The Transmission of Reliable and Unreliable Information*

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Abstract

Information often shapes behavior regardless of its quality: unreliable claims wield influence, while reliable ones are neglected. We propose that this occurs in part because word-of-mouth transmission tends to preserve claims while dropping information about their reliability. We conduct controlled online experiments where participants listen to economic forecasts and pass them on through voice messages. Other participants listen either to original or transmitted audio recordings and report incentivized beliefs. Across various transmitter incentive schemes, a claim's reliability is lost in transmission much more than the claim itself. Reliable and unreliable information, once filtered through transmission, impact listener beliefs similarly. Mechanism experiments show that reliability is lost not because it is perceived as less relevant or harder to transmit, but because it is less likely to *come to mind* during transmission. A simple associative-memory framework suggests that reliability information may be less likely to come to mind either because it is less likely to be cued by transmission requests or because attempts to retrieve it face greater interference. Evidence from our experiments, a large corpus of everyday conversations, and economic TV news supports both of these mechanisms.

Keywords: Information Transmission, Word-of-mouth, Reliability, Memory, TV news.

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1 Introduction

The extent to which information spreads and influences beliefs is often unrelated to its quality.

In popular financial advice, unreliable claims ("house prices always go up") circulate widely alongside meticulously well-documented claims backed by longstanding expert consensus ("passive funds on average outperform active funds"). Most people who hear such pieces of advice have little or no idea about the strength of evidence backing them, that information having dropped away long ago in the chain of word-of-mouth transmission.

The "4% rule" for retirement savings, a standard piece of financial advice, originated as a descriptive finding in a 1994 paper. The author of the paper explicitly noted that the data he analyzed were unrepresentative and dangerous to extrapolate from; he later expressed surprise at how quickly his original caveats were dropped as the finding passed from mouth to mouth and solidified into a "rule" (Bengen, 2024).

One of the most viral health tips of the 2000s claimed that eating six small meals a day promoted weight loss. The tip was repeated on broadcast television shows, in bestselling books, and throughout the multi-billion-dollar weight loss industry (Gower, 2002; ABC News, 2005). Those repeating the claim rarely bothered to say something about its provenance or evidentiary basis; it appears to have originated either in a 1967 book by a physician who claimed sensationally to have helped 10,000 patients lose weight, or in a 1991 randomized-controlled trial with a sample size of 7 (Stillman and Baker, 1967; Tai et al., 1991).

In shift-to-shift handoffs, doctors convey facts about patients to their replacements. Information loss during these handoffs is a major source of clinical risk. Anecdotal reports suggest that information about the *certainty level* of doctors' diagnoses is particularly likely to be omitted in these handoffs (Dutra et al., 2018; Cornell et al., 2023), leading confident diagnoses to be underweighted and uncertain diagnoses to be overweighted.

Within organizations, as pieces of information are summarized and move up through hierarchies, caveats and expressions of uncertainty are often lost. A 2014 RAND retrospective about the 2002 National Intelligence Estimate on weapons of mass destruction in Iraq concluded that the report "contained several qualifiers that were dropped" when it was transformed into an executive summary, and that "as the draft NIE went up the intelligence chain of command, the conclusions were treated increasingly definitively" (Gompert et al., 2014).

Economic theory assumes that more reliable information should circulate and influence beliefs more. The preceding examples, however, suggest that unreliable claims frequently spread too widely and wield undue influence, whereas reliable claims struggle to gain traction, in part because the claims themselves are passed from person to person while crucial information about their source or evidentiary basis is lost in transmission.

This paper studies whether, and why, this is true. Borrowing the standard terminology of Bayesian updating and sender-receiver models, we distinguish between the realization of a signal ("a claim") and the precision of that signal ("the reliability of the claim"). This distinction gives us a natural benchmark: we ask whether the precision of signals tends to be distorted through word-of-mouth transmission *more* than the signal realizations themselves. We then ask whether people's transmission decisions are influenced by rational cost-benefit calculations about the payoffs to transmitting different kinds of information, or by cognitive factors such as selective attention or memory. To study these questions, we use controlled online experiments and observational data from everyday conversations and economic TV news.

Our online experiments involve more than 5,000 participants. In a *transmitter* experiment, participants listen to a one-minute message giving a qualitative forecast about an economic variable, and are then incentivized to record themselves faithfully passing on the information they heard. In a subsequent *listener* experiment, participants listen to either the original forecasts or transmitted versions of those forecasts before stating incentivized beliefs. Listeners' beliefs give us quantitative measures of the information content of original and transmitted messages, which allows us to estimate loss of level and reliability information using methods we describe below.

We base the original forecasts in our transmitter experiment on actual news coverage, and cross-randomize their level and reliability. We vary the *level*—high or low—by switching whether the original message argues for an increase or a decrease in the relevant variable. We vary the *reliability*—reliable or unreliable—using manipulations that weave certainty- or uncertainty-denoting words into an otherwise-identical text, and manipulations that change multiple implicit and explicit signals of reliability, including the speaker's confidence, credentials, stated sources of evidence, fluency, and vocabulary. Both level and reliability are communicated in qualitative terms only, i.e., not using numbers, thereby mimicking how people naturally communicate in many real-world settings.[1]

Transmitters are incentivized based on how close the belief updates induced by their voice messages are to the average belief updates induced by the original messages.[2] Such incentives motivate a *faithful* transmission of information, which is ubiquitous in the real world: sales employees relay customer feedback to developer teams, analysts brief executives, and friends share financial advice or expectations sourced from media consumption.

Our main finding is that information about the reliability of a prediction is lost in transmission about three times as much as information about the prediction's level. We refer to this finding as *differential information loss,* and document it using three complementary sets of analyses.

In our first analyses, we directly examine the transcripts of transmitted messages. While nearly all of the transmitted messages include some statement about the level of the original prediction, only about a third mention the original prediction's reliability or include other markers of reliability, such as uncertainty prefixes. Transmitted messages, containing an average of 114 words (8-10 sentences), tend to be only half as long as the original messages. Yet even the longest 10 percent of transmitted messages, which are about as long as the original messages, mention reliability less than 30% of the time. Many messages go on at length, and in great detail,

[1]Robustness experiments show that our findings also hold when communication includes numerical expressions for level and reliability.

[2]Transmission under these baseline incentives depends on which content transmitters believe is relevant for updates. We directly study these beliefs as well as alternative incentive schemes in our analysis of mechanisms.

about the level of the original forecast without mentioning its reliability.

What ultimately matters is preservation of the *information content* of the original messages, which is imperfectly captured by our transcript analysis: the same information could be passed on in fewer or different words. In our second set of analyses, we examine listeners' beliefs about the level and the reliability of the predictions in the original messages.

Consider the loss of level information. Among listeners who directly hear the original messages, switching from a low-level message to a high-level message shifts beliefs about the prediction's level by 1.37 standard deviations (SDs). Among listeners who hear transmitted versions of those messages, beliefs shift by only 0.88 SDs. This indicates $100 \times [(1.37-0.88)/1.37] \approx 34\%$ loss of sensitivity to variation in the level of the original prediction, induced by transmission.

By contrast, loss of reliability information is nearly three times as large. Among listeners who hear the original messages, switching from a weak-reliability message to a strong-reliability message shifts beliefs about the message's reliability by 1.18 SDs. The corresponding shift for listeners who hear transmitted recordings is 0.12 SDs, meaning 91% of the variation in information about a message's reliability is lost in transmission.

In both cases, the loss of sensitivity to our manipulations is driven by a *symmetric* compression of beliefs towards an intermediate value. After transmission, reliable messages are perceived as less reliable, but unreliable messages are perceived as more reliable. Both effects have similar magnitudes, meaning that transmission does not change the average perceived reliability of messages. Similarly, forecasts in the high condition are perceived as predicting a less high level, and low forecasts as predicting a less low level.

In our final set of analyses, we examine listeners' belief updates about the economic variables discussed in the recordings (the object of ultimate economic relevance, and the object on which transmitters are incentivized). Listeners who directly hear the original messages update their beliefs in a qualitatively Bayesian way: they update in the direction of the message's prediction, and those who hear strong-reliability versions of a message update twice as strongly on average as those who hear weak-reliability versions. By contrast, listeners who hear transmitted versions of the messages update about the same amount on average from weak-reliability and strong-reliability messages—the distinction between weak- and strong-reliability messages is almost completely lost in transmission. We calculate that transmission causes the sensitivity of listeners' belief updates to our level manipulations to decrease by 30%, and their sensitivity to our reliability manipulations to decrease by 90%.

Our results show that reliable and unreliable information, once filtered through transmission, impact listener beliefs similarly. This effect of transmission may operate alongside and compound a distinct *updating* bias: Griffin and Tversky (1992) and Augenblick et al. (2025), among others, argue that even conditional on knowing the precision or diagnosticity of a signal, people overinfer from unreliable signals and underinfer from reliable ones.[3] In our experiments, the effect of such an updating bias is held constant across listeners to original and transmitted messages by design,

[3] Note that signal "strength" in the model of Griffin and Tversky (1992) is related to level information in our framework, and signal "weight" to reliability information.

allowing us to identify the distinct effect of transmission. Jointly, transmission-induced loss of reliability indicators and people's insufficient sensitivity to the reliability indicators that do reach them may contribute to the spread of unreliable news and misinformation.

While real-world communication is typically qualitative, many important settings involve transmission of quantitative information. In a robustness experiment, we replicate our main results when the original forecasts include quantitative level and reliability statements (a percentage point estimate and percentage confidence level). This pre-registered experiment additionally addresses concerns that our baseline results are driven by some extraneous difference between the way level and reliability are communicated in our baseline design, for example that qualitative level manipulations feel sharper or more binary than qualitative reliability manipulations.

We next ask what drives the differential information loss we document. On the one hand, reliability information could be disproportionately lost as the result of a deliberate tradeoff, either because the perceived benefits of transmitting reliability information are lower than for level information, or the perceived cognitive costs of transmitting reliability information are higher. On the other hand, differential loss could result not from a deliberate constrained optimization process, but from some non-deliberate mechanism. For example, reliability information might not *come to mind* at the moment of recording the voice message. In a series of mechanism experiments, we reject the first two explanations and find support for the third.

We begin by examining participants' perceived benefits of communicating level versus reliability information and report two pieces of evidence. After transmitters in our main experiment record their messages, we ask a subset of respondents how important it is to pass on level and reliability information to maximize the likelihood of obtaining the incentive payment. Respondents on average deem them equally important, correctly anticipating that listeners' belief updates are highly sensitive to both our level and reliability manipulations. Second, we conduct an additional experiment that explicitly and equally incentivizes transmitters to pass on level and reliability information, effectively fixing beliefs about the relative benefits of transmitting the two dimensions. Even under these more conservative incentives, we find pronounced differential information loss, at about 30% for level information and 70% for reliability. Differences in beliefs about the benefits of transmitting level versus reliability information therefore cannot account for much of the differential loss we document.

Next, we ask whether the perceived cognitive costs of transmitting reliability information are higher. We conduct an additional experiment where transmitters are allowed to decide whether their bonus payment will depend on their transmission of level information or reliability information. *Ex ante*, a majority choose to be incentivized based on their transmission of *reliability* information and expect it to be easier to communicate. These beliefs do not change much *ex post*, after participants have experienced the task. This suggests that higher perceived difficulty of transmitting reliability information cannot account for differential information loss.

Finally, we extend our analysis of mechanisms beyond perceived benefits and costs to embrace the potential constraints memory introduces into the transmission process, outside of the transmitter's awareness. Leveraging a standard distinction in memory research (e.g., Kahana, 2012), we distinguish between *cued recall* of specific pieces of information from the original message once explicitly prompted for them, and *free recall* of information that occurs while transmitters record their message ("what comes to mind"). Transmitters may be unable to remember the reliability of the original message, even when explicitly asked about it (a failure of cued recall), or it may simply fail to come to mind during the transmission process (a failure of free recall).

Starting with cued recall, we analyze memory loss among transmitters by eliciting their beliefs about the level and reliability of the predictions in the original recordings after they have recorded their messages. We find that transmitters' post-transmission beliefs are just as sensitive to variations in the original recordings as the beliefs of listeners directly hearing original recordings. This indicates minimal memory loss among transmitters in cued recall.

However, even though transmitters remember reliability information when prompted, reliability information may not come to mind *when completing their recordings*, i.e., in a free recall setting and facing significant cognitive constraints. Our previous results hint at this possibility: more than 60% of transmitters do not mention reliability information at all in their messages, even when *ex post* remembering this information, agreeing that it is equally important as level information, and believing it is even easier to transmit. We conduct an additional experiment to directly test the hypothesis that reliability does not come to mind unless specifically cued. This experiment replicates our previous designs while ramping up the during-recording salience of level and reliability information. We show salient text on the recording screen reminding respondents to communicate both level and reliability. In this experiment, differential information loss is eliminated entirely. Our findings hence reveal that important information may fail to be transmitted even if it is explicitly known to be important and remembered when directly prompted.

We conclude from our series of mechanism experiments that reliability information is lost in transmission largely because it fails to come to mind during the cognitively taxing process of verbal transmission. The final section of the paper considers potential reasons for this and brings in observational evidence from everyday conversations and economic TV news.

Drawing on a workhorse framework of associative episodic memory (Kahana, 2012; Bordalo et al., 2020), we distinguish between two reasons reliability could be less likely to come to mind during the transmission process. First, real-world requests for transmission may only rarely cue reliability information, meaning transmitters are not used to retrieving reliability. Second, reliability information may tend to be communicated in more generic ways than corresponding claims, making reliability statements more similar to each other. If different pieces of reliability information are less distinctive from each other, attempts to retrieve a specific piece of reliability information may face more *interference*.

Evidence from the British National Corpus, a large collection of everyday conversations in English, supports the first possibility. Requests for information virtually never explicitly ask about the reliability of the requested information, and indirect cues of reliability (in the form of reliability markers or indicators) appear in only about a quarter of requests. This scarcity of reliability cues matters: in three different contexts, we show that reliability is much more likely to be transmitted when directly or indirectly cued. This holds true for irrelevant cues randomly varied in our experiment; it is true on TV news, where expressions of uncertainty in economic segments are substantially more responsive to a benchmark measure of true economic uncertainty on days where the preceding day's coverage featured a higher volume of uncertainty language that could serve as an indirect cue; and it is true in the British National Corpus, where answers to questions containing indirect reliability cues are substantially more likely to contain reliability indicators themselves.

The interference hypothesis also finds support in the British National Corpus: expressions of reliability information we extract using an LLM are about 40% more semantically similar to each other than expressions of level information are to each other. This is because reliability information is often communicated through generic language ("maybe," "I'm quite sure"), while level information typically comes in the form of rich, contextually-specific arguments, examples, and statements. This suggests greater scope for interference in the retrieval of reliability information than in the retrieval of level information.

Overall, we find that word-of-mouth transmission leads reliable and unreliable information to converge in influence on downstream beliefs because reliability markers are disproportionately likely to be lost in transmission. This reflects that reliability information often fails to come to mind automatically during the transmission process, a failure that might be due both to the relative rarity of reliability cues in practice and the lower distinctiveness of pieces of reliability information.

This paper is connected to work in various fields. Our focus on the transmission of qualitative stories about economic variables relates to a growing literature on the diffusion of qualitative information in the form of narratives (Shiller, 2017; Hirshleifer, 2020).[4] Recent contributions in this literature have focused on the role of narratives for belief formation (Andre et al., 2025; Kendall and Charles, 2025; Graeber et al., 2024b; Barron and Fries, 2024). We relate to work by Graeber et al. (2024a), who study how explanations shape the contagion of truths and falsehoods. Serra-Garcia (2025) studies how incentives to attract attention affect the transmission of scientific information. Thaler (2025) studies how strategic incentives shape the supply of false messages in a politicized context and Thaler et al. (2025) study how individuals strategically use the imprecision of language. Our experiments identify which kinds of information are more likely to be successfully passed on from one person to another through spoken communication. The loss of reliability we document in oral transmission may be part of a broader hypothesized phenomenon (e.g. Hirshleifer, 2020): as stories get told and re-told, they are simplified in the specific sense that nuance is lost.

We also relate to a literature on how belief formation is shaped by selective attention (Graeber, 2023; Ba et al., 2024; Hartzmark et al., 2021; Graeber et al., 2025), complexity (Oprea, 2020; Enke and Graeber, 2023; Enke et al., 2025), and memory (Bordalo et al., 2025, 2021, 2023, 2024; Conlon and Kwon, 2025). Previous research suggests that people pay insufficient attention to the "weight" (or precision, predictive validity) of evidence (relative to its "strength",

[4]In his presidential address to the American Finance Association, Hirshleifer (2020) argues that "a key, underexploited building block of social economics and finance is social transmission bias: systematic directional shift in signals or ideas induced by social transactions."

or magnitude) when forming their beliefs in abstract and quantitative updating tasks (Griffin and Tversky, 1992; Massey and Wu, 2005). Our paper differs from this literature in its focus on how cognitive constraints shape the verbal transmission of information, and hence how they affect the *supply* of information. While much of this previous literature relies exclusively on stylized laboratory experiments, we also provide evidence from the field, studying a large corpus of everyday conversations and the coverage of economic uncertainty on cable news shows. Our evidence from both controlled experiments and observational data suggests an important role for selective memory in driving the differential loss of reliability information. The experimental and field evidence suggest that sparse reliability cues and higher interference may make information about reliability less likely to come to mind.

Our paper builds on a large literature on social learning (Weizsäcker, 2010; Mobius and Rosenblat, 2014; Banerjee, 1992; Bikhchandani et al., 1992; Bursztyn et al., 2014; Golub and Jackson, 2010; Golub and Sadler, 2016), information diffusion (Banerjee et al., 2013, 2019; Han et al., forthcoming; Akçay and Hirshleifer, forthcoming), face-to-face interactions (Atkin et al., 2022; Battiston et al., 2021; Braghieri et al., 2024), and verbalization (Batista et al., 2024). Conlon et al. (2025) show in the context of a classic balls-and-urns belief updating paradigm that people are much less sensitive to quantitative information discovered by others, compared to equally-relevant information they discover themselves. We differ from this literature in our focus on (i) the transmission of qualitative information in the form of spoken narratives, and (ii) the investigation of underlying cognitive mechanisms that shape transmission of different kinds of information.

Finally, information transmission has also been the subject of work outside of economics. For example, Carlson (2019, 2018) finds that political information is partially lost when people transmit it in writing. Similar "chain of transmission" paradigms have also been used to study how culture shapes the effects of transmission on content (e.g., Mesoudi and Whiten, 2008). In the cognitive sciences, interest in information transmission reaches back at least to Bartlett's seminal 1932 studies on *serial reproduction* of stories from memory (Bartlett, 1995). Work in these fields does not examine economic information or the differential transmission of information about level and reliability, nor does it study transmission in a real-world setting with field data.

2 Baseline Experimental Design

Our baseline design comprises two experiments. In the transmitter experiment, respondents listen to a recording and are incentivized to pass on the information contained in the recording. In the listener experiment, different respondents listen to either the original recordings or transmitted versions before forming their beliefs.[5]

Our baseline study design is guided by the following objectives: (i) an experimental setting in which we can quantify the transmission rates of different kinds of information in natural-language spoken messages, (ii) well-defined incentives for transmission, (iii) systematic variation

[5]The full set of experimental instructions for all experiments can be found at the following link: `https://raw.githubusercontent.com/cproth/papers/master/LiT_instructions.pdf`.

in different types of information in the original recordings, and (iv) an incentive-compatible belief elicitation in the listener experiment to quantify information loss due to transmission.

2.1 Transmitter Experiment

Structure of the experiment. In the transmitter experiment, respondents listen to one recording containing two separate opinions about two economic variables, in a random order: home price growth in an anonymous U.S. city and revenue growth of an anonymous U.S. retail company. The city and retailer are New York City and Walmart, respectively, which is not revealed to participants so that they lack strong priors and cannot search for additional information. This ensures that belief formation is, as much as possible, based only on the information we provide in the original recordings. The opinions are written and recorded by us; respondents are informed that these opinions are based on real media commentary on these topics, and are told at the end of the survey that other participants heard recordings arguing for the opposite conclusions. The recording containing both opinions lasts for 2-3 minutes, with each opinion lasting 1-1.5 minutes.[6] Respondents are then asked to separately record their own verbalizations of the two opinions they listened to, and finally answer several belief questions about each topic. Appendix Figure A1 shows the structure of the transmitter survey.

Speech recordings. We collect audio recordings, which have several advantages over written text for our purposes. First, oral information transmission is natural: it is the dominant form of communication in daily life, and an important source of information through conversations as well as consumption of television, radio, or podcasts. Second, unlike written communication, the spontaneity of oral communication provides a testing ground for analyzing how cognitive constraints affect information transmission and social learning. A vast literature has examined differences between written and spoken text production (e.g. Chafe and Tannen, 1987; Akinnaso, 1982; Berger and Iyengar, 2013). Written text tends to be more formal, structured, premeditated, and involves higher cognitive effort (e.g., Bourdin and Fayol, 2002). Third, speech data allow us to capture critical features of natural language that are mostly absent from written texts and may be essential to the communication of reliability, including tone, emphasis, and disfluencies such as pauses, repetitions, revisions, hesitations, or filler words.

Transmitter incentives. The design of our baseline transmitter incentives directly follows our conceptualization of a message's information content as *the average belief movement induced by that message.* For each topic, transmitters are tasked with recording a message that induces

[6] We provide people with the two forecasts consecutively in the same recording, rather than separately playing each forecast before the respondent records their verbalization of it, because this mimics an aspect of transmission in the real world: people are, over time, exposed to multiple pieces of information on various topics, before eventually relaying some information to others. In Section 4.3 we report evidence that this feature of the experiment is inconsequential: transmitter's beliefs about an original forecast at the very end of the experiment are similar to those of a listener immediately after hearing just that one forecast.

belief changes that are as close as possible to the average belief changes induced by the original message they listened to. Specifically, one in ten transmitters is selected to be eligible for a $20 bonus payment. Their probability of receiving the payment (conditional on eligibility) is a quadratic function of the distance between the average belief change induced by their message and the average belief change induced by the original message, among two sets of listeners who will hear either their message or the original message. We explain to respondents that in order to maximize their chances of receiving the bonus, they should pass on anything from the original message that they think would be relevant for how people change their beliefs.

