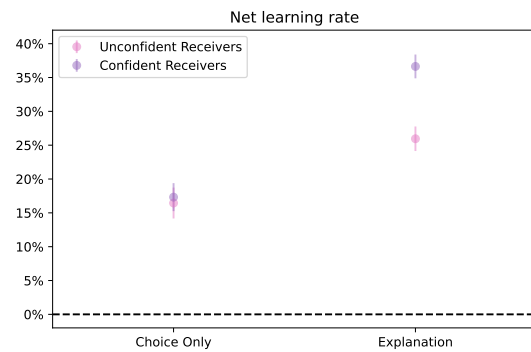
To look at this difference more precisely, Figure ?? reports the net learning rate, which we define as the imitation rate in learning situations minus the imitation rate in unlearning situations. It is positive in both treatments, but roughly two times larger in Explanation. The effect of Explanation versus Choice Only on the imitation rate remains substantial and highly significant both among unconfident and confident receivers ($p = 0.004$ and $p < 0.01$ respectively). We conclude that our effects are not driven by a subsample of confident or unconfident orators.

At the same time, the effect of explanations are stronger among confident orators. The imitation rate stands at 15.72% for unconfident against 17.62% for confident receivers in Choice Only, a small and insignificant difference ($p = 0.53$). On the other hand, it is 25.31% for unconfident against 35.02% for confident receivers in *Explanation*, a substantial and highly significant gap ($p < 0.01$). These additional analyses show that the learning benefits of explanations show up at all confidence levels, but are especially strong among confident receivers. Put simply, confident but wrong receivers are remarkably open to having their mind changed by a correct explanation.

²⁵Because of an error in the survey which allowed respondents to skip the question, prior confidence is missing for 108 observations, which represent only 0.5% of the full sample. We drop these observations for the analyses of this Section only.



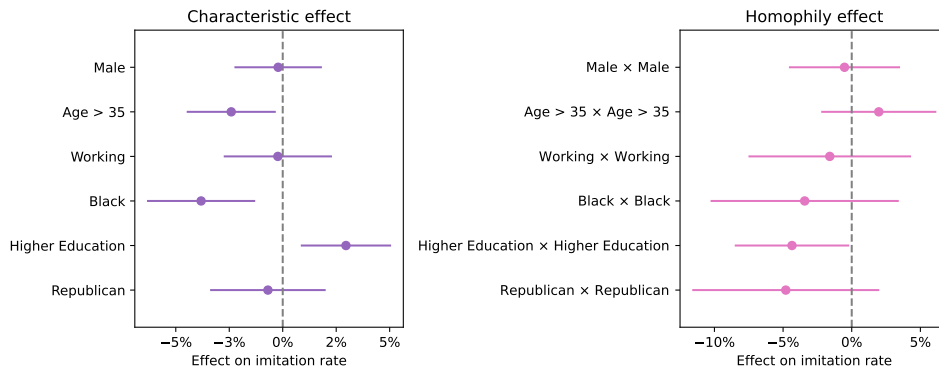
a) Imitation rate by situation and confidence