This incentive scheme is motivated by our conceptualization of information content and is thus the natural starting point for our experiments. However, there are many alternative possible schemes, some of which may seem less complicated and/or more explicit. Four remarks are in order. First, transmission under this scheme is guided by which elements of a message transmitters *believe* are most relevant for listeners' belief changes. Those beliefs may be biased, which would be a source of transmission distortions that we would want to capture. We examine these beliefs directly in Section 4.

Second, incentives based on listeners' *belief changes* (rather than *posteriors*) incentivize transmission of all relevant pieces of information in the original message. If transmitters were incentivized by the accuracy of listeners' posteriors, the optimal strategy might be to "do the updating for the listener:" form a Bayesian posterior after listening to the original recording and simply report this quantitative posterior in the transmitted message. Because transmitters do not know listeners' priors or how their beliefs might react to different pieces of information, incentives based on belief changes encourage them to pass on all information in the original message.[7] We consider this a naturalistic feature of our scheme: in practice, people most often transmit information without knowing which aspects of the original information the audience wants to learn about and what their priors are, motivating transmission of the substantive information content.

Third, although the quantitative formula underlying the incentive scheme is complicated, we explain the scheme in intuitive terms ("you should pass on all information you think is relevant to how people change their beliefs"). To ensure high levels of understanding, only participants who pass a comprehension question on transmitter incentives are allowed to take part in our study. In Section 4, we explore alternative transmission incentive schemes.

Finally, while our experiment *requires* transmitters to pass on the information they hear, transmitters in real-world contexts can often decline to do so. For example, a transmitter may choose not to transmit information they are uncomfortable with, do not agree with, or think is not worth sharing. This extensive-margin decision of whether or not to pass on a message will also shape the supply of information. For simplicity, our design focuses on the intensive margin of transmission and examines loss of information conditional on an attempt to transmit

[7]Even under our incentive scheme, rational transmitters might, instead of passing on the original information, communicate the degree of belief movement they think should occur given their assumed distribution of prior beliefs, updating rules, etc. However, in practice, we consider this to be extremely unlikely. Our data confirm this: we obtained no transmitter recordings indicating an attempt to communicate a predicted belief movement.

the message. In Section 5, our field evidence also captures extensive-margin sharing decisions.

Structure of original recordings. The original recordings have the following general structure. First, they introduce the variable of interest, i.e., home price growth or revenue growth of a retailer. They then put forward some arguments justifying why the variable of interest will increase or decrease. For example, the speaker mentions that as consumers' disposable incomes decrease due to inflation, they often switch towards lower-price retailers, such as the U.S. retailer in question; or that issuance of new residential construction permits in the U.S. city being discussed has slowed down recently, meaning housing supply will increasingly fall behind growing demand. Towards the end of the message, the speaker states explicitly whether they believe the variable will increase or decrease over the coming year. Throughout the recording, the reliability of the prediction is explicitly or implicitly communicated using techniques we discuss below. Full transcripts of the messages as well as links to the audio recordings of the messages are available in Appendix E.

The design of these messages is motivated by the nature of real-world commentary on economic topics such as house price or company revenue growth. Such commentary usually justifies predictions with substantive arguments about the variables of interest, e.g., relating to market conditions or broader trends in the economy. The arguments in our messages are drawn from real media reporting on these topics. Moreover, such messages communicate reliability with both explicit and implicit markers.

Experimental variation: original recording contents. The design of our original recordings is guided by our distinction between the *level* and *reliability* of a prediction about a variable. We make the following observations about this distinction. First, this distinction is parsimonious, theoretically appealing, and general. To perform a belief update from any piece of information, a Bayesian agent always requires both a signal value and a signal precision. Moreover, level and reliability are always—implicitly or explicitly—conveyed by any forecast. For example, even the absence of explicit confidence or reliability statements could itself be an indicator of the forecast's reliability. Second, our distinction connects with previous belief formation research: for example, some research suggests that people pay insufficient attention to the *weight* or precision of evidence when forming their beliefs in abstract and quantitative updating tasks (Massey and Wu, 2005; Griffin and Tversky, 1992; Augenblick et al., 2025). Third, note that our taxonomy is different from the distinction between information about the first and second moment of the forecast state. Specifically, reliability is an attribute of a signal structure rather than a property of the distribution of the forecast state.

To leverage the level-reliability distinction in our experiments, we randomize these two features of the original message recordings. First, we randomize whether the message argues for an increase or a decrease in the level of the variable (*level manipulation*). Second, we randomize whether the message is reliable or unreliable (*reliability manipulation*).

We randomly assign respondents to two kinds of reliability manipulations. Respondents in the *naturalistic condition* hear recordings that vary reliability using a combination of explicit statements about confidence, evidence quality, and speaker competence, as well as implicit markers of reliability such as verbal fluency and vocabulary. For example, a high-reliability message sounds highly fluent with a sophisticated vocabulary, cites respectable sources of evidence, and mentions relevant credentials. A low-reliability message is full of disfluencies, expresses low confidence, cites obviously unreliable sources, and admits a lack of relevant credentials.

Meanwhile, respondents in the *modular condition* receive recordings that are identical except for a set of explicit markers indicating either high or low reliability (e.g., "definitely" vs. "possibly", "will" vs. "might", etc.) and explicit confidence statements ("I am highly confident" vs. "I am not at all confident"). Respondents in this condition are assigned to one of the following three conditions: (i) Strong reliability; (ii) Weak reliability; and (iii) Neutral reliability (where the markers and confidence statements are simply omitted).[8]

These two types of manipulations serve different purposes: the *naturalistic condition* embraces the full range of linguistic tools through which reliability of a statement may be expressed in practice, at the cost of a loss of control about which precise component drives perceptions of reliability. The *modular condition*, by contrast, provides this control by allowing us to trace the loss of specific reliability words or phrases, at the cost of focusing attention on just these modular elements. While interpretation of verbal uncertainty prefixes can vary from person to person (Vogel et al., 2022), this variability is constant between listeners to original and transmitted messages, meaning tracking the loss of these words should suffice to decompose information loss. Because both manipulations end up producing very similar results, we report our main results pooling both conditions, and show disaggregated results in Appendix Figure A6.

Our reliability manipulations most closely approximate real-world situations where a person is learning from a stranger, about whose reliability they have no strong prior. In these cases, people infer a speaker's reliability from the way the speaker talks, the claims the speaker makes, and what the speaker says about their background. All of the participants in our experiment are strangers to each other and must infer reliability only from the contents of voice recordings. Situations like this abound in everyday life, in contexts such as social media, television, conferences, public venues, social gatherings or professional settings.

Finally, we randomize whether the recording has a male or female voice. This is not a focus of analysis and we randomize simply for symmetry, and so that each topic a transmitter listens to is discussed by a different voice. We find no evidence that the effects of any of our manipulations, or the effects of transmission, vary with the original voice's gender. We create the recordings using two human actors.

The different margins of randomization in the transmitter experiment are stratified: each transmitter hears two recordings, one with an "increase" and one with a "decrease," one with "strong reliability" and one with "weak reliability," and one with a male voice and one with a female voice.[9]

[8]As pre-specified, our main analysis focuses on comparisons between weak and strong reliability for simplicity. Appendix Figure A4 shows belief updates including the neutral-reliability condition.

[9]Then, if exactly one of the two topics is in the modular condition, that topic has a 33% chance of

Beliefs. After recording themselves, transmitters answer the same beliefs questions that listeners do, so we defer discussion of those questions to the following subsection.

2.2 Listener Experiment

Structure and treatments. This experiment draws on the speech recordings collected in the transmitter experiment. It lets us quantify transmission-induced information distortions by measuring and comparing the information content of the original messages and transmitted versions of those messages.

Recall that our experiments involve forecasts about two topics: (i) the change in home price growth in a U.S. city and (ii) the change in revenue growth of a U.S. retailer, both for the upcoming year. For each of the two topics, participants in the listener survey first state their prior belief about the outcome variable of interest and then listen to a recording about the variable before answering a set of beliefs questions. The order of the topics is randomized. For each topic, respondents are randomly matched to a transmitter and listen either to the same original recording as the transmitter heard, or that transmitter's message. We implement a 30% chance of hearing the original and a 70% chance of hearing a transmitted recording. We oversample transmitted recordings as they are by construction more heterogeneous compared to original recordings. Appendix Figure A2 shows the survey structure.

Listeners are told whether they are listening to the original message or another participant's transmitted version. They could take this information into account when updating their beliefs about the message content, e.g., by discounting the reliability of *any* transmitted message relative to a corresponding original message. However, as discussed in our baseline results (Section 3), we find no evidence that transmission has any average effect on the perceived level or reliability of the original messages.

Beliefs. After listening to a recording, respondents are incentivized to guess the realization of the target variable—change in house price growth or change in revenue growth over the next 12 months—as well as the level of the prediction in the original message and the reliability of that prediction.

We separately elicit beliefs about the state of the variable under discussion, referred to as *state beliefs* henceforth, as well as beliefs about the original message's contents, called *message beliefs*, for two reasons. A listener's state beliefs are the most economically relevant object. However, belief movements about the state are also affected by respondents' priors and prior confidence, making it difficult to back out respondents' perceptions of the level and reliability of the original prediction. Directly eliciting beliefs about the message's level and reliability circumvents this issue and brings us closer to the objects of interest in our guiding distinction and our treatment manipulations. Moreover, belief updates about the state are *simultaneously determined* by a message's level and reliability. This means that loss of level information affects respondents'

getting switched to "neutral reliability". If both topics are in the modular condition, there is a 66% chance that one of the two topics is randomly switched to "neutral reliability."

sensitivity to reliability information and vice versa, preventing us from cleanly distinguishing level and reliability information loss based solely on state belief updates. The same is not true for message beliefs, which separate out the original message's level and reliability.

For each topic, we hence elicit three key outcome variables: state belief movements (the respondent's posterior about the economic variable minus their prior); and two message beliefs: the respondent's belief about the level of the original message's prediction and the respondent's belief about its reliability. We elicit respondents' priors about the state, and use belief movements as our outcome rather than posteriors. This reduces noise resulting from idiosyncratic respondent heterogeneity in usage of the belief scales. Because respondents do not know anything about the context the message concerns, their priors are not informed and simply capture any tendencies in their response behavior.

To measure respondents' state beliefs we ask them about the change of the variables of interest in the next 12 months. For home price growth, this question reads as:

> How will house price growth in this city change over the next 12 months?

Our two unknown states are *changes in growth rates* because this permits a natural prior of zero and reasonably symmetric possibilities around that prior. This lets us shift beliefs symmetrically up or down with our high- or low-level messages, creating clean variation in the information content of the recordings. To elicit respondents' corresponding message beliefs about the level of the prediction, we ask the following question:

> How do you think the person [whose opinion you just heard/whose opinion was summarized in the recording] predicts house price growth in this city will change over the next 12 months?

To measure respondents' message beliefs about the reliability of the prediction, we ask the following question:

> How reliable do you think the prediction given by the person [whose opinion you just heard/whose opinion was summarized in the recording] is? Specifically, what do you think is the probability that this person's forecasts about changes in house price growth in this city are roughly correct? Concretely, assuming that the true change in house price growth is a number called X, what do you think is the likelihood that this person's prediction will fall within 1% of X, i.e., between X-1% and X+1%?

Incentives for accuracy. Respondents are told that one in ten respondents will be randomly chosen to be eligible for a $20 bonus payment, which will be based on one of the incentivized items in the survey. State beliefs are always directly incentivized based on the true development of the variable over the next year.[10] Message beliefs are unincentivized for a randomly selected 50% of respondents. For the other half of respondents, the question is phrased as a second-order

[10] State beliefs are incentivized with the following formula: Probability of winning $20 [in %] $= 100 - 10(\text{Estimate [in \%]} - \text{True state of the world in 12 months [in \%]})^2$.

question ("your job is to predict what people who heard the same recording as you would on average respond to the direct question") and responses are incentivized based on the accuracy of their guess about other participants' average guess.[11] Results based on incentivized versus unincentivized message beliefs are virtually identical, as shown in Appendix Figure A7.

2.3 Sample and Procedures

We conducted our transmitter and listener experiments on Prolific, a widely used online platform to conduct social science experiments (Eyal et al., 2021). The transmitter experiment and listener experiment were run with 540 and 1,510 U.S. respondents, respectively, in November 2023. Table A3 records summary statistics for all our experimental samples. All of the data collections were pre-registered on the AEA RCT registry: `https://www.socialscienceregistry.org/trials/12119`. As pre-registered, we drop recordings below the 5th percentile of recording length or transcript word length (as a proxy for empty or content-less recordings). Following this restriction, our baseline transmitter experiment yields a total of 1,010 valid speech recordings. These were obtained by collecting speech recordings using the service Phonic, which we embed into Qualtrics.[12]

3 What is Lost in Transmission?

Our main finding in this paper is *differential information loss*: information about the reliability of a forecast is lost in transmission much more strongly than information about its level. In this section, we demonstrate differential information loss in three distinct and complementary ways: first, by examining the transcripts of transmitted messages for mentions of level and reliability; second, by analyzing listeners' *message beliefs* about the level and reliability of the original forecast, separately for listeners who hear original messages versus listeners who hear transmitted versions; and third, by analyzing listeners' *state beliefs* about the economic variables discussed in the original forecasts. Each set of analyses has its own advantages and drawbacks, which we discuss while presenting them.

3.1 Transcript Analysis

We begin by examining the transcripts of transmitted messages to see whether they contain statements about the level or reliability of the original forecasts.

Panel (a) of Figure 1 displays the share of transmitter transcripts classified as containing statements about the level of the original prediction or about its reliability. For reliability, we

[11]Responses are incentivized with the following formula for beliefs about the originator's prediction and reliability, respectively: Probability of winning \$20 [in %] $= 100 - \alpha$(Response [in %] $-$ Average response to direct question [in %]$)^2$, where $\alpha = 10$ for level and $\alpha = 2$ for reliability. This approach allows us to incentivize these beliefs in the absence of a "true state", since the original recordings were provided by us and there is no corresponding originator belief. The differing α's simply account for the differing units and standard deviations of level and reliability beliefs—level beliefs have a standard deviation of 8.8 and reliability beliefs have a standard deviation of 24.5.

[12]We rely on an Amazon Web Services backend to feed the recordings into the Listener experiment.

adopt a maximally broad notion of what counts as communicating reliability, incorporating all of the components we use to vary reliability in the original recordings. This includes explicit statements about reliability or confidence as well as the use of certainty or uncertainty markers like "might" or "definitely." We separately show results of human coding and of automated coding using the large language model GPT-4. The figure illustrates that the different coders and the large language model come to similar conclusions.[13] See Appendix Table A2 for some examples of transmitted messages and their handcodings.

The key finding of Panel (a) is that while most transmitted scripts contain statements about the level (between 87 and 95 percent), a far smaller fraction of transmitted scripts contain statements indicating the reliability of the original message (between 30 and 45 percent). Panel (b) shows that this is true independent of the length of the transmitted message: even among transmitted messages that are 200-300 words long (longer even than the original messages), only 20% are unanimously agreed upon by our coders to contain statements about reliability. Longer messages tend to differ from shorter ones primarily in providing a much higher level of detail about the original message's arguments for its level prediction. Appendix Figure A9 also shows that the fraction of scripts containing statements about level or reliability is fairly stable across our four level × reliability conditions (high versus low level, and weak versus strong reliability).

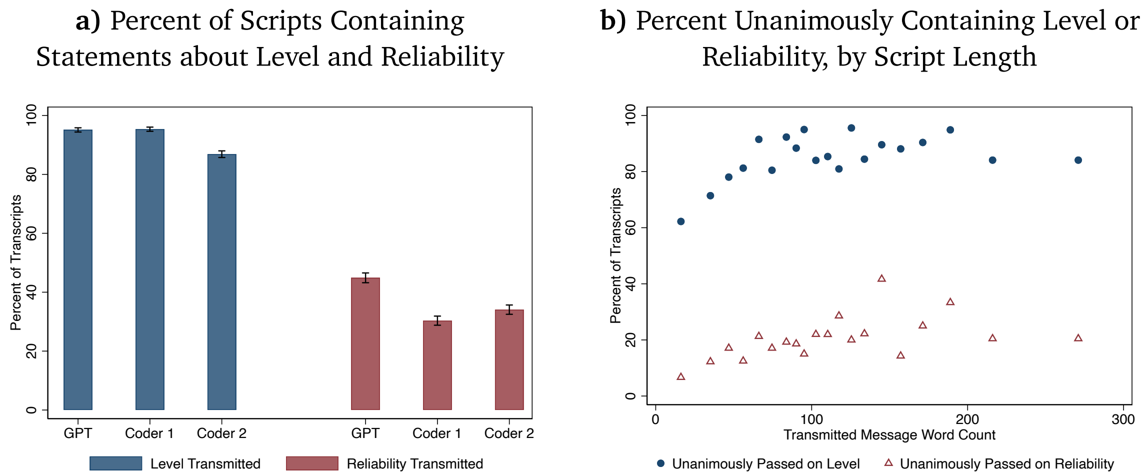


Figure 1: This figure presents data from our baseline experiment (Belief Movement Incentives). Panel (a) shows the percent of transcripts that are coded as conveying any information about the level and reliability of the original forecast, separately by two human coders and GPT-4, with standard error bars. Panel (b) shows binned scatterplots of the percentage of scripts unanimously classified by our coders and GPT as containing statements about level or reliability, respectively, against the word count of the script. $N = 540$ transmitters, each of whom contributes two transcripts.

[13]For level, if one human coder identifies level as being passed on, the other does with 91% probability, and GPT does with 98% probability. For reliability, the corresponding numbers are 60% and 75%. In our analysis of beliefs data where we split according to handcoded classifications, we restrict to transcripts where our coders agree unanimously.

Transmitted recordings also include many disfluencies—hesitations, "um" statements, self-corrections, and so on—which could influence how listeners perceive the reliability of the original forecast. However, Appendix Figure A10 shows that the average number of disfluences in transmitted scripts does not vary with whether the original forecast was high- or low-reliability, and the presence of disfluencies in transmitted scripts does not affect listener beliefs about the reliability of the original forecast (analyzed in the next section). The reliability of the original forecasts does not appear to be effectively communicated through disfluencies.

Result 1. *Transmitted messages are about three times more likely to mention the level of the original prediction than to mention its reliability.*

These results, while transparent and strongly suggestive, do not conclusively establish that reliability information is lost in transmission more than level information. For example, perhaps listeners only need to hear 10% of the reliability cues in the original messages to grasp their true reliability, so that 90% of the original cues can be dropped without information loss; or perhaps reliability is passed on in some way not picked up by our codings. To address this possibility, we turn to an analysis of listeners' *message beliefs*, their beliefs about the level and reliability of the original messages. We will find that our binary hand-codings from this section do not tell the full story: there is substantial loss of reliability information even among messages we coded in this section as passing on at least some reliability information.

3.2 Message Beliefs

To provide independent measures of level and reliability information, we separately elicit listeners' message beliefs about the level and reliability of the original prediction, using questions described in Section 2.2. Figure 2 presents results on message beliefs. We z-score message beliefs within each topic × reliability manipulation quadrant to make the aggregation across experimental conditions more comparable; results with raw beliefs are available in Appendix Figure A3.

Panel (a) examines message beliefs about the level of the original prediction. The blue dots show the average beliefs of listeners who directly hear original recordings. Listeners who hear a *low*-level original recording believe the level of the prediction is 1.37 SDs lower on average than listeners who hear a *high*-level original recording. Meanwhile, the orange dots show the beliefs of listeners who hear transmitted versions of the original recordings. Here, the difference between the beliefs of listeners who hear transmitted versions of *low*-level recordings and those who hear transmitted versions of *high*-level recordings is only 0.88 SDs, indicating $100 \times [(1.37 - 0.88)/1.37] \approx 34\%$ loss of sensitivity to level information. In other words, listeners who hear transmitted recordings are 34% less sensitive to variations in the level of the original predictions, compared to listeners who directly hear the original predictions. Formally, the *change in slope* statistic printed in the plot is calculated from a regression of the form

$$\text{LevelBelief}_i = \beta_0 + \beta_1 \text{HighLevel}_i + \beta_2 \text{Transmitted}_i + \beta_3 (\text{HighLevel}_i \times \text{Transmitted}_i) + \varepsilon_i, \quad (1)$$

where LevelBelief_i is the listener's belief about the level of the original prediction (z-scored at the topic by reliability manipulation type level); HighLevel_i is a dummy for the original forecast having a high level; and Transmitted$_i$ is a dummy for the participant listening to a transmitted version of the original forecast. Standard errors are two-way clustered at the voice recording and listener level.[14] The change in slope statistic is simply $-100 \times (\beta_3/\beta_1)$.

Panel (b) examines listeners' message beliefs about the reliability of the original predictions. Here, the sensitivity loss is nearly three times as strong. Listeners hearing the original messages believe the strong-reliability messages are 1.18 SDs more reliable than the weak-reliability messages on average. Among listeners hearing transmitted versions of the original messages, this difference is only 0.12 SDs, indicating roughly 90% loss of sensitivity. A formal test of equality of the two information loss statistics rejects the null at $p < 0.001, \chi^2 = 74.5$.

Figure 2 further illustrates that, in both cases above, transmission weakens the distinction between high- and low-level messages (or weak- and strong-reliability messages) by *symmetrically compressing listeners' beliefs towards an intermediate value*. This is compatible with the following dynamic: listeners hold an average prior about level or reliability that is located halfway between our two manipulations; they update away from this prior when hearing a message; and the strength of this update is weakened by noise introduced during transmission. If more noise is introduced for the reliability than the level, this compression will be stronger for reliability beliefs, as we note below.

The finding of nearly symmetrical compression also shows that, contrary to an intuitive hypothesis, the fact that a message is transmitted does *not* reduce its perceived reliability on average: instead, transmission causes strong-reliability messages to be perceived as less reliable, and weak-reliability messages to be perceived as more reliable.