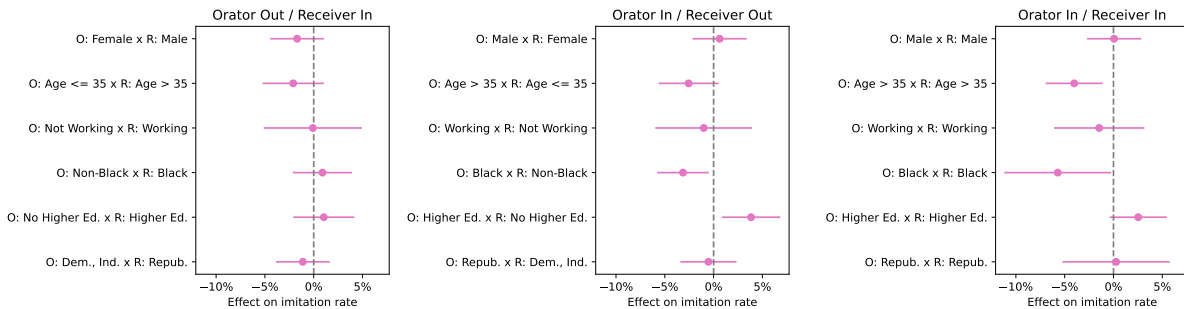
b) Net learning rate by confidence

Appendix Figure A5: Effect of receiver prior confidence on imitation in the main experiment. *Notes:* Confident or unconfident receivers reported a prior confidence above or below the sample median (71.00%), respectively. The net learning rate is defined as the imitation rate in learning situations minus the imitation rate in unlearning situations. *Explanation* sample is the main Receiver survey (1,103 receivers), *Choice Only* sample is pooled from all collections (2,733 receivers). Whiskers show standard errors.

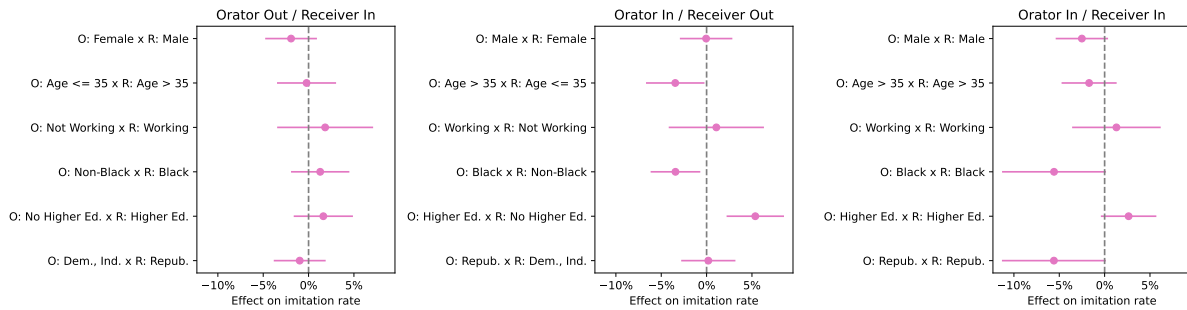
B.4 Additional results on orator & receiver characteristics



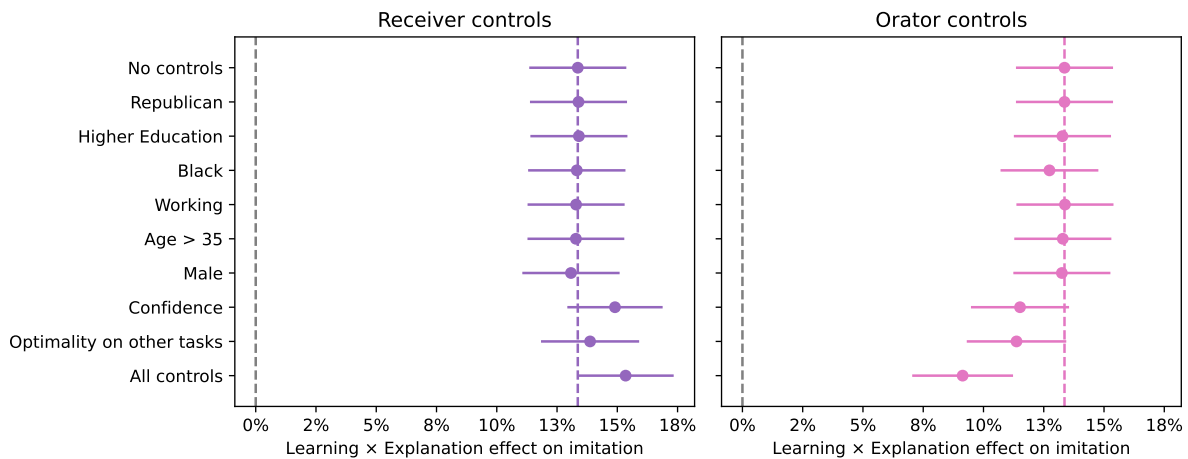
Appendix Figure A6: Effect of orator and orator-receiver characteristics on imitation in *Explanation Transcript* treatment. *Notes:* See notes in 10. *Transcript* sample is the corresponding Receiver survey (917 receivers). *Choice Only* sample is pooled from all collections (2,733 receivers).