Result 2. *Verbal transmission induces substantial information loss. This information loss differs for different types of information: Loss of reliability information is about three times as large as loss of level information.*

[14]Standard errors are virtually identical for different ways of clustering.

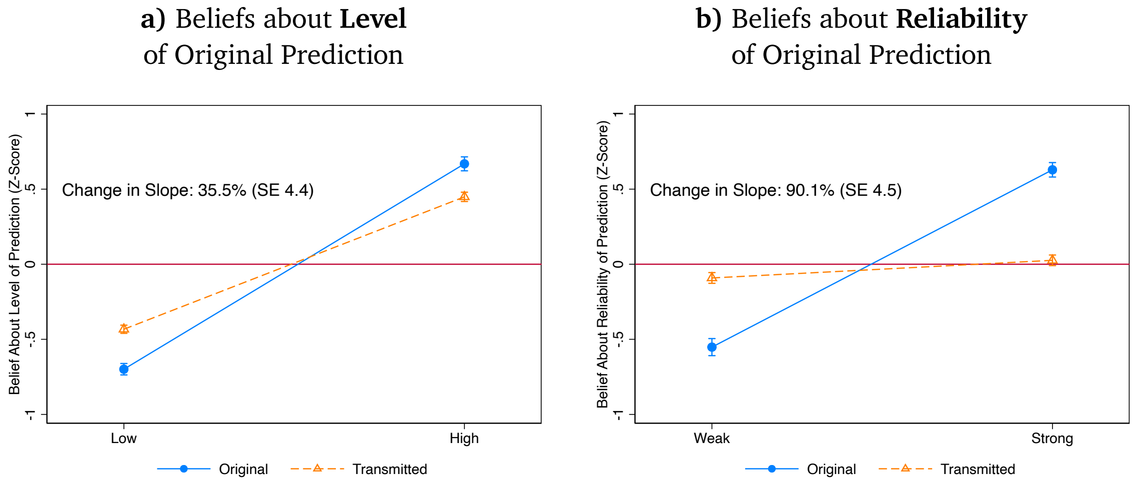


Figure 2: This figure presents data from our baseline experiment (Belief Movement Incentives). It shows listeners' beliefs about the level and reliability of the prediction in the original message, separately by whether the original message is low- vs high-level or weak- vs strong-reliability, and separately by whether the listener hears the original message or a transmitted version of it. Dots are mean beliefs (z-scored at the topic by reliability manipulation level) and bars are standard error bars (1 SE each direction). See Appendix Figure A3 for results with raw (non-z-scored) beliefs and Tables A5 and A6 for regression tables. $N = 1,510$ listeners and 540 listeners.

Formal interpretation. In Appendix A, we write down a simple model of noisy transmission that can rationalize the symmetric compression documented above. Briefly, a sender observes a realization of a signal ("level") about a normally distributed state, as well as the precision of that signal ("reliability"). The sender communicates both the signal realization and precision to a receiver with a normal prior; the process of transmission adds noise to each, meaning the receiver observes a noisy signal of the original signal realization and a noisy signal of its precision. The receiver then forms posteriors about the level and reliability via Bayesian updating (these correspond to our message beliefs), and a posterior about the state via quasi-Bayesian updating (Bayesian updating ignoring the uncertainty about the level and reliability posteriors; this corresponds to our state beliefs, analyzed in the next section).

The introduction of noise in the transmission process creates a symmetric attenuation of listeners' message beliefs towards default beliefs (the listeners' prior beliefs about level and reliability). If this noise is higher-variance for the communication of reliability than for the communication of level, this attenuation is more severe for reliability, as observed in Figure 2.

This simple model of transmission as adding symmetric noise to the level and reliability draws on the intuitions and formal structure of noisy processing models popular in the recent literature (e.g., Enke and Graeber, 2023; Ba et al., 2024; Augenblick et al., 2025). Alternatively, transmission-induced compression towards an intermediate belief could reflect a form of ignorance or feeling of "I don't know" (Fischhoff and Bruine De Bruin, 1999), or a process of anchoring-and-adjustment (Tversky and Kahneman, 1974) caused by listening to a transmitted message. This could be true if listeners find it difficult to decode or interpret the contents of transmitted messages, give up, and retreat to a default belief. Under this interpretation, the weights λ reflect the difficulty of decoding each type of information. While we consider the noisy transmission account to be compelling in our setting—transmission garbles messages in ways that add noise to the level and reliability communicated, inducing the listener to shrink to a prior level—we remain agnostic about which exact interpretation is the most accurate.

Relation to transcript analysis. How much of the differential information loss in Figure 2 simply reflects the complete omission of reliability indicators from two-thirds of transcripts documented in the previous section? Appendix Section C decomposes differential information loss into a component driven by the absence of reliability indicators (extensive margin) and a component that remains even in messages with at least one reliability indicator (intensive margin). We find that only 30-50% of the differential loss in Figure 2 is driven by the extensive margin; as we show, even messages that contain at least one reliability cue drop many of the cues seeded in the original messages, and this matters for listeners' beliefs.

3.3 State Belief Updates

Message beliefs, analyzed above, enable us to separately track level and reliability information through the transmission process. However, they are artificial objects. The objects of immediate economic relevance are listeners' *state belief updates*, their belief updates about the economic variables discussed in the recordings (revenue growth and home price growth). We now examine these state belief updates.

Differential information loss in state belief updates. We can adapt the specification in Equation 1 to measure level and reliability information loss using state belief updates instead of message beliefs. The results of this analysis are printed in Panel (c) of Figure 3. We calculate that transmission reduces the sensitivity of listeners' belief updates to our level manipulations by 30%, and reduces the sensitivity to reliability manipulations by 90%, strikingly similar to the numbers calculated using message beliefs.

Informally, Panel (c) of Figure 3 shows that listeners to the original messages update twice as much on average from strong-reliability messages compared to weak-reliability messages. Listeners to transmitted versions, meanwhile, update almost the same amount from weak- and strong-reliability messages. This is what underlies our finding of 90% reliability information loss.

Interpreting the effects of transmission loss on state belief updates. In addition to showing strong differential loss of reliability information, Figure 3 displays a rich set of patterns that we now discuss. Panel (a) displays the average state belief updates of listeners who directly hear original recordings, across the four categories of our level/reliability cross-randomization. We pool data from both topics, revenue and home price growth, and separately z-score belief movements for comparability. The panel shows that state belief updates are sensitive to both our level and reliability manipulations. In particular, listeners adjust their beliefs in a qualitatively Bayesian manner: they move in the direction of the forecast they receive, with the strength of the update moderated by the reliability of the forecast.

Panel (b) of Figure 3 shows predictions for the effects of transmission loss on state belief updates; we derive these predictions formally in Appendix A and describe the intuition behind them here. Panel (c) shows the actual effects of transmission, which match the predicted effects.

To understand the predictions and results, observe that the loss of *level* information should uniformly shrink listeners' belief updates towards zero (the mean belief update, given z-scoring). This is because, as Panel (a) of Figure 2 shows, transmission symmetrically compresses beliefs about the level of the original prediction towards the mean value. This should in turn compress belief updates towards the mean belief update, given that average priors are the same across experimental conditions. Hence, across all four conditions, we predict that level information loss should attenuate belief updates towards zero (the green arrows in Panel (b) of Figure 3).

Meanwhile, the loss of *reliability* information should have different effects in the strong versus weak reliability conditions. Loss of reliability information symmetrically compresses listeners' beliefs about the reliability of the original messages towards the mean (Panel (b) of Figure 2). This means that transmission causes *strong-reliability* messages to be perceived as *less reliable*. This, in turn, should shrink belief updates from strong-reliability messages, since the size of a listener's belief update should be smaller the lower the perceived reliability of the signal. Hence we predict that in the strong-reliability conditions, reliability information loss should attenuate belief updates towards zero (the purple arrows in the leftmost and rightmost conditions in Panel (b) of Figure 3). Conversely, transmission causes *weak-reliability* messages to be perceived as *more reliable*. This means reliability information loss should strengthen belief updates *away* from zero in the weak-reliability conditions (the purple arrows in the two middle conditions in Panel (b) of Figure 3).

Overall, we obtain an unambiguous prediction that in the strong-reliability conditions—where both level and reliability information loss push in the same direction—transmission should cause belief updates to shrink strongly towards zero. Meanwhile, in the weak-reliability conditions, level information loss pushes towards zero and reliability loss pushes away from zero; without knowing which effect dominates, we have an ambiguous prediction for the effect of transmission belief updates in these conditions.[15]

Panel (c) of Figure 3 shows empirical results that exactly bear out these predictions. In the strong-reliability conditions, transmission causes average belief updates to shrink in size by about 50%. Meanwhile, in the weak-reliability conditions, the opposing effects of level and reliability information loss seem to roughly cancel out, and average belief updates barely change.

Appendix Figure A5 validates our comparative-static explanation of the empirical results by splitting transmitters according to whether they are coded as passing on reliability (see Section 3.1). Consistent with our story, transmitters who fail to pass on reliability information induce overreactions among listeners in the weak-reliability buckets and more severe underreactions among listeners in the strong-reliability buckets.

[15]While reliability information loss is stronger than level information loss, this does not mean that the reliability effect will dominate; Panel (a) of Figure 3 shows that switches from high to low level matter about twice as much in the belief updating process as switches from weak to strong reliability.

Implications of transmission loss. Summing up, Figure 3 shows that transmission-induced information loss has two impacts on downstream belief updates. First, averaging across all four conditions, listeners' absolute belief updates are 30% smaller when listening to transmitted messages, an effect that is entirely driven by the strong-reliability conditions.[16] This means that transmission *reduces the average impact of new information on beliefs*, implying that if a population starts with polarized priors, new information will cause less belief convergence in the presence of verbal diffusion of the information. Second, listeners to original messages update about twice as much from strong-reliability messages as from weak-reliability messages; by contrast, listeners to transmitted versions update the same amount from weak- and strong-reliability messages. This means that transmission *increases the relative influence of weak-reliability messages* on overall belief updates: through transmission, information about the quality of messages gets garbled.

Result 3. *Verbal transmission weakens the average effect of new information on beliefs. It also increases the relative influence of weak-reliability information compared to strong-reliability information.*

[16]Technically, the figure shows that *z-scored* belief updates are smaller, but this is also true for mean raw belief updates; the mean raw belief update is ≈ 0.

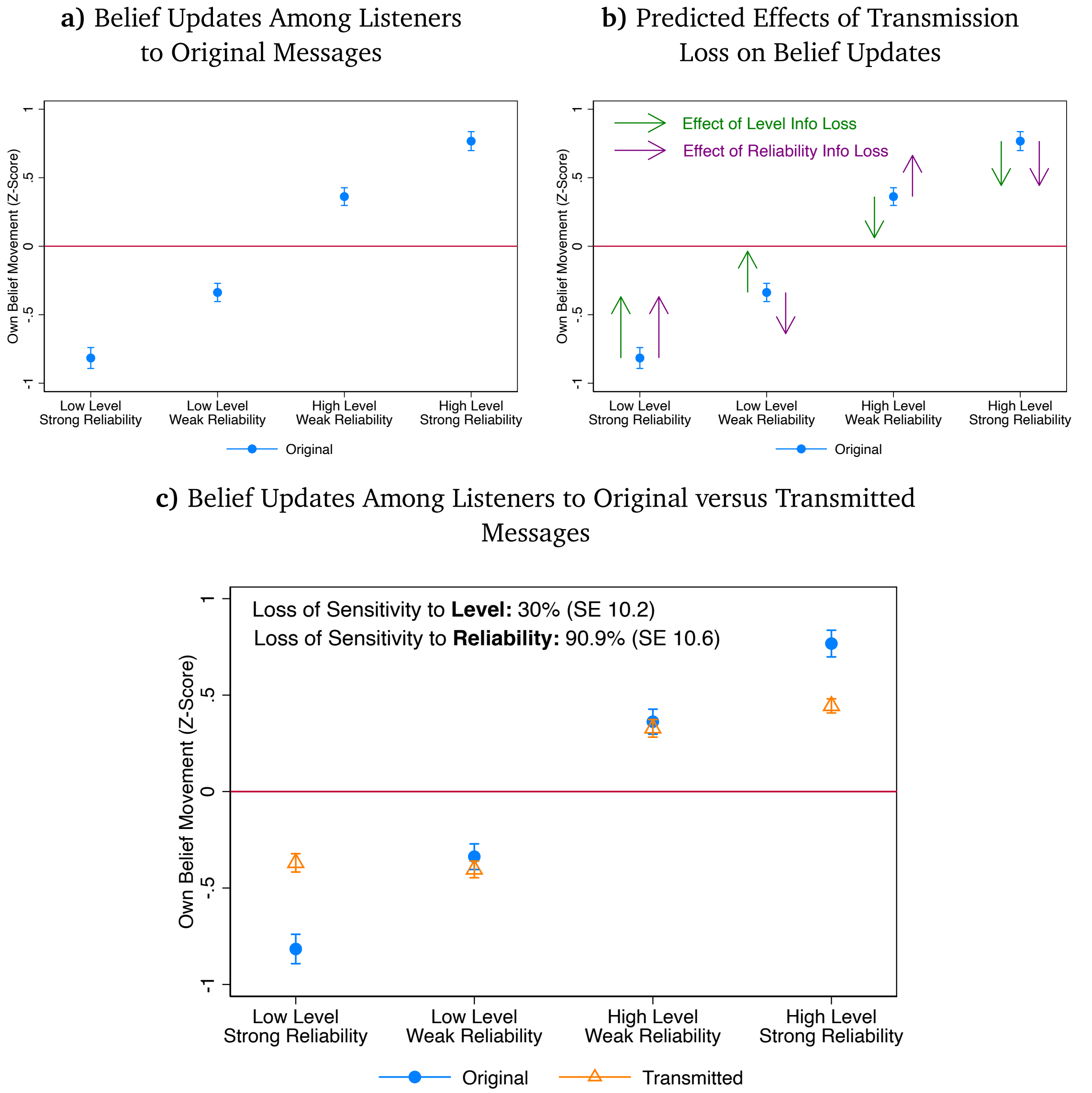


Figure 3: This figure shows average belief movements (posterior minus prior) about the economic variable from our baseline experiment (Belief Movement Incentives). Panel (a) shows average belief movements about the economic variable across the four different level-reliability conditions, only for listeners who directly hear the original messages. Dots are mean beliefs and bars are standard error bars (1 SE each direction). Panel (b) adds illustrative arrows. Panel (c) adds the corresponding beliefs of listeners hearing transmitted versions of the messages. $N = 1{,}510$ listeners and 540 transmitters. The loss of sensitivity to level information is calculated from a regression of the form: $\text{Belief Update}_i = \alpha_0 + \alpha_1 \text{HighLevel}_i + \alpha_2 \text{StrongReliability}_i + \alpha_3 \text{Transmitted}_i + \alpha_4 (\text{Highlevel}_i \times \text{Transmitted}_i) + \xi_i$. The loss of sensitivity to reliability information is calculated from a regression of the form $\text{Belief Update}_i \times (2 \times \text{HighLevel}_i - 1) = \gamma_0 + \gamma_1 HighLevel_i + \gamma_2 \text{StrongReliability}_i + \gamma_3 \text{Transmitted}_i + \gamma_4 (\text{Highlevel}_i \times \text{Transmitted}_i) + \zeta_i$, where we flip the sign of low-level belief updates to make the effects of StrongReliability comparable across low- and high-level messages. Appendix Table A4 gives regression versions of these results. Figure A4 shows these results restricting to the Modular manipulation and including the neutral-reliability condition. Appendix Figure A5 shows empirical results validating the arrows in Panel (b). Appendix Figure A3 shows raw (non-z-scored) beliefs.

3.4 Robustness: Quantitative Communication

Our baseline experiment used purely qualitative scripts because this imitates the majority of real-world communication. However, many important situations do involve the transmission of quantitative predictions or statements of numerical subjective probabilities. We therefore examine the robustness of our results to the addition of numerical statements about level and reliability to our original scripts, in an additional preregistered experiment.

This experiment has the added benefit of alleviating potential concerns that our baseline results are driven by people perceiving our level manipulations as "more binary" or "more qualitative" than our reliability manipulations, and finding it easier to pass on binary or qualitative information. By communicating both level and reliability in exactly the same way at one point in the transcripts (through a single numerical percentage, e.g., an 8% increase in house price growth and a 90% confidence level), this experiment minimizes extraneous differences in the way level and reliability information are communicated.

Design. The experimental design is virtually identical to our baseline but adds quantitative information about both level and reliability to the original scripts. Quantitative information about the level is conveyed by providing a point estimate of the change in revenue growth. Quantitative reliability information is communicated via a probabilistic confidence statement. The quantitative statements are added to the final part of the script, where the speaker sums up their forecast and confidence level. In the context of a high reliability revenue growth forecast, quantitative information is conveyed as follows:

> Overall, I am confident this means that the revenue growth of this company will definitely fall strongly over the forthcoming year, by about 8%. I am more than 90% confident in this forecast.

In the low reliability revenue growth forecast quantitative information is presented as follows:

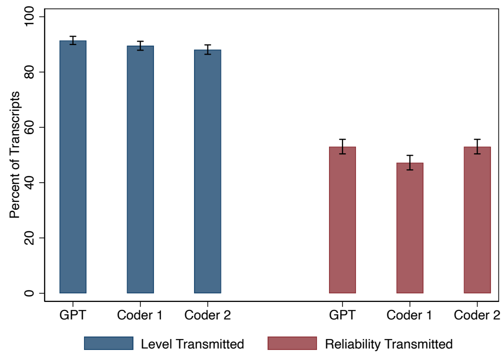
> Overall, I think it is conceivable that this means that the revenue growth of this company will imaginably fall strongly over the forthcoming year, by about 8%. That said, I am only 10% confident about this forecast.

The quantitative forecast was an 8% increase or decrease in the case of revenue growth and a 10% increase or decrease in the case of home price growth; confidence levels were either 10% or 90%. See Appendix Section E for the full set of quantitative scripts.

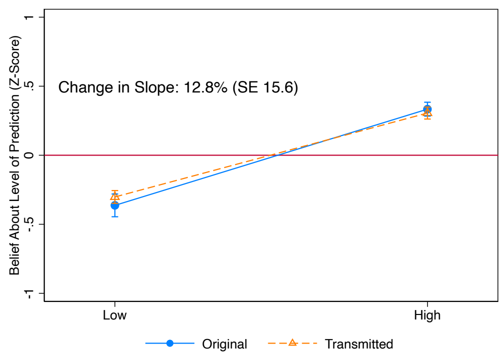
Logistics. The additional transmission and listener experiments were run with 181 and 834 U.S. respondents from Prolific, respectively, in June 2024. This collection was also pre-registered at `https://www.socialscienceregistry.org/trials/12119`.

Results. Figure 4 Panel (a) shows that the differential loss of reliability indicators in transcripts remains highly statistically significant ($p < 0.01$) and economically sizable. The level-reliability gap is somewhat smaller than in our baseline experiment: about 50% of transmitters now mention reliability in their messages, compared to 30% in our baseline experiment, suggesting that numerical confidence statements increase the salience of reliability information or make it easier to transmit. As before, over 90% of respondents mention the level.[17]

a) Fraction of Scripts Containing Level/Reliability Statements



b) Beliefs About **Level** of Original Prediction



c) Beliefs About **Reliability** of Original Prediction

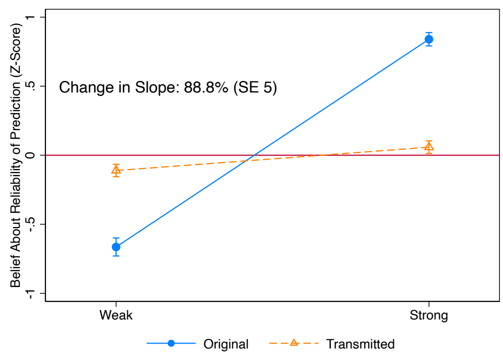


Figure 4: This figure presents data from our version of the baseline experiment that uses quantitative scripts. Panel (a) replicates Figure 1. It shows the fraction of transmitted messages classified by GPT-4 and our two human coders as containing statements about the level or reliability of the original forecast. Panels (b) and (c) replicate Figure 2, showing listeners' beliefs about the level and reliability of the prediction in the original message, separately by whether the original message is low- vs high-level or weak- vs strong-reliability, and separately by whether the listener hears the original message or a transmitted version of it. Dots are mean beliefs and bars are standard error bars (1 SE each direction). $N = 181$ listeners and 834 listeners.

However, the increased fraction of transmitters mentioning reliability does not translate into a reduction in differential information loss according to our belief-based measures. Panels (b) and (c) show that differential loss *strengthens*: level information loss halves, to 12.8%, while reliability loss is unchanged. A formal test of equality of the two information loss statistics rejects the null at $p < 0.001$, $\chi^2 = 21.7$. Appendix Figure A12 shows that this is also true when analyzing listeners' state belief updates instead of message beliefs.

[17]About 45% of transmitters pass on the level number and 25% pass on the reliability number.

Differential loss strengthens despite the increase in the fraction of scripts mentioning reliability because the quantitative scripts increase the impact of our original recordings on the reliability beliefs of listeners directly hearing them,[18] so that the omission of reliability information has a greater impact on beliefs than in our baseline experiment. (In other words, a given fraction of scripts omitting reliability information has a larger impact on information loss as measured by message or state beliefs, because of the stronger first-stage effect of the original recordings on beliefs.)

Taken together, these findings demonstrate that the differential information loss persists when both level and reliability information are also conveyed quantitatively.

4 Mechanisms Underlying Differential Loss

What drives the differential loss of reliability and level information? In this section, we systematically test different potential mechanisms. To structure this analysis, we distinguish between mechanisms that involve a deliberate decision by the transmitters to prioritize passing on level information, and mechanisms that involve transmitters subconsciously or non-deliberately failing to pass on reliability information. If differential loss results from transmitters' deliberate decisions, it arises either because (i) the *perceived benefits* of transmitting reliability information are lower or (ii) the *perceived costs* of transmitting reliability information are higher. If differential loss does not result from a deliberate cost-benefit tradeoff, the reason may be one that the decision-maker herself considers suboptimal.[19] Specifically, (iii) reliability information may simply *fail to come to mind* at the moment of recording the voice message, e.g., due to some kind of attention or memory constraint. We examine each of these three possibilities in turn.

4.1 Perceived Benefits of Transmitting Level and Reliability

We first consider the perceived benefits of, or incentives for, communicating level versus reliability information. Perceived incentives are a natural starting point: in practice, people pass on information in a variety of different circumstances, and the objective of such information transmission can vary widely, from informing to persuading to entertaining the recipient. It is likely that people (at least partly) tailor the contents they transmit to the specific requirements of the situation. The differential loss observed in our data might be an artifact of our setup that induces specific (perceived) transmission incentives, or it may be a more fundamental property of transmission that is likely to occur robustly across different transmission settings.

[18]Among listeners hearing original recordings, the reliability manipulation in this experiment generates a 44-point gap in reliability beliefs on a scale of 0-100, compared to 30 points in the baseline.

[19]Here we mean suboptimal not relative to a fully unconstrained, rational decision-maker. Rather, we use a subjective notion of optimality given the decision-maker's perception of her own constraints. The constraints that she is aware of enter her constrained optimization, reflected in her perceived benefits and costs. Additionally, however, there may be uninternalized constraints that she is not aware of, which affect behavior but are not accounted for in the decision-maker's subjective tradeoff, and hence suboptimal in that precise sense.

4.1.1 Evidence from Baseline Experiment

We begin by examining several additional pieces of evidence from our baseline experiment. Participants in our main transmitter survey are randomized into seeing one of three sets of supplementary questions. First, we test for the role of biased beliefs about the relevance of reliability versus level information. In particular, participants may (mistakenly) believe that passing on reliability information would not affect listeners' belief updates and hence their probability of receiving the bonus payment. At the end of the transmitter experiment, we ask one-third of respondents how much passing on the reliability and level of the speaker's prediction increases the likelihood of receiving a bonus. We find that respondents believe that passing on reliability information is roughly equally likely to increase their chance of receiving a bonus as passing on level information: the average response is 71% for level and 68% for reliability. This is true even among respondents whom we classify as *not* passing on reliability information in their recordings (averages of 73% versus 66%).

Second, to test whether respondents are aware that they are omitting specific information, we ask another one-third of respondents explicit questions about whether they included level information and whether they included reliability information in their recordings. In line with our findings from the transcripts analysis, we find that 64% of respondents admit to not passing on reliability information, and 31% state they did not pass on level information.[20]

Third, to examine whether people forget or do not pay attention to the incentive scheme, we examine whether, at the end of the survey, the final one-third of respondents still pass the initial comprehension checks about their incentives. We find that 90% of respondents correctly answer both questions about the incentives,[21] strongly suggesting that respondents ignoring or misremembering incentives cannot explain the patterns in our data.

Taken together, these separate pieces of evidence from the baseline transmitter study show that people infer from the incentive scheme that reliability is as important to pass on as the level, that they do not forget the incentive scheme over the course of the experiment, and yet they admit to not passing on reliability in their actual recordings. This provides a first sign that the differential loss of reliability information is not due to explicit beliefs about lower benefits of transmitting reliability.

[20]The fact that 31% of respondents report not passing on level, despite our handcoders classifying almost everyone as passing on level, may suggest that these respondents do not correctly understand these concepts. However, first, our baseline incentives make no mention of level and reliability (instead, holistic transmission of relevant information is incentivized), so there is no need to understand (and no room to misunderstand) the level/reliability distinction. Second, when we restrict to people who said they passed on level in this question, we see the same differential information loss (27% for level and 84% for reliability).

[21]These questions are: (1) Which of the following is true? To maximize my earnings, ... (A) I should imitate the original recording, but in a different accent or voice. (B) I should describe the general topic of the original message without being specific about its contents. (C) I should pass on all information from the original message that I think will influence how people change their beliefs. And (2): Which of the following is true? I will be paid based on... (A) How many questions I can answer correctly about the original recording. (B) How close the average belief change induced by my recording is to the average belief change induced by the original recording. (C) I will be paid based on how similar other respondents say my recording is to the original recording.

4.1.2 Additional Evidence: Incentives for Content Transmission

To more directly probe the importance of the perceived benefits of transmitting level versus reliability information, we conduct an additional experiment. In the baseline experiment, transmitter bonuses were based on the induced belief movements of listeners, leaving transmitters free to pick and choose which dimensions of the original content they believe will be relevant for listeners' belief updates. In this supplementary experiment, transmitters are directly incentivized to pass on all of the original message's content, with 50% of respondents explicitly told to pass on level and reliability information. We still observe large differential information loss, albeit slightly smaller in magnitude than in our main results.

Design. This experiment is virtually identical to the baseline experiment, except that half of respondents are generically incentivized to pass on *all* of the information in the original messages (*implicit incentives*), while half are explicitly and equally incentivized to pass on both the level and reliability of the original forecast (*explicit incentives*).

In particular, respondents are informed that one in ten transmitters will be selected for bonus eligibility and that, if selected, a different group of participants will score transcripts of their recordings on a scale of 0 to 10, where 0 corresponds to "Nothing conveyed in meaning" and 10 corresponds to "Everything conveyed in meaning". This group, which we refer to as the *evaluators*, is distinct from the listeners. If the average score a transmitter's recordings receive is at least an 8, the transmitter will receive a $20 bonus payment. Between subjects, we randomly assign transmitters to two variants of the incentive scheme. In *implicit incentives*, participants are given the following instructions:

> The other participants will answer the following question about your voice message:
>
> How accurately did the voice message convey the content and meaning of what the speaker said?

Compared to the original transmitter incentives, this incentive scheme should incentivize transmitters to pass on reliability information regardless of their beliefs about its importance for listeners' belief updates, because the instructions encompass *all* the contents of the original message.

In the *explicit incentives* condition, we go one step further by informing respondents that the evaluators will answer two questions about the message, one about the level of the prediction and one about the reliability of the prediction:

> The other participants will answer two questions about your voice message.
>
> How accurately was the speaker's prediction about the level of the economic variable conveyed in the voice message?
>
> How accurately was the speaker's assessment of the reliability of their forecast conveyed in the voice message?

The explicit incentive scheme has two main features. First, unlike the baseline scheme it ensures that transmission of the reliability of the prediction is, by design and explicitly, equally as payoff-relevant as the transmission of the prediction's level. Second, unlike both the baseline and implicit schemes, it introduces transmitters explicitly to the level-reliability distinction. In the other treatments, transmitters were not introduced to this distinction before producing their own recordings.

Logistics. The additional transmission and listener experiments were run with 501 and 1,509 U.S. respondents from Prolific, respectively, in September 2023. This collection was also pre-registered at `https://www.socialscienceregistry.org/trials/12119`.

Results. Figure 5 shows results, pooling the explicit and implicit incentive schemes. Panel (a) shows substantial differential loss in our analysis of scripts: only 30-40% of scripts mention reliability, compared to 85-95% mentioning level. Panels (b) and (c) analyze message beliefs, showing 33.5% loss of level information and 69.6% loss of reliability. This is similar to, albeit slightly smaller than, the 34% vs. 91% differential information loss in our baseline experiment. A formal test of equality of the two information loss statistics rejects the null at $p < 0.001, \chi^2 = 27.1$. Appendix Figure A14 shows that results are fairly similar across the implicit and explicit incentive schemes. The loss of sensitivity to level is 39.8% for explicit incentives and 32.1% for implicit incentives. The loss of sensitivity to reliability is 65.1% for explicit incentives and 73% for implicit incentives. Taken together, increasing the payoff relevance and salience of reliability information through implicit and explicit incentive schemes reduces reliability information loss only modestly. Thus, differences in perceived importance of transmitting level versus reliability information do not fully explain our main result of differential information loss.

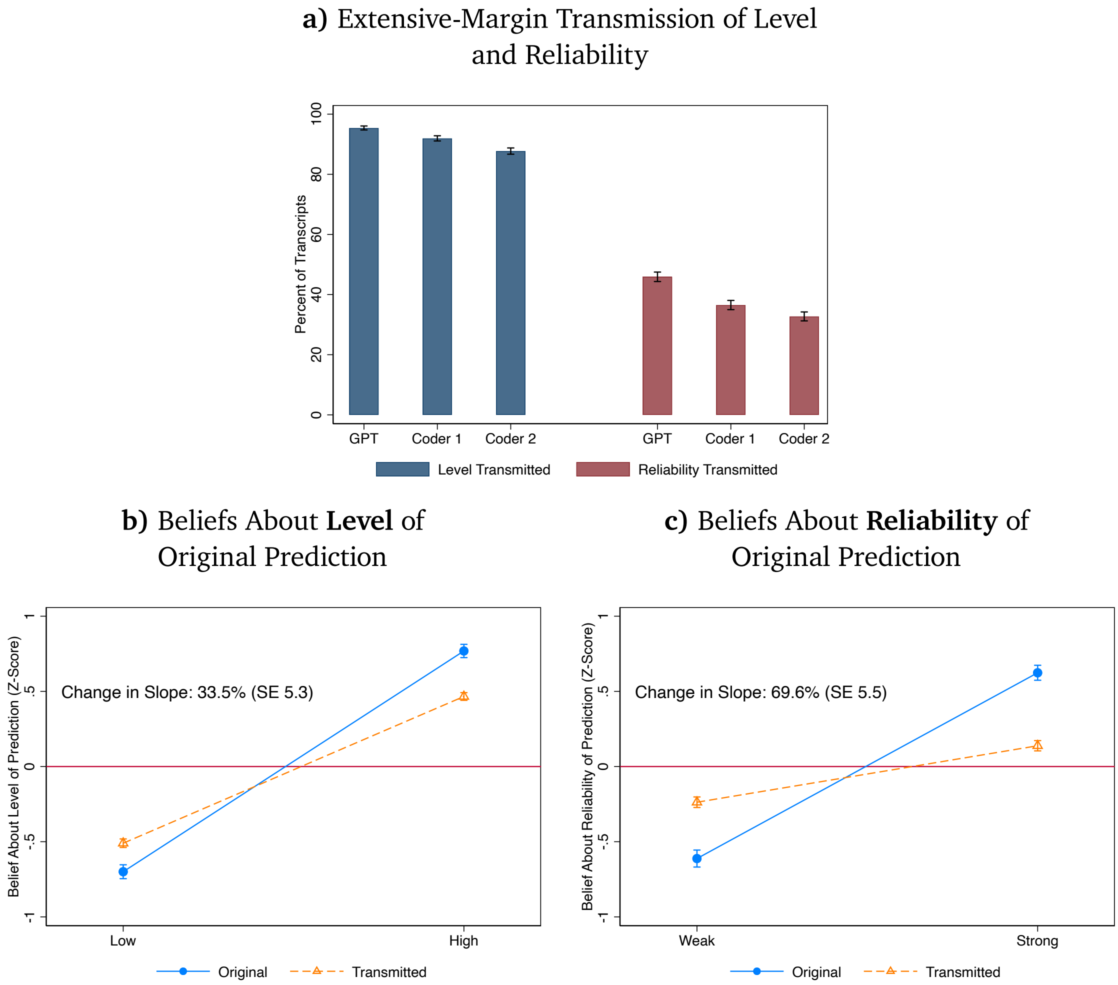


Figure 5: This figure presents data from our version of the baseline experiment that uses explicit incentives for transmission of level and reliability. Panel (a) replicates 1. It shows the fraction of transmitted messages classified by GPT-4 and our two human coders as containing statements about the level or reliability of the original forecast. Panels (b) and (c) replicate Figure 2, showing listeners' beliefs about the level and reliability of the prediction in the original message, separately by whether the original message is low- vs high-level or weak- vs strong-reliability, and separately by whether the listener hears the original message or a transmitted version of it. Dots are mean beliefs and bars are standard error bars (1 SE each direction). $N = 1{,}509$ listeners and 501 transmitters. Appendix Figure A13 shows belief updates about the economic variable from this experiment and Appendix Figure A14 splits these graphs by implicit versus explicit incentives.

4.2 Perceived Costs of Transmitting Level and Reliability

Next, we turn our focus to the second possible driver of differential loss and examine the subjectively perceived *costs* or *difficulty* of transmitting level versus reliability information. Here we can distinguish between the *(ex-ante) anticipated* and *(ex-post) experienced* costs of transmitting each type of information. Transmitters might deliberately omit reliability information because they *expect* it to be more costly or difficult to transmit; alternatively, they might try to transmit reliability information but then *experience* it as being very difficult to properly transmit. Our analysis in Section 3.1, which found that 60% of transmitted transcripts do not include anything about the reliability of the original message, suggests that transmitters are not even *trying* to transmit reliability, suggesting that anticipated costs are more likely to be relevant than experienced ones.

Design. As a direct test of the initially *anticipated* costs of transmitting level versus reliability information, we study whether transmitters prefer to be paid for their performance in transmitting information about (i) the level of the original prediction or (ii) the reliability of the original prediction. By "performance," we mean an external evaluator's assessment of how well the transmitter's message passed on the level or reliability, respectively. We also elicit transmitters' expectations about how difficult transmitting level or reliability information will be. To test whether experienced costs deviate from anticipated ones, we study whether transmitters' beliefs about the difficulty of transmitting level versus reliability information change after experiencing the transmission process.

The setup of this experiment closely mirrors the *explicit incentives* treatment presented in Section 4.1, where transmitters were told that an external evaluator will compare the transcript of their message to the transcript of the original recording and separately rate how well the level and reliability of the original recording were communicated. Departing from that design, respondents here *choose* which of the evaluator's two responses will determine their bonus payment, and are told that they should focus purely on transmitting that dimension of the original message. Moreover, we elicit respondents' perceived difficulty of transmitting level versus reliability information, both before and after they actually create their recordings.

Logistics. We conducted this experiment with 97 respondents on Prolific in November 2023. This collection was also pre-registered at `https://www.socialscienceregistry.org/trials/12119`.

Results. Panel (a) of Appendix Figure A15 shows that 62 percent of respondents choose to transmit information about the reliability of the prediction, and the average perceived difficulty of transmitting reliability information is slightly lower than for level. Differences in the perceived difficulty of communicating level and reliability information are relatively small, both measured before (Panel (b), $t = 0.64, p = 0.53$) and after the recording (Panel (c), $t = 2.4, p = 0.02$). This suggests that transmitting reliability information is, if anything, *easier*, and makes it hard to see how higher anticipated or experienced costs of transmitting reliability information could play a role in driving differential information loss. Virtually all respondents pass on the characteristic they chose.

Heterogeneity. There is no heterogeneity in perceived costs that could generate the pattern of differential information loss we observe. For example, suppose that the 60% of people choosing to transmit reliability are capable of transmitting both types of information in the main experiment, but the 40% choosing to transmit level information find transmitting reliability to be prohibitively costly. This could generate differential information loss even if transmitting level is perceived as harder on average. But we find no such heterogeneity in the data: the groups choosing to transmit level versus reliability information give similar average difficulty ratings and have similar 15-point average difficulty gaps between the parameter they choose to transmit and the other parameter.

Result 4. *Mechanism experiments suggest that differential transmission loss of reliability information is not the result of a deliberate decision: it is not driven by the subjectively perceived benefits or costs of transmission.*

4.3 Memory Constraints and What Comes to Mind

Having established that differential loss does not appear to be the result of a deliberate prioritization of level information, we examine the possibility that transmitters subconsciously or non-deliberately neglect to include reliability information. In particular, one possibility is that reliability information simply *does not come to mind* in the cognitively challenging moment of transmission.

To structure our investigation, we follow the canonical distinction in memory research between *cued recall* and *free recall* situations (e.g., Kahana, 2012). In cued recall, people are given prompts related to the specific piece of information to be retrieved, and these prompts guide the retrieval process. In the free recall paradigm, researchers test whether and which information people recall in the absence of specific cues or prompts related to the target piece of information.

In our context, we apply these concepts to the recall of level and reliability information. On the one hand, transmitters may generally struggle to retrieve from memory the reliability information contained in the original messages, preventing them from passing it on to listeners. To test for this possibility, in a *cued recall* intervention, we ask transmitters about the level and reliability information in the original messages, after they have completed their tasks.

On the other hand, reliability information might be accessible from memory if actively sought out but may not come to mind automatically during transmission. While the transmission task prompts transmitters to recall the original messages, they are not explicitly prompted (on the transmission task page) to recall the level and reliability information contained in those messages. Consequently, the transmission process is best characterized as a free recall setup with respect to retrieving level and reliability information. To test for the role of constraints in free recall, we design an additional experiment that strongly increases the salience of reliability and level information *at the time of recording*, possibly increasing the ease with which reliability information comes to mind. In effect, this manipulation turns the free recall situation of the recording into a cued recall setting.

4.3.1 Memory Constraints in Cued Recall

We start by analyzing the beliefs of transmitters in the baseline experiment, measured after they complete their recordings.[22] Specifically, we present transmitters with the same set of three beliefs questions we pose to listeners, i.e., we elicit transmitters' state beliefs as well as their message beliefs (see Section 2).[23]

Appendix Figure A11 demonstrates that there is virtually no memory loss among transmitters about the original message's reliability: several minutes after hearing the original recording and after performing the cognitively demanding task of recording their own voice message in the interim, transmitters are *just as sensitive to variations in reliability* as listeners whose beliefs are elicited immediately after hearing the original recordings. If anything, there is more memory loss for level information than reliability information.

These data also allow us to characterize differential loss *accounting for memory constraints*: we compare the sensitivity of listeners hearing transmitted recordings to the sensitivity of *transmitters* (instead of the sensitivity of *listeners hearing original messages*, as in our baseline analyses). We still find strong differential information loss, with reliability information loss of 87.2% and level information loss of 7.1%.

This evidence establishes that transmitters, when explicitly prompted, recall reliability information to the same degree as listeners. However, as pointed out above, the actual process of recording resembles a free recall situation rather than cued recall. This hence leaves open the possibility that reliability information simply does not come to transmitters' minds when recording their voice messages.

4.3.2 Memory Constraints in Free Recall

We conduct an additional *high salience* experiment that increases the *during-transmission* salience of the distinction between the level and reliability of the original message. This experiment tests the hypothesis that differential information loss decreases when transmitters are directly reminded about the level-reliability distinction during the recording process, which effectively turns the free recall setup of the recording into a cued recall situation.

Design. The design closely follows the *explicit incentives* treatment described in Section 4.1.2, in which transmitters were explicitly incentivized to transmit both the level and reliability of the original message's prediction. It adds three features to increase the salience of the level-reliability incentives at the time of recording: First, we add additional, more heavy-handed comprehension questions in which respondents need to correctly answer which types of information they need to transmit in the experiment. Second, just prior to each recording we ask respondents: "What do you have to pass on well to maximize your chances of receiving a bonus? Tick all that apply"

[22]This should provide us with a lower bound for the role of memory constraints as beliefs are elicited after and not during the recording.

[23]A random 50% of transmitters also give their priors about the two states before hearing the recordings, allowing us to calculate state belief updates.

with the following response options: (i) level of the speaker's prediction; (ii) reliability of the speaker's prediction. Respondents can only proceed once they correctly answer this question by selecting both. Third, on the actual recording page we add the following reminder: "Remember: Your bonus payment is based equally on how well you pass on both of the following: (i) The level of the speaker's prediction. (ii) The reliability of the speaker's prediction." This reminder is presented in large, red font.

Logistics. This experiment was conducted on Prolific in November 2023 with 244 transmitters and 1,010 listeners. This collection was also pre-registered at `https://www.socialscienceregistry.org/trials/12119`.

Results. Figure 6 visualizes the results of the *high salience* experiment. In line with our hypothesis that reliability information comes to mind more easily under the added cues, we document a strong reduction in reliability information loss and a convergence in the degrees of level and reliability information loss.

Panel (a) shows that transmitters in the high salience experiment talk much more about reliability, with nearly 80% of transmitted transcripts containing at least some information about the original prediction's reliability, compared to just 30-40% in our previous experiments. The share of transcripts containing level information decreases slightly, from 90-95% to 80-90%.

Analyzing message beliefs, Panels (b) and (c) of Figure 6 show that reliability information loss decreases to 39% (from 65.1% in the *explicit incentives* treatment), while level information loss increases slightly from 39.8% to 53%, possibly reflecting crowding-out of level information as transmitters talk more about reliability. Interestingly, Panel (c) shows that distortions of reliability information disappear entirely for weak-reliability messages but remain for strong-reliability messages. On the one hand, this may suggest that indicators of weak reliability are more salient or easier to transmit once transmitters have reliability in mind. On the other hand, this pattern may reflect a symmetric loss akin to the one documented before, coupled with an overall downward shift of perceived reliability that equally applies to all transmitted messages.