Appendix Figure A7: Effect of orator-receiver characteristics on imitation in *Explanation Speech* treatment. *Notes:* Coefficients on *Explanation* interacted with orator-receiver characteristics, in a linear regression of the imitation rate on orator and receiver optimality, *Explanation*, orator-receiver characteristics and *Explanation* interacted with orator-receiver characteristics. *Explanation* sample is the main Receiver survey (1,103 receivers), *Choice Only* sample is pooled from all collections (2,733 receivers). Here, orator-receiver characteristics are an 'Orator Out / Receiver In' dummy equal to 1 if the receiver characteristic has the characteristic but not the Orator; 'Orator In / Receiver Out' and 'Orator In / Receiver In' are similarly defined; 'Orator Out / Receiver Out' is left out and serves as reference level. Whiskers show 95% confidence intervals.



Appendix Figure A8: Effect of orator-receiver characteristics on imitation in *Explanation Transcript* treatment. *Notes:* See notes in A7. *Transcript* sample is the corresponding Receiver survey (917 receivers). *Choice Only* sample is pooled from all collections (2,733 receivers).



Appendix Figure A9: 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. In the left panel, Controls are receiver controls. In the right panel, Controls are orator controls. All regression except 'No controls' and 'All controls' contain a single control. *Explanation* sample is the main Receiver survey (1,103 receivers), *Choice Only* sample is pooled from all collections (2,733 receivers), both restricted to Learning and Unlearning situations. See also Table 2.

B.5 Additional results from robustness checks

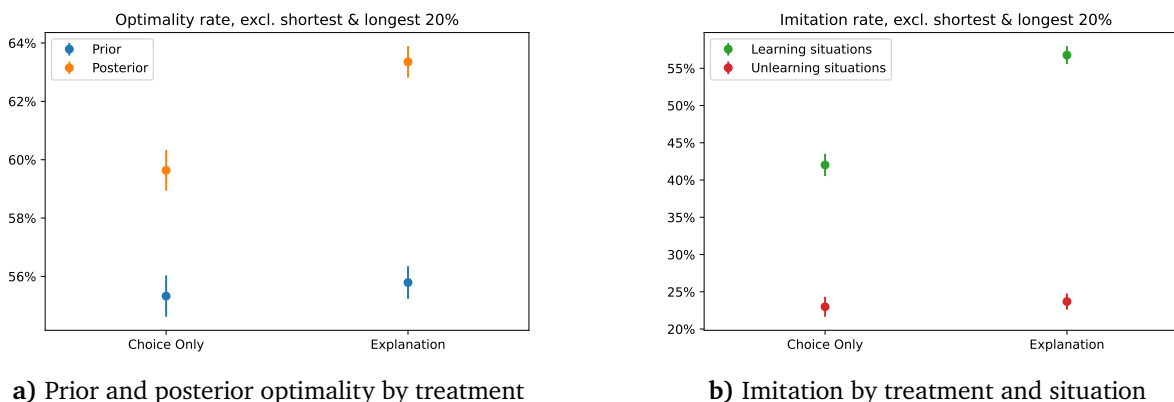
B.5.1 Excluding the shortest and longest recordings

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

Figure A10b shows the resulting optimality rates, mirroring Figure 2. 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 A10b repeats the analysis by learning and unlearning situations as in Figure 2. 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 A10: Robustness of main findings to dropping shortest and longest recordings. *Notes:* In the two panels, the analyses and starting samples are the same as in Figures 1 and 2 respectively. We additionally drop the 20% of shortest and 20% of longest explanations, measured by length of the associated audio file. Whiskers show standard errors.

B.5.2 Heterogeneity by prior accuracy

Our main analyses in Section 3 focus on the difference between learning opportunities, where an initially incorrect receiver hears an explanation from a correct orator, and unlearning opportunities, where the opposite happens. This is motivated by our conceptual framework, which shows that the difference between learning and unlearning rates is a sufficient statistic for aggregate improvements.

The assumption that receivers do not change their answer when confronted with confirming orators is largely borne out in the data. In situations where the orator and receiver are both correct, the imitation rate is 99.1% for *Choice Only* and 99.2% for *Explanation* ($p = 0.77$). When both are incorrect, the imitation rates are only 82.6% and 82.2% respectively ($p = 0.73$). Since we define imitation as the receiver picking the same option as the orator, the lower imitation rate when both are wrong is principally due to tasks with three options where receivers gave a wrong answer different from the orator's and maintained it.

Looking at posterior optimality rates shows they stand at 99.1% for *Choice Only* and 99.2% for *Explanation* ($p = 0.77$) when both are correct, and at 2.0% and 3.8% ($p < 0.01$) respectively when both are incorrect. This means a small but significant number of receivers switches to the correct answer upon hearing a confirming incorrect explanation. However, this 1.8 p.p. effect is much smaller than the 13.0 p.p. effect in unlearning situations, while both situations occur similarly often (23.5% and 20.3% respectively). Decomposing our main 3.2 p.p. effect from explanations on posterior optimality, we find that approximately 80% of it is driven by learning situations, 12% by situations where both are wrong and 8% by unlearning situations.

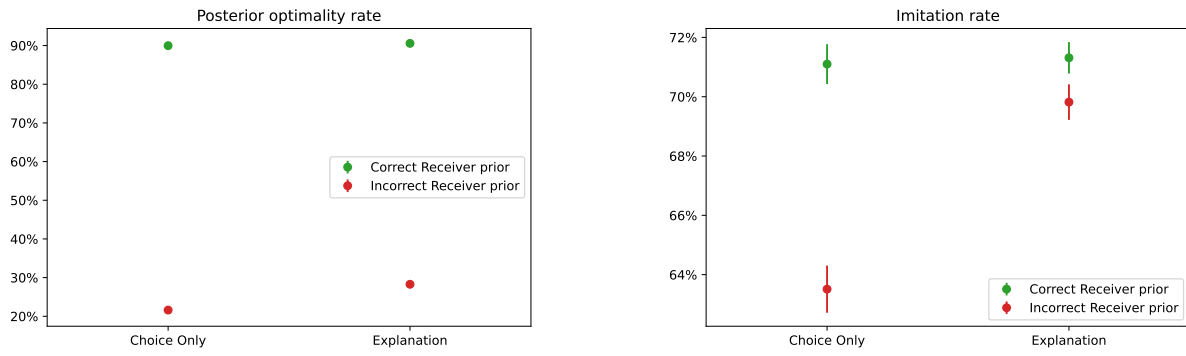
This justifies focusing on the decisive learning-unlearning margin in the rest of our analyses. We nonetheless show that our main results are robust to keeping all situations by distinguishing simply by prior accuracy, thereby analyzing the whole sample.

Figure A11b shows the share of receivers giving a correct answer after having been exposed to the orator's answer, split by treatment and by receiver prior accuracy. Among receivers that were initially correct, the share of correct posteriors is 90.0% for *Choice Only* and 90.6% for *Explanation*, an insignificantly small difference ($p = 0.29$). On the other hand, among receivers that were initially incorrect, the posterior optimality rates are 21.6% for *Choice Only* and 28.3% for *Explanation*, a significant 6.7 p.p. increase ($p < 0.01$).

Figure A11b repeats the same analysis for imitation rates. Among initially correct receivers, imitation rates are very close at 71.1% in *Choice Only* and 71.3% in *Explanation* ($p = 0.80$). Among initially incorrect receivers, imitation rates are 63.5% and 69.8% re-

spectively, a significant 6.3 p.p. increase ($p < 0.01$).

Our main conclusion that hearing an orator's explanation has an effect *via* receivers that are initially wrong, but not *via* receivers that are already right, is therefore robust to keeping the whole sample instead of considering only learning and unlearning situations.



a) Posterior optimality by receiver prior accuracy

b) Imitation rate by receiver prior accuracy

Appendix Figure A11: Robustness of main findings by prior accuracy. *Notes:* *Explanation* sample is the main Receiver survey (1,103 receivers) with 13,111 observations, *Choice Only* sample is pooled from all collections (2,733 receivers) with 8,232 observations. Whiskers show standard errors.