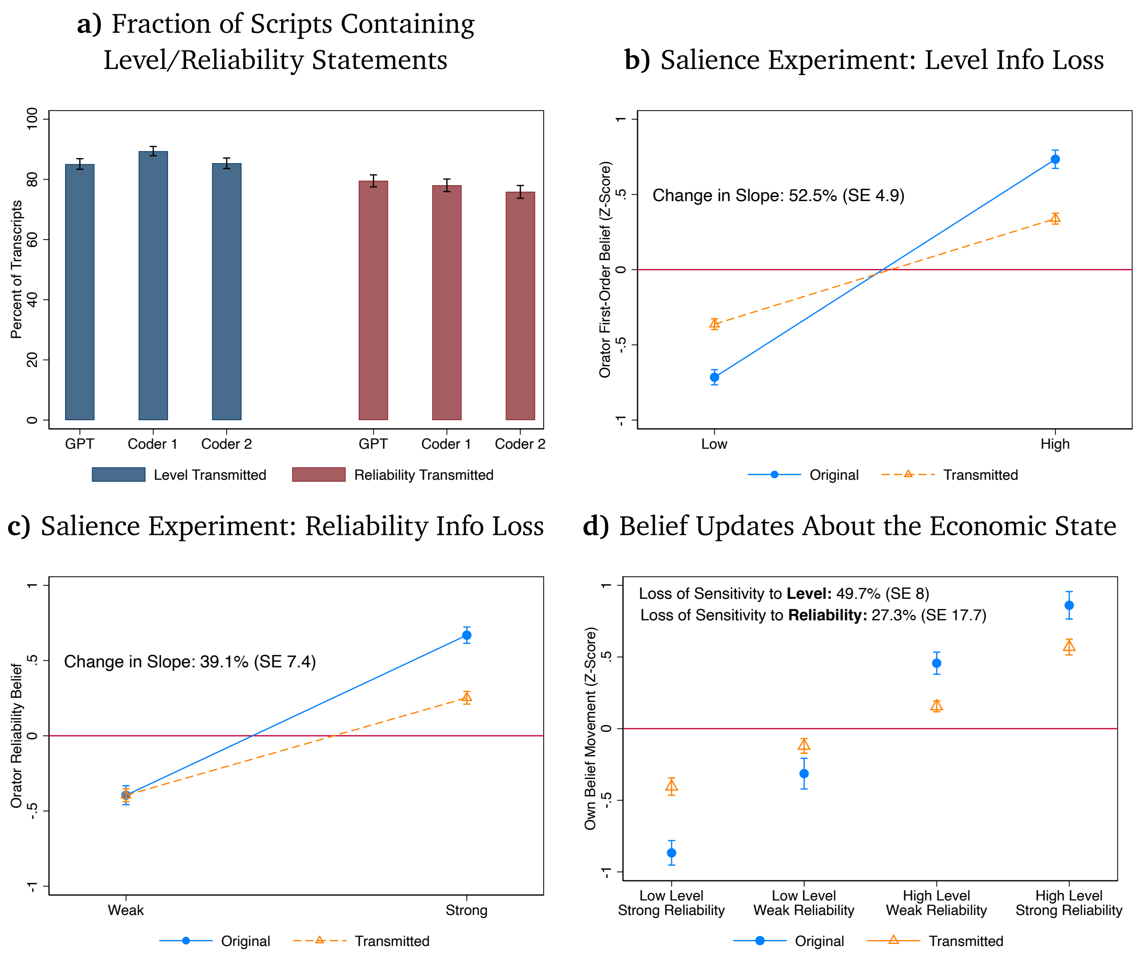


Figure 6: This figure presents data from the High Salience Experiment. Panels (a) and (b) replicate Figure 2, showing beliefs about the original message's level and reliability, separately by whether level is low/high, reliability is weak/strong, and the listener is hearing an original or transmitted message. Panel (c) replicates Panel (a) of Figure 1, showing which fraction of transmitted scripts contain statements about the level or reliability of the original prediction. Panel (d) replicates Panel (c) of 3, showing listeners' average belief updates about the economic variable. Bars are standard error bars. $N = 1,010$ listeners and 244 transmitters.

Panel (d) documents the consequences for the overall pattern of listeners' state belief updates. Transmission strongly attenuates belief movements towards zero on average. This is driven by the level information loss; moreover, the offsetting force of reliability information loss for weak-reliability messages, which pushed belief updates for those messages away from zero, is now absent (see the detailed discussion of forces in Section 3.3). As a result, transmission mostly preserves the distinction between weak- and strong-reliability messages: listeners update less than half as much from weak-reliability compared to strong-reliability messages, regardless of whether they hear original or transmitted recordings. However, this also means that average belief updates from transmitted messages are shrunk even further than in our baseline experiment.

The resulting pattern of state belief updates illustrates a tradeoff arising from our salience intervention: on the one hand, relative to our baseline results, the intervention restores the gap in the influence of weak- and strong-reliability messages. Put differently, transmission no longer renders weak- and strong-reliability messages similarly influential. On the other hand, the intervention further weakens absolute belief updates from transmitted messages, both because it slightly exacerbates level information loss and because it dilutes the partially offsetting force of reliability information loss. As a result, it aggravates the fact that in a population with heterogeneous priors, transmission loss slows down belief convergence on the basis of new information. Of course, such a slowdown may be desirable if this convergence would otherwise happen on the basis of unreliable information.

Result 5. *Reliability information is lost in transmission largely because it fails to come to mind during transmission. We show that differential information loss can be eliminated through interventions that remind people at the time of transmission to also consider the reliability of information.*

5 Why is Reliability Less Likely to Come to Mind?

Our mechanism findings raise the question of *why* reliability information is less likely to come to mind than level information, absent explicit reminders. In this section, we introduce two potential explanations and show suggestive field evidence supporting both of them.

5.1 Framework

We interpret the transmission process through the lens of associative-memory models of retrieved context (e.g., Kahana, 2012; Bordalo et al., 2020, 2021, 2023). When a transmitter encounters an original message, the message is stored in the transmitter's memory as a trace that includes both substantive content (e.g., facts, arguments and examples contained in the message) and meta-features (the message's source and credentials). When the transmitter later encounters a cue that triggers transmission — the transmission task, in our experiments, or a question or conversation in real life — the cue activates stored traces with probabilities that are increasing in the similarity between the cue and the trace and decreasing in the interference between the trace and other traces (Bordalo et al., 2020).

In this class of models of episodic memory, the probability of retrieval is affected both by characteristics of the *cue* (via similarity) and characteristics of the memory database (via interference). This, in turn, suggests two classes of reasons why reliability might come to mind less than level in practice.

Cues. Anecdotal observation suggests that real-life requests for transmission typically cue level information but rarely reliability information. People often ask about substantive economic facts, beliefs, or projections, but rarely directly request confidence levels or reliability assessments from their interlocutors. This could create an association between transmission and level information that leads generic transmission contexts (like our experimental context, which carefully avoids explicitly cuing either level or reliability) to naturally cue level information, but not reliability.

Interference. Predictions about the levels of economic variables are typically supported by, and communicated through, rich contextually-specific claims, arguments, and examples. For example, the level claims in our messages about housing were supported by arguments about residential construction permits, interest rates, and geographic movement of populations. This specificity and richness means that different level claims from different contexts are strongly distinct from each other, leaving little scope for interference between them in the retrieval process.

By contrast, reliability is much more likely to be communicated using semantically generic terms such as certainty or uncertainty prefixes, statements about confidence levels, or the name of a source. This creates much more potential for interference between different pieces of reliability information that could block retrieval. Indeed, a longstanding literature on "source monitoring errors" in memory finds that individuals have difficulty accurately attributing particular pieces of memory to a source (Hovland and Weiss, 1951; Johnson, 1997). Several pieces of evidence connect these source monitoring errors to interference between sources in the memory bank (Lindsay and Johnson, 1989; Johnson et al., 1993; Henkel and Franklin, 1998). Put more simply, richly detailed level arguments may come to mind more easily than short, generic reliability statements because of the greater distinctiveness of the former.

5.2 Evidence on Cues

Almost all questions, by virtue of asking about some specific piece of information, will cue level information. By contrast, questions could cue reliability information either directly (via explicit requests for certainty or uncertainty information) or indirectly (by containing their own certainty or uncertainty markers or other features that remind the person being questioned about reliability).

5.2.1 Direct Cues of Reliability

Our High Salience experiment in Section 4.3 showed that explicit cues of reliability are effective at inducing transmission of reliability information. However, evidence from the field suggests that everyday questions almost never explicitly request reliability information.

Specifically, we examine the British National Corpus, a dataset consisting of 1,251 recordings of everyday conversations between individuals in the UK, recorded at home or in other settings using participants' smartphones (Love et al., 2017). We use a large language model (OpenAI's GPT4o) to annotate each of the $\sim$800,000 lines of usable conversational text in the Corpus. We ask the model to identify lines containing questions; we further distinguish between questions concerning information that the speaker's interlocutor would have direct access to (such as what happened to them that morning) or secondhand information that the speaker would have to source from somewhere else (such as a weather forecast or piece of economic or political news). Such questions, by definition, contain a request for level information of some kind; we ask the model to additionally classify whether the question contains a request for reliability information, such as the interlocutor's certainty level or the source of the information.

Of the 70,974 questions our LLM identifies in the Corpus (8.5% of the conversational lines), only 102 are classified as containing an explicit request for information about the certainty or reliability of the interlocutor's answer. When we restrict to the 19,863 questions that are classified as being about information that the questioner's interlocutor would only have secondhand access to — i.e., requests for the transmission of secondhand information — only two contain such requests. Explicit requests for reliability information are hence vanishingly rare in everyday spoken conversation.

5.2.2 Indirect Cues of Reliability

Requests for transmission may also include indirect cues of reliability information — for example, requests may themselves include reliability markers. Do such indirect cues matter in the sense of successfully raising the rate at which reliability information is transmitted?

Indirect Cues Matter: Evidence from our Experiment. Our baseline transmitter experiments seeded random variation in exposure to indirect reliability cues. One of our reliability manipulations — the Modular manipulation — varied whether an otherwise-identical text contained certainty-denoting prefixes, uncertainty-denoting prefixes, or *no* reliability prefixes. Since transmitters heard two recordings back-to-back before completing their transmission tasks, those who heard two with certainty- or uncertainty-denoting prefixes were exposed to strictly more indirect reliability cues than those who heard one recording with certainty- or uncertainty-denoting prefixes and one with no prefixes.

Column (1) of Table 1 regresses an indicator for whether a transmitter's message for a particular recording is unanimously classified by our LLM and human coders as transmitting reliability markers on an indicator for whether the *other* recording the transmitter heard contained reliability indicators. (The independent variable is 0 for transmitters whose other recording was a no-prefix Modular recording, and 1 for all other transmitters.) The results show that hearing indirect and irrelevant cues in the *other* recording increases the probability of transmitting reliability information for *this* recording by 10 percentage points, or nearly 50 percent — a substantial effect of indirect reliability cues. Column (2) confirms, using our more granular LLM codings, that the effect is entirely driven by increased transmission of reliability indicators consistent with the original recording (high indicators for high-reliability recordings, and low indicators for low-reliability recordings). Column (3) shows, by contrast, that transmitters do not mistakenly adopt reliability indicators inconsistent with the original message. We return to Columns (4) and (5) later in this section.

Table 1: Indirect Reliability Cues Increase Transmission of Reliability

	Experimental Results: Reliability Passed on (Handcoding)			British National Corpus: Answer Contains Reliability Indicator	
	(1) All Words (Unanimous)	(2) Aligned Words (LLM)	(3) Misaligned Words (LLM)	(4) All Questions	(5) Secondhand Info Questions
Other Recording Contained Reliability Prefixes	0.107***	0.100**	-0.014		
	(0.035)	(0.043)	(0.030)		
Question Contained Reliability Prefixes				0.109***	0.101***
				(0.004)	(0.007)
Constant	0.130***	0.274***	0.123***	0.274***	0.298***
	(0.028)	(0.037)	(0.027)	(0.002)	(0.004)
Observations	702	702	702	70974	19863

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note: Columns (1)-(3) report results from our baseline transmitter experiment. An observation is a transmitter-by-topic, restricted to transmitter-by-topics where the transmitter heard a high- or low-reliability recording about that topic. The independent variable in all three columns is an indicator for whether the recording the transmitter heard for the *other* topic was a neutral-reliability modular recording. The dependent variable in Column (1) is an indicator for whether our LLM and human coders unanimously classify the transmitter's transmitted message as containing reliability indicators. In Column (2), it is an indicator for whether the LLM classified the message as containing a reliability indicator aligned with the original message (high-reliability indicators for high-reliability messages, and vice versa; our human coders did not code at this level of granularity). In Column (3), it is an indicator for whether the LLM classified the message as containing a reliability indicator misaligned with the original message. Columns (4) and (5) use data from the British National Corpus. An observation is a line in one of the conversations in the Corpus. Column (4) restricts to conversational lines that our LLM identifies as being questions, while Column (5) additionally restricts to questions that are about secondhand information the questioner's interlocutor would not have direct access to (e.g., not questions about the interlocutor's name or experience at a restaurant). The dependent variable in both columns is an indicator for whether the response to the question in the next conversational line contains any reliability indicators and the independent variable is an indicator for whether the question itself contained any reliability indicators.

Indirect Cues Matter: Evidence from Economic Cable News. We now turn to a high-stakes field setting for an additional test of whether indirect cues matter. Specifically, we measure the transmission of economic uncertainty through cable TV news segments and quasi-experimentally test whether uncertainty cues on preceding days increase the fidelity of this transmission. For the sake of brevity, we here describe the main ideas behind our methodology and the main results, deferring a detailed exposition and comprehensive robustness checks to Appendix D.

To measure the transmission of economic uncertainty, we combine a newspaper-based benchmark measure of economic uncertainty (Baker et al., 2016) with a measure of word-of-mouth transmission of uncertainty on economic cable news broadcasts, both at the daily level. Our measure of the fidelity of uncertainty transmission is the correlation between the word-of-mouth cable news measure and the benchmark newspaper measure. In other words, we examine the degree to which variation in "true" economic uncertainty (which we approximate with newspaper language) translates into variation in the use of uncertainty language on cable news broadcasts. Our use of newspapers as a benchmark approximation for "true" economic uncertainty fits our previously-discussed distinction between written text — which is more premeditated and less subject to cognitive and memory constraints — and spontaneous word-of-mouth discussion or punditry, which is more vulnerable to the cognitive constraints we study.

We test whether higher quantities of uncertainty language on a channel's news segments *yesterday* — which we treat as indirect cues of reliability — are associated with a greater responsiveness of uncertainty language in economic segments to (our benchmark of) true economic uncertainty *today*. Since the outcome we are interested in is how the *slope* between TV and newspaper language varies over time, neither serial correlation in uncertainty language on cable news nor any mechanical relationship between newspaper and TV language threatens our empirical strategy. Our main specification includes channel fixed effects interacted with calendar month and economic coverage quantities.

Figure 7 shows that on days with above-median volumes of uncertainty language on yesterday's news, uncertainty language in today's economic segments is substantially more sensitive to our benchmark measure of economic uncertainty. Recent indirect cues of uncertainty hence seem to make news commentators more attentive to uncertainty, increasing the fidelity of their transmission of uncertainty.

Appendix Table A7 presents regression versions of these results and subjects them to a battery of robustness and placebo tests. These include specifications that add interactions between channel fixed effects and lagged measures of benchmark economic uncertainty and economic coverage; specifications that control for calendar *day* fixed effects, zooming in on variation across channels in channel-specific uncertainty language yesterday; specifications that exclude the Covid years; and placebo tests that use uncertainty language on *other* channels and uncertainty language in *non*-economic coverage. Results remain highly robust across all of these checks.

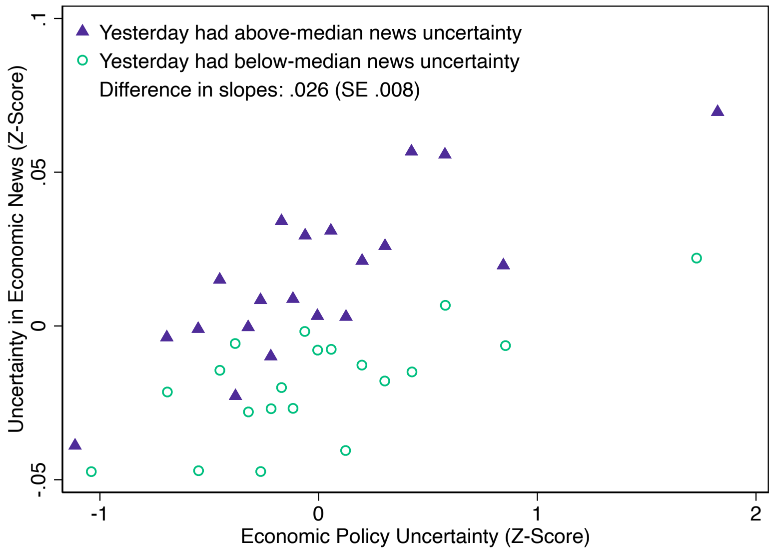


Figure 7: This figure plots channel-specific daily economic uncertainty on cable TV news against newspaper-based Economic Policy Uncertainty (EPU), splitting days by whether the previous day's channel-specific uncertainty was above or below median. Variables are standardized (Z-scores). Data from CNN, Fox, and MSNBC, 2010–2024. We control for calendar month fixed effects interacted with channel fixed effects, and contemporaneous economic coverage interacted with channel fixed effects. See Appendix D for details.

Indirect Cues in Everyday Conversations. Finally, we return to the British National Corpus. While virtually none of the 70,974 questions identified by our LLM contain explicit requests for reliability information, 26% of them are classified by our LLM as containing indirect cues of reliability in the form of certainty, uncertainty, or reliability markers. Column (4) of Table 1 show that a question containing such a marker is 10 percentage points more likely to be followed by an answer that contains a reliability indicator, compared to a question that contains no such indicators. This remains true in Column (5), where we restrict to questions requesting second-hand information.

This analysis is descriptive, but its results are consistent with the evidence from our experiments and TV news: indirect cues appear to help trigger reliability transmission. Despite the apparent efficacy of these indirect cues, they remain relatively uncommon in the Corpus's conversations: while all of the questions we analyze (by definition) request some piece of level information, only a quarter contain any indirect reliability cues.

Cues: Conclusion. One hypothesis is that transmission contexts are naturally associated with level but not reliability information because level information is frequently cued in such contexts but reliability information is not. In this section, we have shown that in everyday conversational contexts where level information is requested, reliability is almost never explicitly cued, and is implicitly cued only about a quarter of the time. We have also shown that cues matter: both explicit and implicit cues of reliability induce greater transmission of reliability information in our experiment, in everyday conversations, and in TV news.

5.3 Interference

Our second hypothesis concerns interference: if expressions of reliability tend to be more similar to each other than expressions of level, reliability information will be harder to retrieve because retrieval attempts will face more interference.

To test this hypothesis, we return to the British National Corpus.[24] We take the set of conversational lines containing reliability markers and compute the average cosine similarity of 100,000 randomly selected pairs. We then take the set of conversational lines containing statements about substantive claims (which we treat as level statements) and similarly compute the average cosine similarity of 100,000 randomly selected pairs.[25]

The leftmost columns of Figure 8 shows that pairs of conversational lines containing reliability indicators are about 15% more semantically similar to each other than pairs of lines containing level statements.[26] This difference is attenuated by the fact that many of the con-

[24]Because the Stanford Cable TV News Analyzer, which we used for our TV analysis, does not allow us to access raw transcripts (just query them for specific words), we cannot perform this exercise in that dataset.

[25]We exclude trivial statements, such as "My name is John".

[26]Cosine similarity scores range between 0, representing complete orthogonality, and 1, representing identity; the baseline semantic similarity of both types of statements is between 0.15 and 0.20, indicating relatively low similarity, due to the diversity of conversation topics in our corpus.

versational lines containing reliability indicators *also* contain level statements, and many of the lines containing level statements also contain extraneous words. To narrow down to our objects of interest, we use our LLM to extract the core snippets of lines containing expressions of reliability or level statements. When comparing the semantic similarity of randomly chosen pairs of these subsets, our result strengthens substantially: the rightmost columns of Figure 8 shows that expressions of reliability are about 40% more semantically similar to each other than statements about level.

This is not mechanical: in principle, expressions of reliability could be just as semantically diverse as expressions of level statements. This could be true if, for example, reliability is communicated via rich contextual information about a source ("the person who told me this was a bit drunk and seemed to have a poor memory"). However, in practice, the fact that reliability is often communicated through a stock set of modifiers ("maybe," "I'm not so sure") causes considerable semantic similarity across reliability expressions. This makes each reliability statement less distinctive and hence potentially harder to recall.

a) Reliability Claims are More Semantically Similar to Each Other than Level Claims (British National Corpus)

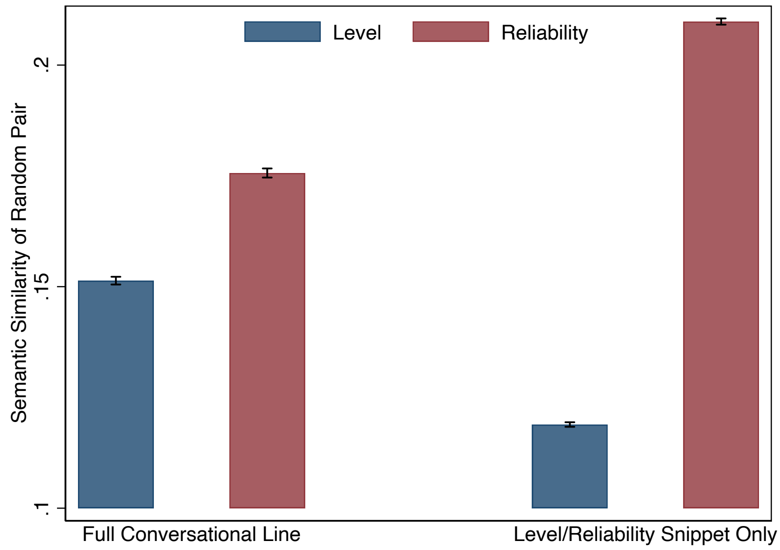


Figure 8: This figure presents results from the British National Corpus. The sample for the Level bars is the set of conversational lines our LLM classifies as being statements about a subject that could conceivably involve some uncertainty (i.e., excluding "my name is John". The sample of the Reliability bars is the set of conversational lines our LLM classifies as containing reliability indicators. In the leftmost columns, we use the text of the full conversational line; in the rightmost column, we use only the snippet containing the level statement or reliability markers, as extracted by the LLM. Each bar shows the average cosine similarity of 100,000 randomly selected pairs from within the relevant set, calculated using a BERT-based sentence-embedding model.

Result 6. *A simple associative memory framework suggests that reliability information might be less likely to come to mind either because it is not naturally cued in transmission contexts or because attempts to retrieve reliability information face greater interference. Evidence from everyday conver-*

sations suggests that requests for transmission virtually never explicitly cue reliability information and only indirectly cue it about a quarter of the time. This matters: evidence from our experiments, everyday conversations, and economic TV news suggests that reliability is much more likely to be transmitted when it is directly or indirectly cued in the transmission request. Meanwhile, evidence from everyday conversations suggests that reliability statements are much less semantically distinctive from each other than level statements, supporting the idea that reliability retrieval may face greater interference.