B.6 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

Appendix Figure A12: Recording screen from the Orator experiment.


a) *Choice Only* treatment

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 outperform passively managed ones.




b) *Explanation* treatment

Listen to 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 outperform passively managed ones.



Appendix Figure A13: Observation screens from the Receiver 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%

Appendix Figure A14: *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 fun then a lot of that risk that would just go on, you know, uncontrolled gets mitigated.

Appendix Figure A15: *Transcript* treatment screen from the Receiver experiment in Section 4.3.

C 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 RA’s and machine coding by a Large Language Model (LLM). For the latter, we use the state-of-the-art OpenAI GPT-4-Turbo, 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 pure restatement 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 the number of analogical arguments. Third, 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.

C.1 Explanation categorization

We first categorize speeches into general categories to acquire a broad overview of the different type of explanations. For that, we asked a team of RA 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 A4 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%.

Appendix Table A4: 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)certainty 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.”
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.”	Incorrect Explanation
Unclear Explanation	The explanation is very unclear or non-sensical.	“Passively managed funds, outperform, actively managed funds. And this is why hedge funds have a very short life spans. So question number two”

C.2 Feature identification

We identify 31 text features in explanation, 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. Additionally, we generate 6 textual & speech features via direct computation. Table A5 provides an overview of features.

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).

C.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).

C.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. Table A7 shows all arguments appearing in the final scheme. Each has a title used to denote it in Figures and a detailed description used in the annotation.

Table A6 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 A5: Explanation features annotated via GPT-4

Feature	Description
<i>Language Markers</i>	
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”.
<i>Disfluencies</i>	
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”.
<i>Certainty Markers</i>	
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”.
<i>Reasoning Content</i>	
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”.
<i>Addresses to Receiver</i>	
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”.
<i>Computed Features</i>	
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 score, flipped so higher values indicate higher complexity.

Appendix Table A6: 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.”

Appendix Table A7: 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
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
<i>Task: Bid ask spread</i>		
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
<i>Task: Crypto mining</i>		
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

Continued on next page

Argument	Description	Category
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
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, leading to a total of 110 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		

Continued on next page

Argument	Description	Category
Higher growth brings higher returns	Investing in the firm with higher growth prospects will yield higher returns due to its potential for growth.	Fallacious
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
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		

Continued on next page

Argument	Description	Category
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
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		

Continued on next page

Argument	Description	Category
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 misinfo 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
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

D Instructions

D.1 Orator Experiment

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 \$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.
- After you click to submit a recording, it can take a little while to upload. We kindly ask you to be patient.

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 selected 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.

[Comprehension questions]

PAGEBREAK

Remember!

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

Main Part: Example Question (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.

PAGEBREAK

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:

- i) More than today
- ii) Exactly the same as today
- ii) Less than today

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

[Recording box, activated manually]

PAGEBREAK

Provide your best answer

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

[Question text with multiple answer 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? i) Yes ii) No

PAGEBREAK

[Elicitation of sex, age, ethnicity, education, employment and political affiliation]

D.2 Receiver experiment

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:

- (i) You provide your best answer to the question.
- (ii) 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.
- (iii) 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 \$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?

[Comprehension questions]

PAGEBREAK

Main Part: Example Question (Inflation)

[Explanation and Choice Only treatments]

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:

- i) More than today
- ii) Exactly the same as today
- ii) Less than today

How certain are you that your above answer is correct?

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

PAGEBREAK

[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.

[Choice Only treatment]

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

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

PAGEBREAK

[Explanation treatment]

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]

Read the other respondent's answer

[Box with question text]

Other person's answer: [Answer of other respondent]

PAGEBREAK

[Explanation and Choice Only treatments]

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.

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

[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)]

PAGEBREAK

Additional questions

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

ii) No

PAGEBREAK

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...

i) ...more from sparse explanations than from rich explanations.

ii) ...more from rich explanations than from sparse explanations.

iii) ...equally much from rich and sparse explanations.

Why do you think this is the case?

[Open text box]

PAGEBREAK

[Elicitation of sex, age, ethnicity, education, employment and political affiliation]