6 Conclusion

Our economic decisions often rely on information sourced from others through verbal communication. Does the process of verbal transmission systematically distort economic information? We conduct a series of tightly controlled experiments to answer this question. Participants in our experiments are tasked with listening to audio clips discussing economic variables, and conveying the information in the clips through voice messages. Other participants listen to either the original recorded voice messages or transmitted versions of those messages, then state incentivized beliefs. Our experiments show that different types of information are subject to different degrees of transmission loss: the reliability of a prediction dissipates much more in the transmission process than the prediction's level. Mechanism experiments demonstrate that reliability information is lost in transmission largely because it fails to come to mind during the transmission process, not because of gaps in perceived benefits or costs of transmitting level versus reliability information. A simple associative-memory framework suggests that reliability may be less likely to come to mind either because it is less likely to be cued in everyday contexts or because attempts to retrieve reliability information face greater interference. An examination of everyday conversations and economic TV news yields support for both of these possibilities.

Our findings yield two economically important insights regarding how verbal transmission shapes beliefs. First, transmission markedly amplifies the influence of messages characterized by low reliability, thereby systematically distorting belief formation toward less accurate sources of information. Second, transmission reduces the magnitude of average belief updates, allowing belief polarization to persist despite exposure to novel information. We experimentally document a trade-off between these two effects: interventions to restore the distinction between weak- and strong-reliability messages can further weaken average belief updates. These results underscore that cognitive frictions in information transmission can have pronounced implications for belief convergence and economic decision-making.

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A A Model of Noisy Transmission

This Appendix briefly lays out a model of noisy transmission that can rationalize our main results, as discussed informally in Section 3. It presents the inference and transmission problem as a coherent, global noisy inference problem.

All participants believe that the true state ℓ is drawn from some prior distribution $\ell \sim \mathcal{N}(\ell^d, v)$, where ℓ^d stands for the prior or *default* level of the state and v for the state's variance. The original message provides a noisy signal about the state to the transmitter. This noisy signal, ℓ^o, has a specific reliability r^o:

$$\ell^o = \ell + \varepsilon \quad \text{with} \quad \varepsilon \sim \mathcal{N}(0, e^{-r^o}) \tag{2}$$

The transmitter conveys their noisy signal, but the process of transmission adds additional *level transmission noise*, η. As a result, the receiver of the transmitted message gets a different noisy signal about the level of state:

$$\ell^t = \ell^o + \eta = \ell + \varepsilon + \eta \quad \text{with} \quad \eta \sim \mathcal{N}(0, v_\eta) \tag{3}$$

The listener of the transmitted message does not know the original signal reliability r^o, only that it is drawn from the prior $r^o \sim \mathcal{N}(r^d, v_r)$. Along with the signal about the state, the transmitter sends a signal about the original message's reliability to the receiver, which in turn is subject to *reliability transmission noise*, χ:

$$r^t = r^o + \chi \quad \text{with} \quad \chi \sim \mathcal{N}(0, v_\chi) \tag{4}$$

We interpret beliefs about the signal realization ℓ^o as our level message beliefs and beliefs about its precision r^o as our reliability message beliefs. Listeners who hear the original messages directly observe these; listeners who hear the transmitted versions observe the versions with added noise in Equations (3) and (4), and form Bayesian posterior message beliefs that are shrunk towards the defaults ℓ^d and r^d. This produces the symmetric compression documented in Figure 2, with the size of each compression determined by the variance of the transmission noise v_η and v_χ.

Specifically, we assume that listeners of the transmitted message behave as if they treat the signal extraction problem sequentially, by forming *message beliefs* that serve as the input for their *state belief*. They first infer a posterior estimate for the reliability as:

$$\hat{r} = r^d + \frac{v_r}{v_r + v_\chi}(r^t - r^d) \tag{5}$$

Listeners then infer a posterior estimate for the level information in the original message as:

$$\widehat{\ell^o} = \ell^d + \frac{v + e^{-\hat{r}}}{v + v_\eta + e^{-\hat{r}}}(\ell^t - \ell^d) \tag{6}$$

Given these message beliefs, they form a posterior estimate for the true state as:

$$\hat{\ell} = \ell^d + \frac{v}{v + v_\eta + e^{-\hat{r}}}(\ell^t - \ell^d) \tag{7}$$

These reduced forms represent a modest deviation from full Bayesian inference. In fact, (5) is fully Bayesian. (6) and (7) are only fully Bayesian conditional on r^o and on setting aside non-linearities that have no first-order effect. This approach also assumes that agents do not make cross-inference from the extremity of the level signal, ℓ^t, about the reliability of the original signal r^o.

Attenuation of reliability message beliefs is hence given by $\lambda_r := \frac{v_r}{v_r + v_\chi}$, while level attenuation is given by $\lambda_\ell := \frac{v + e^{-\hat{r}}}{v + v_\eta + e^{-\hat{r}}}$.

The predictions about state belief updates, discussed in Section 3.3, can also be found here. Transmission always attenuates message beliefs towards the prior. Indeed, (5) shows that reliability beliefs are more compressed when reliability transmission noise v_χ increases. Similarly, (6) shows that level message beliefs are more compressed when message transmission noise v_η increases. On the other hand, transmission has a more intricate effect on state belief movement. (7) shows that level transmission noise, which is higher when v_η is higher, always shrinks absolute belief movements. On the other hand, (5) and (7) show that reliability transmission noise, which is higher when v_χ is higher, has an effect on belief movement that depends on the level of reliability r^o: it reduces belief movement when reliability is high, i.e., $r^o > r^d$, but increases belief movement when reliability is low, i.e., $r^o < r^d$.

Under some simplifications, these comparative static statements can be turned into a more precise statement about sample means. Conditional on a signal ℓ^o and a reliability r^o, orators form the belief:

$$\hat{\ell}^o = \ell^d + \frac{v}{v + e^{-r^o}}(\ell^o - \ell^d) \tag{8}$$

In turn, listeners form the average belief:

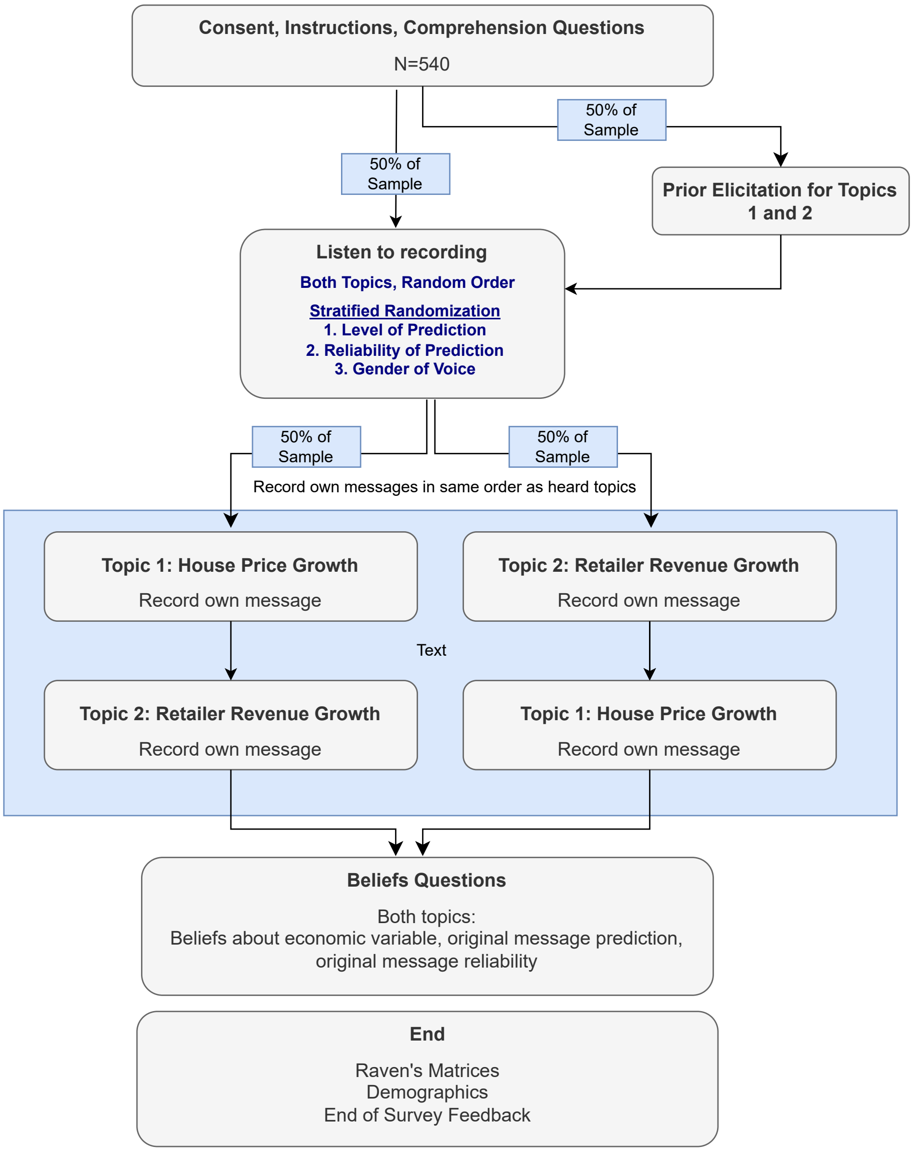
$$E(\hat{\ell}|\ell^o, r^o) = \ell^d + E\left(\frac{v}{v + v_\eta + e^{-\hat{r}}}\right)(\ell^o - \ell^d) \approx \ell^d + \frac{v}{v + v_\eta + e^{-r^d - \frac{v_r}{v_r + v_\chi}(r^o - r^d))}}(\ell^o - \ell^d) \tag{9}$$

The first-order approximation used above applies in the small reliability transmission noise limit ($v_\chi \to 0$). Since we are faced with the expectation of a logit-normal variable, for which there is no analytic formula, little can be said in full generality. Moreover, the sigmoid function of $\hat{r}^t$ will feature concavity or convexity depending on the value of r^o, so that even the second-order effect of transmission noise v_χ cannot be signed without parametrizing the model.

This shows that the contrasting effects of transmission noise on belief movement, applied above, also apply to sample means, given appropriate simplifying assumptions.

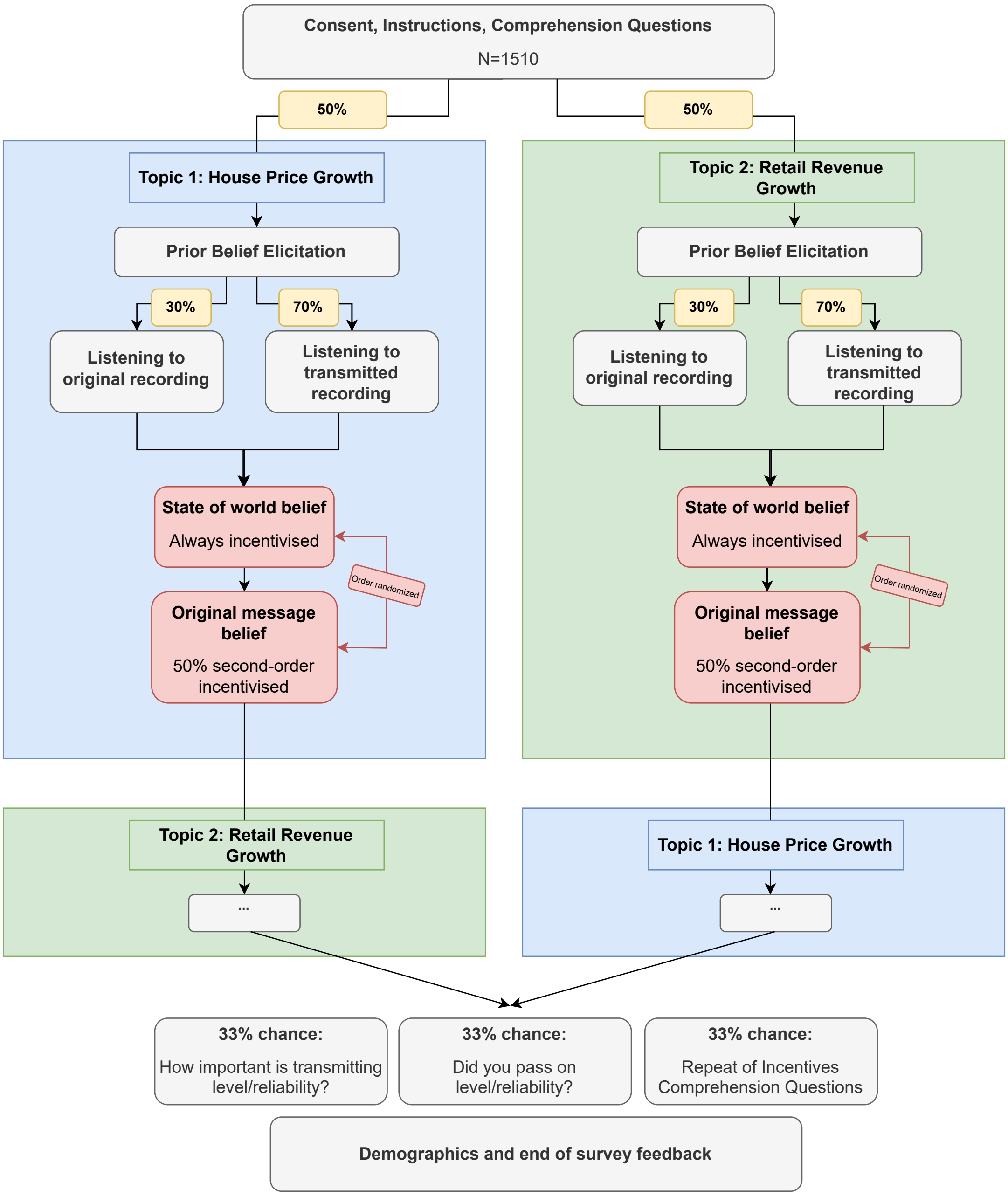
B Additional Exhibits

a) Transmitter Experimental Design



Appendix Figure A1: This figure shows the design of our baseline transmitter experiment.

a) Listener Experimental Design



Appendix Figure A2: This figure shows the design of our baseline listener experiment.

Appendix Table A1: Overview of main data collections

Collection	Sample	Content Treatments	Additional Features/Treatments	Main outcomes
Baseline experiments				
Transmitter Experiment: **Belief Movement Incentives**	Prolific (540 respondents)	High level, high reliab.; High level, low reliab.; Low level, high reliab.; Low level, low reliab.	None	Speech recordings, beliefs about originator level prediction and reliab..
Listener Experiment: **Belief Movement Incentives**	Prolific (1,510 respondents)	High level, high reliab.; High level, low reliab.; Low level, high reliab.; Low level, low reliab.	Original versus transmitted recording	Own beliefs about state, beliefs about originator level prediction and reliab..
Robustness experiment				
Transmitter Experiment with quantitative information: **Belief Movement Incentives**	Prolific (834 respondents)	High level, high reliab.; High level, low reliab.; Low level, high reliab.; Low level, low reliab.	Original scripts contain quantitative information about both the level and reliability.	Speech recordings, beliefs about originator level prediction and reliab..
Listener Experiment with quantitative information: **Belief Movement Incentives**	Prolific (181 respondents)	High level, high reliab.; High level, low reliab.; Low level, high reliab.; Low level, low reliab.	Original versus transmitted recording	Own beliefs about state, beliefs about originator level prediction and reliab.
Mechanism experiments				
Transmitter Experiment: **Content Transmission Incentives**	Prolific (501 respondents)	High level, high reliab.; High level, low reliab.; Low level, high reliab.; Low level, low reliab.	Explicit versus implicit incentives for transmission of reliab. information	Speech recordings, own beliefs about state, beliefs about originator.
Listener Experiment: **Content Transmission Incentives**	Prolific (1,509 respondents)	High level, high reliab.; High level, low reliab.; Low level, high reliab.; Low level, low reliab.	Original versus transmitted recording	Own beliefs about state, beliefs about originator level prediction and reliab..
Transmitter Experiment: **Choice of Incentives**	Prolific (97 respondents)	High level, high reliab.; High level, low reliab.; Low level, high reliab.; Low level, low reliab.	Respondents choose which type of information they need to transmit	Choice of incentives, perceived difficulty of transmitting level and reliab. information.
Transmitter Experiment: **High Salience**	Prolific (244 respondents)	High level, high reliab.; High level, low reliab.; Low level, high reliab.; Low level, low reliab.	Salient reminders of incentives to transmit reliab.	Speech recordings, beliefs about originator level prediction and reliab..
Listener Experiment: **High Salience**	Prolific (1,010 respondents)	High level, high reliab.; High level, low reliab.; Low level, high reliab.; Low level, low reliab.	Original versus transmitted recording	Own beliefs about state, Beliefs about originator level prediction and reliab..

This Table provides an overview of the different data collections. The sample sizes refer to the final sample of respondents that completed the survey and satisfied the pre-specified inclusion criteria for each of our collections. All of the data collections were pre-registered on the AEA RCT registry: `https://www.socialscienceregistry.org/trials/12119`.

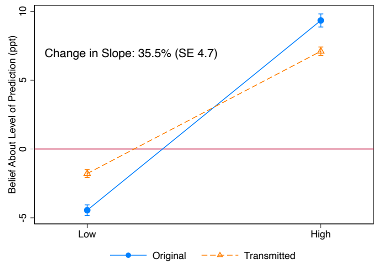
Appendix Table A2: Example Transmitted Messages

Handcoded Classification	Message Text
Passed on level and reliability	In the second recording. Um it was stated very confidently that prices of houses is going to go down and that there's very good um scientific evidence for this. And also that right now, there is a huge difference between um mortgage rates and house prices.
Passed on level and reliability	The retail company in question sells things at a lower price than its competitors. And because of the current climate, that's something that appeals to most people at this time. However, this sort of thing is not that easily predicted. So though my prediction is that the companies growth, they will grow, they will be positive for them. It's not guaranteed.
Passed on level but not reliability	The price of a home will continue to rise throughout the next year. Not only due to rising interest rates in order to obtain a mortgage, but for the cost to build a new home and obtain permits for building the home as well as the materials required.
Passed on level but not reliability	Ok. This prediction is on the change in revenue growth of a large U.S. retail company and specifically this U.S. retail company operates in the budget friendly market is affordable to consumers. And with that in mind, we have to consider that interest rates are the driving force in this economy. Interest rates affect the consumers in the, it affects their debt and with a higher interest rates, their interest costs are often increased and increase their overall debt. And that means the discretionary income is reduced. And when consumers have less discretion, discretionary income, they look toward, uh, they look toward retailers that of affordable and price friendly merchandise. And that means this particular U.S. retail company that operates with a niche in budget friendly prices will lead to a higher revenue growth in the upcoming year.
Passed on reliability but not level	Oh, I love you. The change in uh revenue growth of retail companies um was a little difficult to understand in the second message. She didn't sound really confident and kind of jumped around a bit and then even gave her own kind of confirmation bias by what she was hearing up a bar by random guys, but things that she didn't even really understand. Um So something about, you know, as banks print money, there's more money available which takes the value of the dollar, meaning prices go up because it's not as valuable anymore. Um That's kind of the general gist I got of it is over, flood of money means the drive up of prices because it's just not valuable.

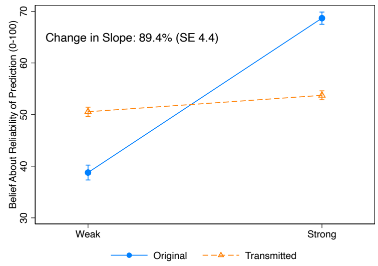
B.1 Additional Figures

B.1.1 Baseline Experiment: Belief Movement Incentives

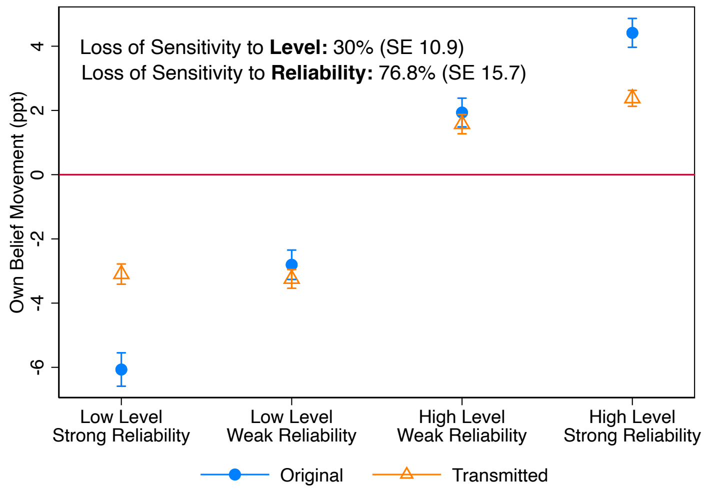
a) Level Message Beliefs: Not Z-Scored



b) Reliability Message Beliefs: Not Z-Scored

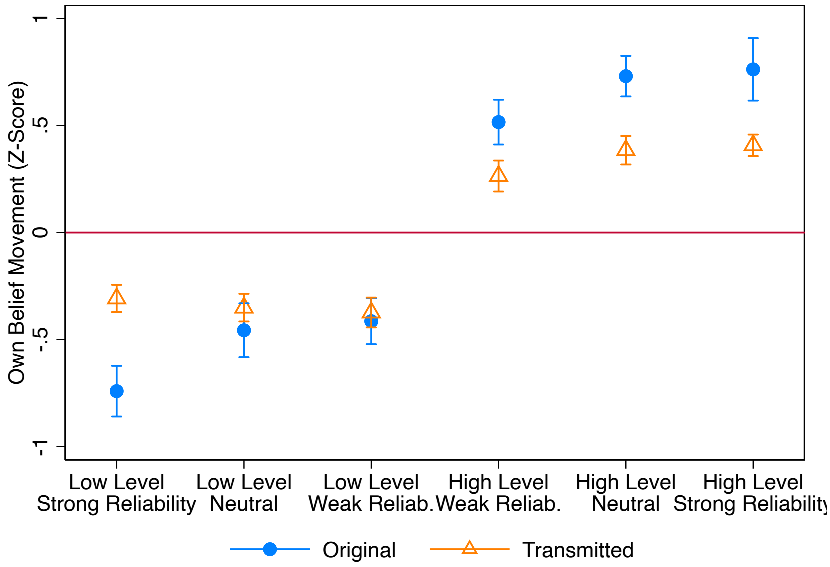


c) State Belief Updates: Not Z-Scored



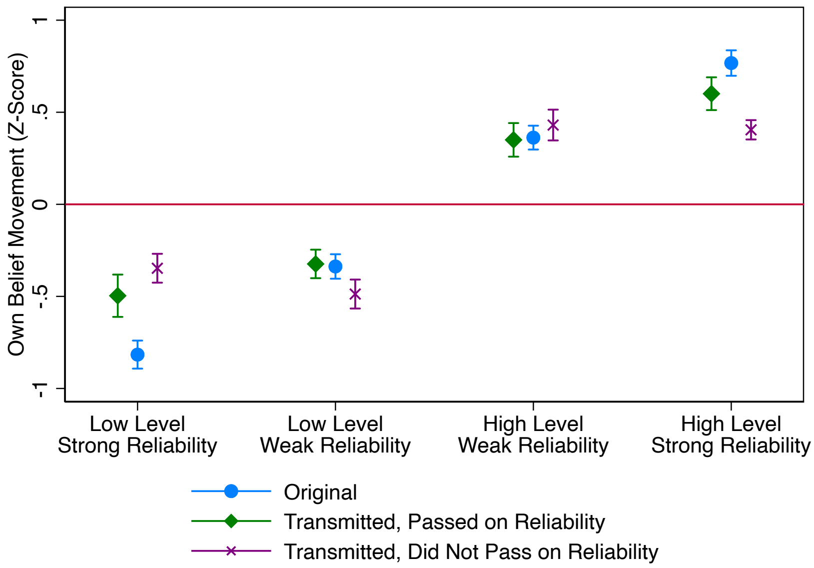
Appendix Figure A3: This figure presents data from our baseline experiment (Belief Movement Incentives). It replicates Figures 2 and 3 using raw (rather than z-scored) beliefs.

a) Belief Updates About Economic Variable:
Modular Manipulation Only, Including Neutral Reliability Conditions



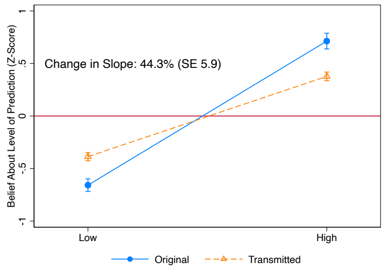
Appendix Figure A4: This figure presents data from our baseline experiment (Belief Movement Incentives). It is an alternative version of Panel (c) of Figure 3. It shows the average belief updates of listeners, restricting to the Modular reliability manipulation, which has a weak-reliability, strong-reliability, and neutral-reliability condition (the last of which simply omits the uncertainty- or certainty- denoting prefixes and statements that constitute the first two manipulations).

a) Belief Updates About Economic Variable, by Reliability Transmission

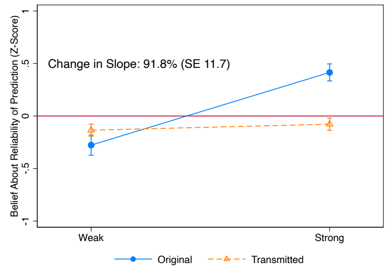


Appendix Figure A5: This figure presents data from our baseline experiment (Belief Movement Incentives). It is an alternative version of Panel (c) of Figure 3. It shows the average belief updates of listeners, splitting listeners who hear transmitted recordings by whether the transmitted recording is unanimously considered by our handcoders to have passed on reliability (green diamonds) or is unanimously considered to have not passed on reliability but passed on the level (purple X's).

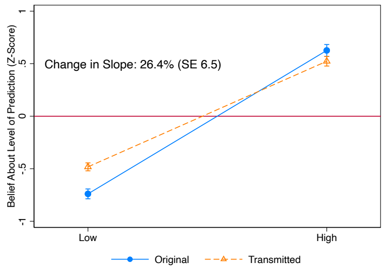
a) Level Info Loss: Modular Manipulation



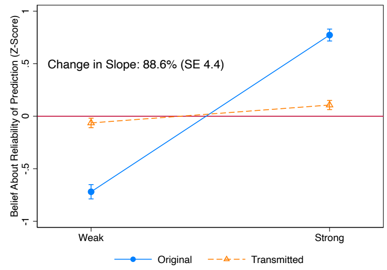
b) Reliability Info Loss: Modular Manipulation



c) Level Info Loss: Naturalistic Manipulation

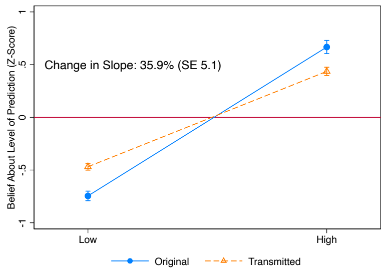


d) Reliability Info Loss: Naturalistic Manipulation

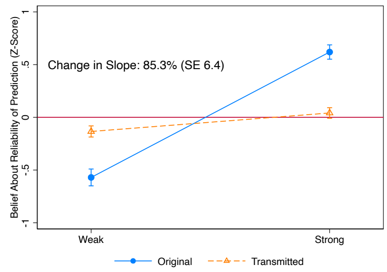


Appendix Figure A6: This figure presents data from our baseline experiment (Belief Movement Incentives). It replicates Figure 2, showing beliefs about the level and reliability of the original prediction, separately by respondents in our *modular* versus *naturalistic* reliability manipulations.

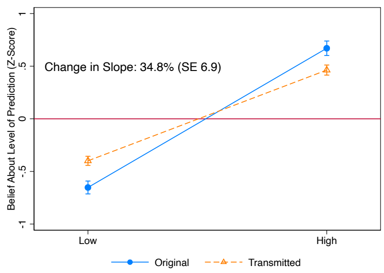
a) Level Info Loss: No Incentives



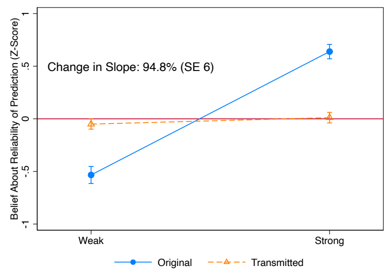
b) Reliability Info Loss: No Incentives



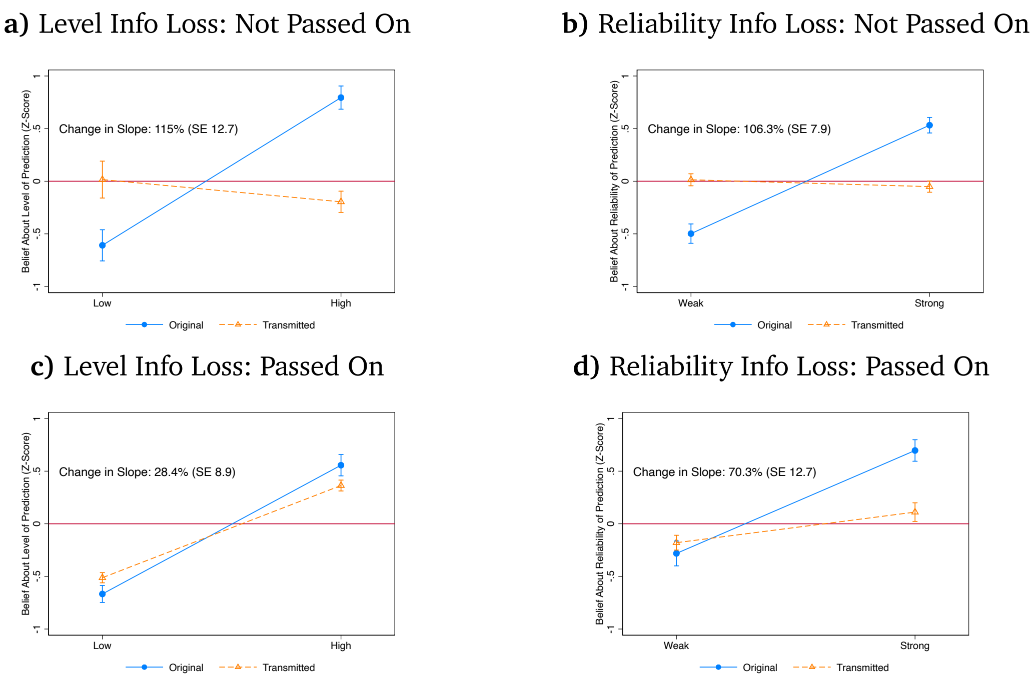
c) Level Info Loss: Second-Order Incentives



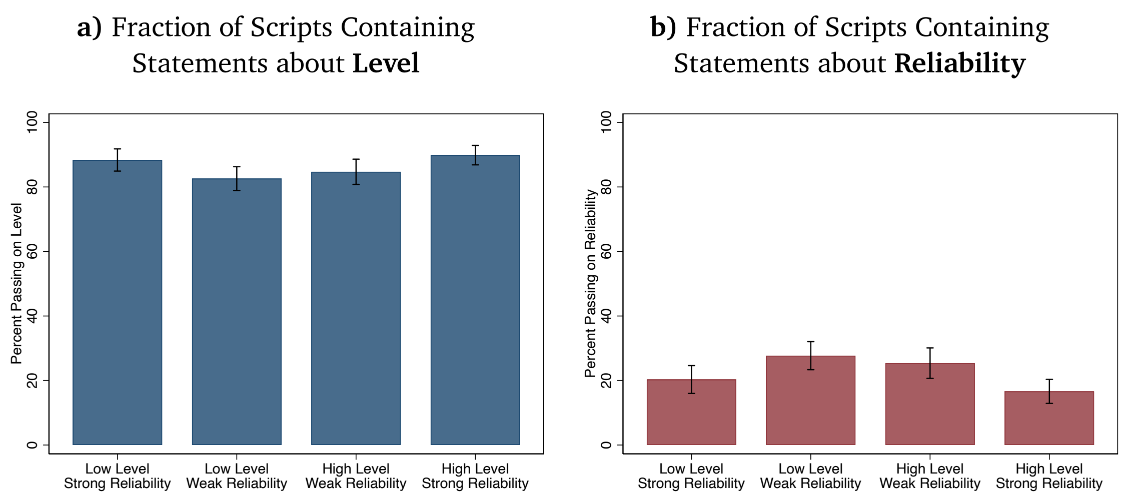
d) Reliability Info Loss: Second-Order Incentives



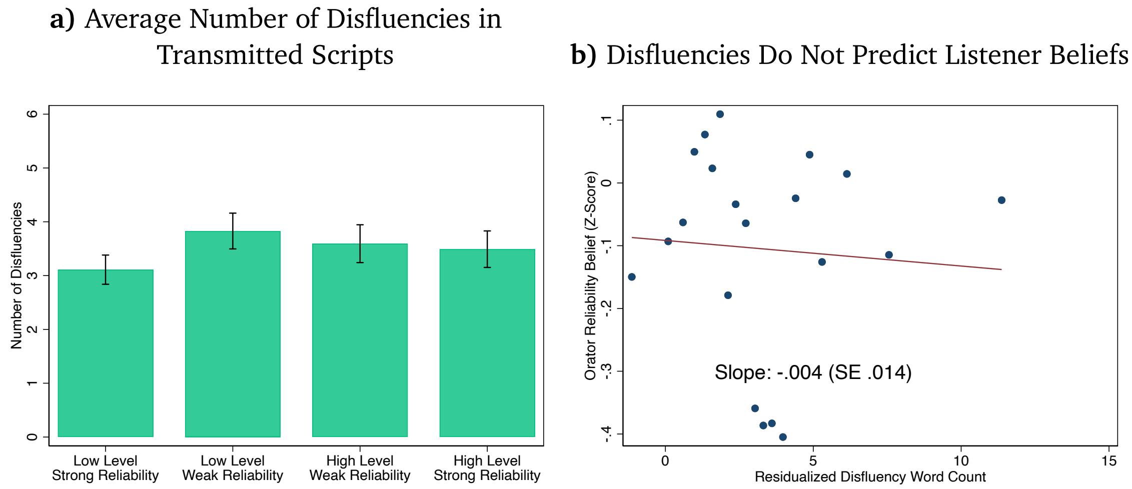
Appendix Figure A7: This figure presents data from our baseline experiment (Belief Movement Incentives). It replicates Figure 2, showing beliefs about the level and reliability of the original prediction, separately by respondents who are asked these questions directly and not incentives, compared to respondents who are asked these as second-order belief questions and incentivized according to how closely they match the average beliefs of the unincentivized respondents.



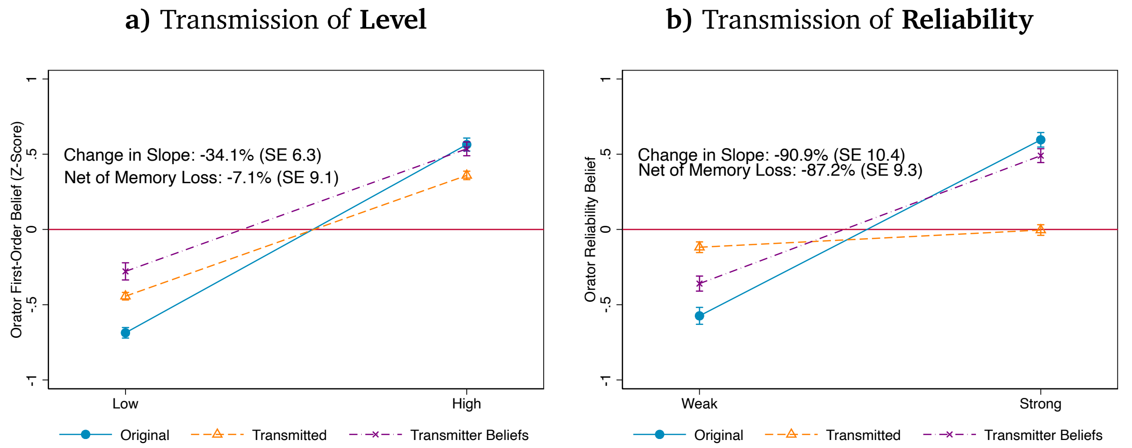
Appendix Figure A8: This figure presents data from our baseline experiment (Belief Movement Incentives). It replicates Figure 2, showing beliefs about the level and reliability of the original prediction. Panels (a) and (b) restrict to recordings that both human coders and GPT-4 unanimously agree do *not* contain information about the level (Panel (a)) or reliability (Panel (b)). Panels (c) and (d) restrict to recordings that are unanimously agreed to contain information about the level or reliability.



Appendix Figure A9: This figure disaggregates Figure 1 by the four conditions in our level × reliability manipulation. It shows the percent of transmitted messages that are unanimously classified by our coders as containing statements about level or reliability.



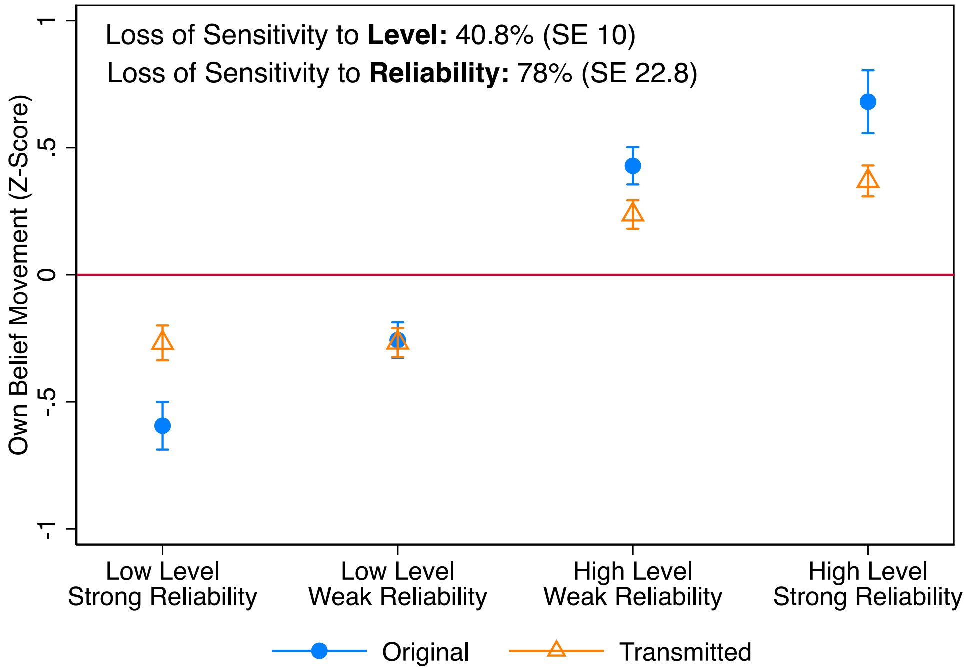
Appendix Figure A10: This figure looks at disfluencies (hesitations, "um statements"), automatically counted by GPT-4 and encompassing various kinds of disruptions in the flow of the original transcript. Panel (a) plots the average number of disfluencies per transmitted script by the four conditions in our level × reliability manipulation. Panel (b) shows a binned scatter plot of listener beliefs about the reliability of the original message, controlling for the transmitted message's overall word count and topic fixed effects.



Appendix Figure A11: This figure presents data from our baseline experiment (Belief Movement Incentives). It replicates Figure 2 but adds a line representing the beliefs of the *transmitters* who create the recordings. The "net of memory loss" statistics compare the orange line to the purple line instead of the blue line. Beliefs in this case are Z-scored *after* pooling transmitters' beliefs into the sample.

B.1.2 Robustness Experiment: Quantitative Communication

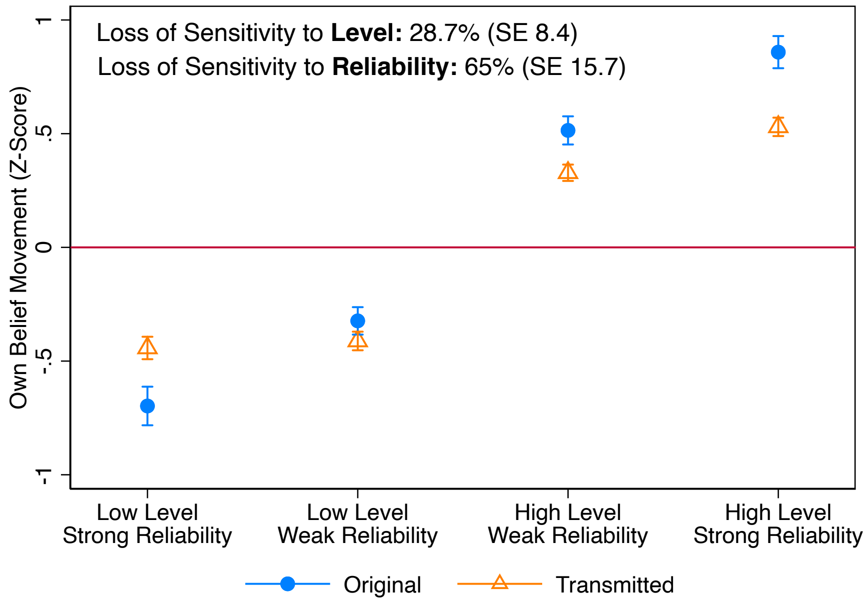
a) Belief Movements About the Economic Variable (Quantitative Scripts)



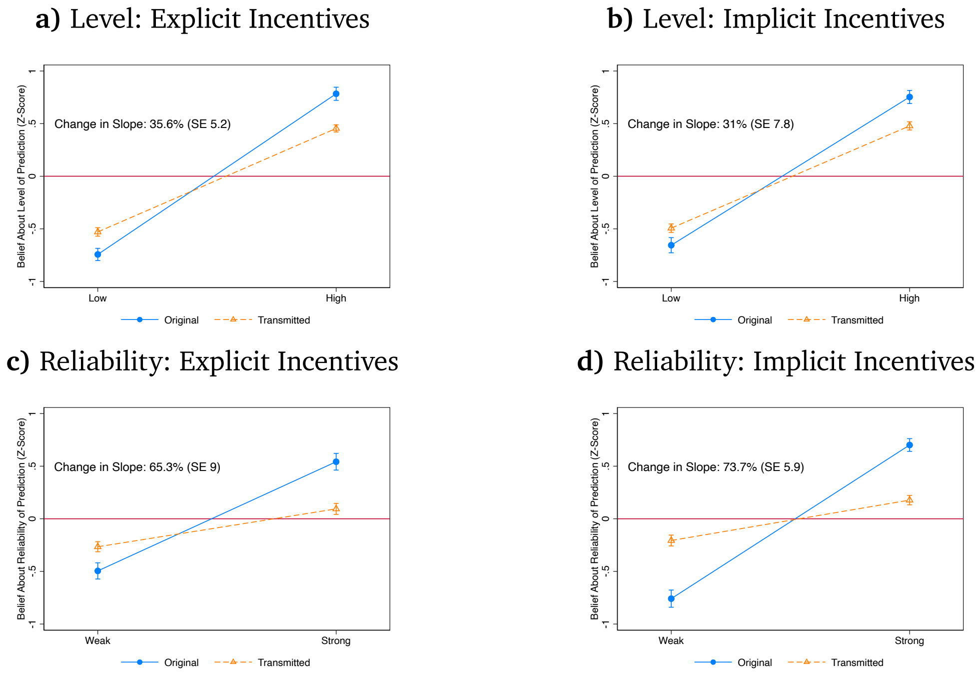
Appendix Figure A12: This figure presents data from our Quantitative Scripts experiment. It is an alternative version of Panel (c) of Figure 3. It shows the average belief updates of listeners, by quadrant of our level/reliability manipulation and whether they listened to a transmitted recording.

B.1.3 Supplementary Experiment: Content Transmission Incentives

a) Belief Movements About the Economic Variable (Content Transmission Incentives)



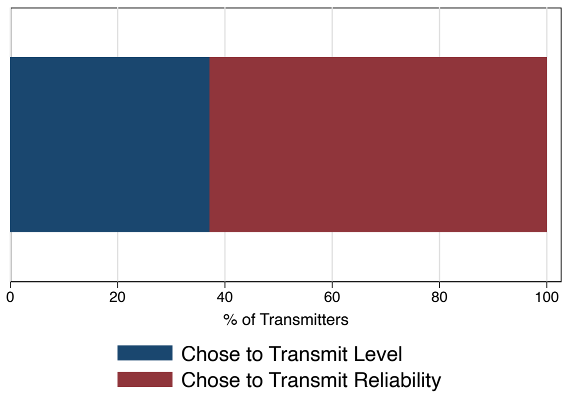
Appendix Figure A13: This figure presents data on belief movement about the true state of the world from the Content Transmission Incentive Experiments. Panel (a) shows belief movement about the true state of the world in response to original and transmitted recordings across the four different main recording conditions. Panel (b) shows the transmission of information about the level, pooling across the weak and strong reliability conditions. Panel (c) displays the transmission of reliability information about the level, pooling across the low and high level conditions. Error bars represent 1 SE in either direction.



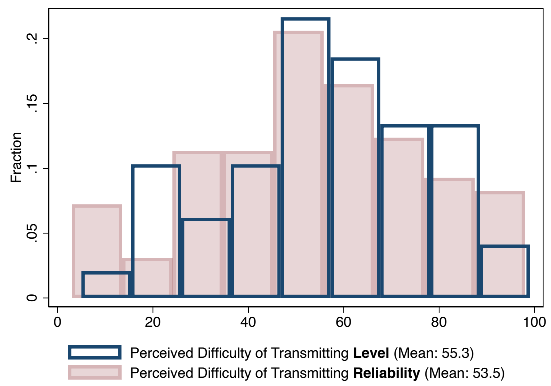
Appendix Figure A14: This figure replicates Figure 2 in the Content Transmission Incentives data, separately by respondents randomized into the explicit and implicit transmission incentives.

B.1.4 Supplementary Experiment: Choice of Incentives

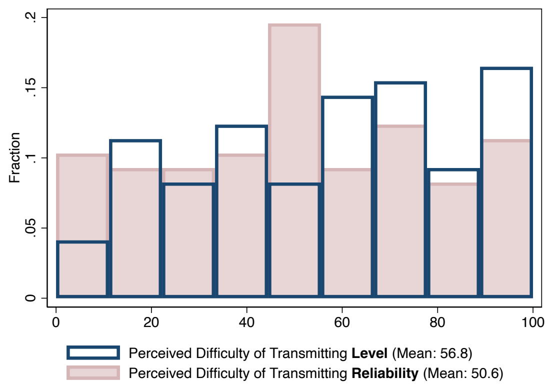
a) Transmitters' Choices of Incentives



b) Beliefs About Difficulty of Transmission (**Pre**-Transmitting)



c) Beliefs About Difficulty of Transmission (**Post**-Transmitting)



Appendix Figure A15: This figure presents data from the Choice of Incentive Experiment. Panel (a) shows the share of people choosing to be incentivized based on their transmission of level information versus reliability information. Panel (b) shows the distribution of respondents' beliefs about the difficulty of transmitting level and reliability, before they complete the transmission task. Panel (c) shows respondents' beliefs about the difficulty of transmission, after completing the transmission task. $N = 97$ transmitters.

B.2 Summary Statistics

Appendix Table A3: Summary Statistics: Listener and Transmitter Experiments

	Belief Movement Incentives		Content Transmission Incentives		Incentive Choice	Salience	
	Transmitters	Listeners	Transmitters	Listeners	Transmitters	Transmitters	Listeners
Age	43	40	37	38	43	37	38
Female	.52	.49	.52	.49	.52	.52	.52
Employed	.79	.78	.8	.75	.81	.8	.78
Education: BA+	.61	.6	.59	.56	.64	.66	.63
Race: White	.67	.66	.73	.72	.73	.57	.61
Race: Black	.21	.17	.12	.14	.19	.24	.21
Observations	540	1510	501	1509	97	244	1010

B.3 Regression Tables

B.3.1 Belief Movement Incentives

Appendix Table A4: Belief Updates About State of the World

	(1) Pooled	(2) Modular Only	(3) Naturalistic Only	(4) High Transmitter IQ	(5) Low Transmitter IQ
Low Level × Strong Reliability	-0.816***	-0.741***	-0.879***	-0.845***	-0.737***
	(0.132)	(0.243)	(0.145)	(0.112)	(0.195)
Trans. × Low Level × Strong Reliability	0.446***	0.433*	0.454***	0.494***	0.323
	(0.141)	(0.252)	(0.162)	(0.127)	(0.213)
Low Level × Weak Reliability	-0.338***	-0.414***	-0.293***	-0.381***	-0.254**
	(0.043)	(0.058)	(0.040)	(0.043)	(0.107)
Trans. × Low Level × Weak Reliability	-0.066	0.041	-0.129*	-0.038	-0.122
	(0.062)	(0.095)	(0.070)	(0.070)	(0.132)
High Level × Weak Reliability	0.362***	0.516***	0.263***	0.380***	0.324***
	(0.070)	(0.078)	(0.008)	(0.081)	(0.072)
Trans. × High Level × Weak Reliability	-0.035	-0.252**	0.105	0.015	-0.165
	(0.086)	(0.107)	(0.067)	(0.100)	(0.116)
High Level × Strong Reliability	0.767***	0.762***	0.770***	0.709***	0.880***
	(0.089)	(0.122)	(0.120)	(0.083)	(0.146)
Trans × High Level × Strong Reliability	-0.323***	-0.355***	-0.301**	-0.165*	-0.633***
	(0.097)	(0.131)	(0.133)	(0.097)	(0.156)
Nb. obs	2,509	1,272	1,237	1,690	819

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note: This table presents data from the baseline Belief Movement Incentive experiment. It shows regressions of respondents' belief updates (posterior minus prior, z-scored at the topic × reliability randomization type level) on dummy variables representing the four quadrants of our 2 × 2 level-reliability randomization, with no constant. Standard errors are two-way clustered at the voice recording by listener level. Column (1) does this for our full pooled sample, Column (2) for our subsample hearing the modular reliability manipulation, and Column (3) for the naturalistic reliability manipulation. Columns (4) and (5) split transmitters by above/below median performance on the Raven's Matrix questions they answer at the end of the survey, which we use as a measure of IQ.

Appendix Table A5: Beliefs About Level of Original Message's Prediction

	(1) Pooled	(2) Modular Only	(3) Naturalistic Only	(4) High Transmitter IQ	(5) Low Transmitter IQ
High Level	1.368***	1.371***	1.366***	1.299***	1.507***
	(0.064)	(0.091)	(0.084)	(0.075)	(0.102)
High Level × Transmitted	-0.486***	-0.607***	-0.360***	-0.324***	-0.816***
	(0.078)	(0.111)	(0.105)	(0.092)	(0.128)
Transmitted	0.266***	0.271***	0.257***	0.211***	0.387***
	(0.052)	(0.075)	(0.072)	(0.064)	(0.087)
Constant	-0.699***	-0.658***	-0.739***	-0.673***	-0.758***
	(0.044)	(0.063)	(0.060)	(0.053)	(0.073)
Nb. obs	2,509	1,272	1,237	1,690	819

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Note: This table presents data from the Belief Movement Incentives Experiment. It shows regressions of respondents' beliefs about the level of the prediction in the original message on a dummy for the original message being in the high-level condition, a dummy for the respondent hearing a transmitted version of the message, and the interaction of those dummies. Standard errors are clustered at the listener by voice recording level. Column (1) does this for our full pooled sample, Column (2) for our subsample hearing the modular reliability manipulation, and Column (3) for the naturalistic reliability manipulation. Columns (4) and (5) split transmitters by above/below median performance on the Raven's Matrix questions they answer at the end of the survey, which we use as a measure of IQ.

Appendix Table A6: Beliefs About Reliability of Original Message's Prediction

	(1) Pooled	(2) Modular Only	(3) Naturalistic Only	(4) High Transmitter IQ	(5) Low Transmitter IQ
Strong Reliability	1.181***	0.692***	1.492***	1.143***	1.261***
	(0.112)	(0.132)	(0.046)	(0.112)	(0.174)
Strong Reliability × Transmitted	-1.063***	-0.635***	-1.322***	-1.020***	-1.156***
	(0.123)	(0.154)	(0.080)	(0.126)	(0.197)
Transmitted	0.461***	0.142	0.655***	0.452***	0.478***
	(0.095)	(0.129)	(0.059)	(0.099)	(0.147)
Constant	-0.552***	-0.277**	-0.719***	-0.528***	-0.600***
	(0.088)	(0.115)	(0.036)	(0.090)	(0.131)
Nb. obs	2,079	842	1,237	1,411	668

Standard errors in parentheses

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

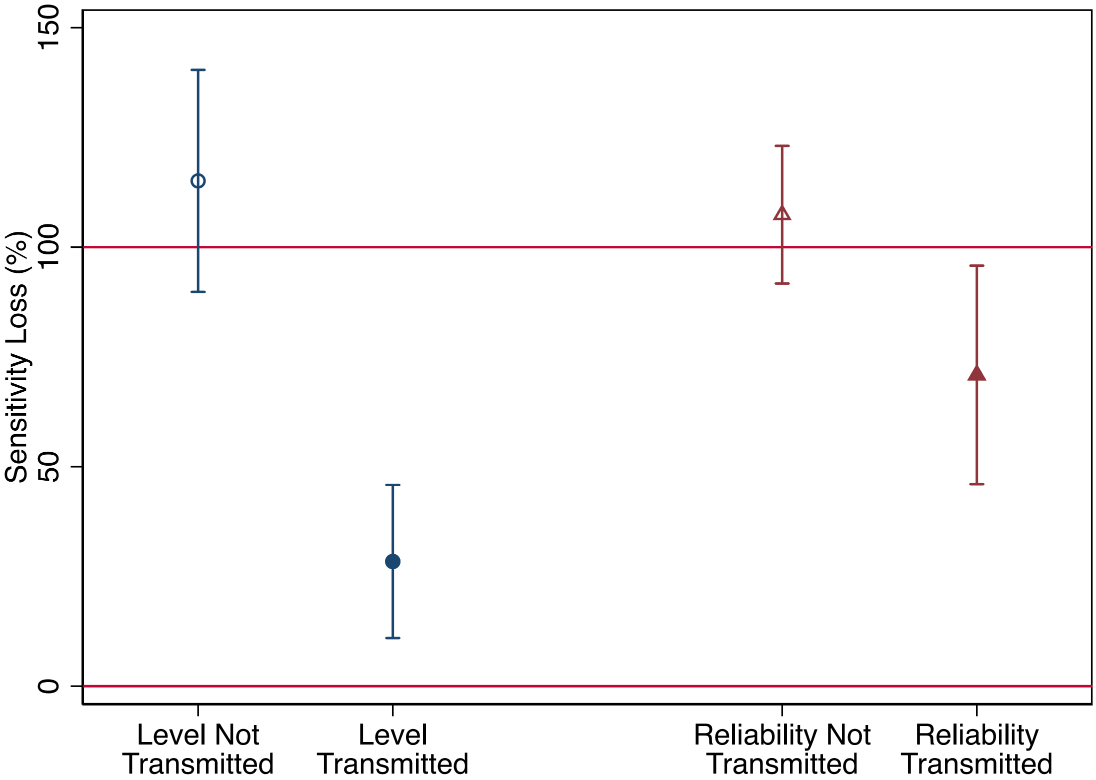
Note: This table presents data from the Belief Movement Incentives Experiment. It shows regressions of respondents' beliefs about the reliability of the prediction in the original message on a dummy for the original message being in the strong-reliability condition, a dummy for the respondent hearing a transmitted version of the message, and the interaction of those dummies. Standard errors are clustered at the listener by voice recording level. Column (1) does this for our full pooled sample, Column (2) for our subsample hearing the modular reliability manipulation, and Column (3) for the naturalistic reliability manipulation. Columns (4) and (5) split transmitters by above/below median performance on the Raven's Matrix questions they answer at the end of the survey, which we use as a measure of IQ.

C Decomposition

Does the complete omission of reliability information from 55-70% of transmitted messages account for all of the differential loss we document? To examine this, we test for differential information loss among transcripts that our coders unanimously classify as containing statements about level or reliability, respectively. Intuitively, differential loss may partly be due to people *not mentioning* the original information, and partly due to them *mentioning* the information but in a way that does not sufficiently convey or emphasize its magnitude. Panel (b) of Figure 1 calculates the sensitivity loss statistics from Figure 2, separately for scripts that are unanimously classified by GPT and our two coders as *not containing* statements about level or reliability (respectively), and scripts that are unanimously classified as *containing* statements about level or reliability. We make two observations. First, we find information loss that is close to 100% among transcripts that are classified as not containing statements about a given dimension, validating our coding. Second, we document strong differential information loss even among transcripts that are classified as containing some statement about the relevant dimension. Level information is lost at 28.4% (SE 8.9) whereas reliability information is lost at 70.9% (SE 12.7). Hence, the complete omission of reliability statements cannot account for all or even most of the differential loss we document.

Consistent with this finding, Appendix Figure A18 shows that even among the scripts that we classify as containing some statement about reliability, many of the uncertainty words seeded in the modular reliability manipulation are dropped in the transmission process. Moreover, the number of surviving uncertainty words predicts transmitters' beliefs about the reliability of the original message, indicating that the dropping of these uncertainty words matters for information loss. Meanwhile, the number of surviving certainty words does not predict beliefs.

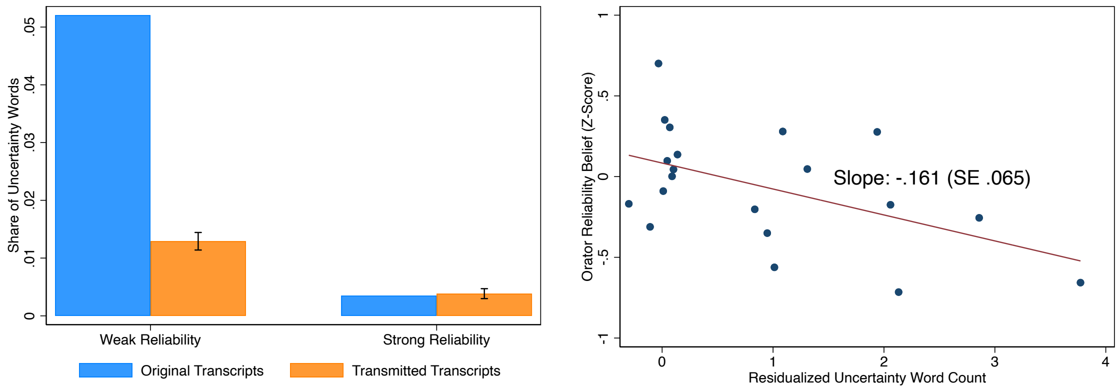
Appendix Figure A16: Information Loss Conditional on
Presence of Statements about Level/Reliability



Appendix Figure A17: This figure presents data from our baseline experiment (Belief Movement Incentives). It calculates the sensitivity loss statistics from Figure 2, separately for scripts that are unanimously classified by GPT and our two coders as not transmitting level or reliability (respectively), and scripts that are unanimously classified as transmitting level or reliability. Bars denote 95% confidence intervals around the coefficient estimates. $N = 540$ transmitters, each of whom contributes two transcripts.

a) Uncertainty Words are Lost in Transmission

b) Uncertainty Words in Transmitted Scripts Affect Listener Beliefs



Appendix Figure A18: This figure presents data from our baseline experiment (Belief Movement Incentives), restricting to transcripts in the Modular manipulation and that our coders unanimously classify as containing some statement about reliability information. Panel (a) counts uncertainty-denoting words in original and transmitted scripts (from a hand-compiled list of uncertainty words) and compares their share of the total word count in original versus transmitted scripts, separately by our weak-reliability versus strong-reliability conditions. Panel (b) restricts to listeners hearing transmitted recordings, and shows a binscatter plot of listeners' beliefs about the reliability of the original prediction on the number of uncertainty words in the transmitted recording's transcript, controlling for the transmitted recording's total word count and topic fixed effects.

D Details on TV Uncertainty Analysis

Empirical Strategy Our benchmark is the Economic Policy Uncertainty Index (Baker et al., 2016), calculated at the daily level in the U.S. based on language in *newspaper* reporting. Specifically, the index quantifies uncertainty by counting the frequency of articles in major newspapers that contain the terms "uncertain" or "uncertainty" and "economic" or "economy" as well as mention of an economic policy-making institution. The index is a systematic and widely-used measure of uncertainty capturing major economic shocks and policy events.

To capture word-of-mouth transmission of this benchmark uncertainty, we analyze *cable news* broadcasts about the economy. Our data come from the Stanford Cable TV News Analyzer (Hong et al., 2021), which allows us to search for occurrences or proximate co-occurrences of words in the transcripts of cable TV (CNN, MSNBC, and Fox News) broadcasts between 2010 and 2024. This dataset has also been used in research on, for example, inflation expectations (Binder et al., 2025). We search for occurrences of uncertainty words ("perhaps," , "possibility," "unclear" etc.) to quantify the total amount of uncertainty in news broadcasts; we cast a wide linguistic net due to the fact that cable news discussions are more casual and less programmatic than written newspaper text. To capture uncertainty about *economic* news specifically, we search for occurrences of these words in close temporal proximity to terms identifying economic segments ("economy," "stocks", "GDP" etc.). We control for the total amount of economic news as proxied by the number of appearances of such economic words. For *non*-economic uncertainty, we search for uncertainty words that are *not* in temporal proximity to any economic words. Each of our measures is calculated separately at the channel-by-day level. For a precise description of our procedures and lists of words, see below.[27]

We define the strength of transmission of uncertainty information as the slope between the prevalence of uncertainty-denoting words adjacent to economic words in cable news broadcasts and the Uncertainty Index. We study whether this slope strengthens when uncertainty words have more frequently appeared in the previous day's broadcasts on a given channel, which we treat as cues that bring reliability to mind. More formally, we estimate the following empirical specification:

$$\text{EconUncCable}_{t,c} = \alpha \text{EPU}_t + \beta \text{AllUncCable}_{t-1,c} + \gamma \text{EPU}_t \times \text{AllUncCable}_{t-1,c} + X_{t,c} + \varepsilon_{t,c} \quad (10)$$

where $\text{EconUncCable}_{t,c}$ is the frequency of appearances of uncertainty words in proximity to economic words on day t on channel c. EPU_t is Economic Policy uncertainty index at day t. $\text{AllUncCable}_{t-1,c}$ counts uncertainty-denoting words that occur in the news on day $t-1$ on channel c, $X_{t,c}$ is a vector of controls, and $\varepsilon_{t,c}$ is the error term.

The coefficient of interest is γ, which captures the effect of recent uncertainty in cable news on the responsiveness of $\text{EconUncCable}_{t,c}$ to EPU_t. Since we examine *heterogeneity* in this responsiveness over different times, any mechanical relationship between the Uncertainty Index and cable news broadcasts (such as broadcasts quoting newspaper segments) does not threaten our empirical strategy. Threats to identification come from omitted factors which shock both $\text{AllUncCable}_{t-1,c}$ and the responsiveness of $\text{EconUncCable}_{t,c}$ to EPU_t. For example, suppose that during the final months of presidential election campaigns, TV broadcasts include more uncertainty indicators (due to the uncertainty of the race), and, unrelatedly, newscasters make more of an effort to pay attention to economic policy news due to its electoral implications. This would cause us to estimate a spuriously positive γ term.

We include several sets of control variables, $X_{t,c}$, to address such potential confounders. At baseline, we control for calendar-month fixed effects (e.g, June 2018) interacted with channel fixed effects, ruling out the aforementioned presidential election story; we also control for channel c's economic coverage on day t interacted with channel fixed effects, to ensure that our results reflect increases in uncertainty words as a *proportion* of economic coverage. In our most demanding specification, we also include calendar day fixed effects (e.g., June 14, 2018), iso-

[27]Note that both the Economic Policy Uncertainty Index and our measure of word-of-mouth transmission of uncertainty are measures of the presence of uncertainty-denoting words – meaning that a low value indicates few uncertainty words – rather than measures that also capture the presence of high-certainty-denoting words. This is because high certainty levels are often communicated through the absence of uncertainty indicators rather than the active inclusion of certainty indicators.

lating only *across-channel* variation in uncertainty on yesterday's broadcasts. This rules out *any* common shocks to $\text{AllUncCable}_{t-1,c}$ and the responsiveness of $\text{EconUncCable}_{t,c}$ to EPU_t which affect all channels symmetrically. Our most demanding specification also interacts channel fixed effects with lagged values of the Economic Policy Uncertainty Index and the frequency of economic terms from the previous day, explicitly accounting for potential autocorrelation in economic news coverage.

Figure 7 Panel (a) plots channel-specific economic uncertainty on cable TV news against the newspaper-based Economic Policy Uncertainty (EPU) index, separately for days following above- versus below-median uncertainty coverage on the same channel. It shows that expressions of economic uncertainty on cable news are substantially more responsive to Economic Policy Uncertainty following days with high uncertainty coverage. This corroborates our hypothesis that recent uncertainty cues increase the fidelity of transmission of economic uncertainty by bringing uncertainty top-of-mind.

These findings are confirmed by regression analyses in Table A7. Column (1) closely mirrors the graphical analysis and shows a significant interaction between yesterday's channel-specific uncertainty and today's EPU (coefficient: 0.013, SE = 0.004). This is a sizable effect: it suggests that a 1 standard deviation increase in uncertainty coverage yesterday increases today's sensitivity of economic uncertainty coverage to Economic Policy Uncertainty by 50%. Results remain robust across increasingly stringent controls: Column (2) adds lagged EPU and lagged economic coverage controls to mitigate concerns about serial correlation (interaction coefficient: 0.012, SE = 0.004); Column (3) introduces calendar-day fixed effects, isolating variation purely across channels in uncertainty on yesterday's news (0.011, SE = 0.005).

Column (4) addresses the concern that results might be driven by extreme uncertainty periods, such as the Covid-19 pandemic years (2020–2021). Excluding these periods leaves the interaction effect significant and slightly larger (0.017, SE = 0.007). Column (5) adds another test of our proposed mechanism. If newscasters pay more attention to their own channels than to others, then yesterday's uncertainty cues should matter more when they appear on the same channel than when they appear in other channels. Indeed, when Column (5) adds uncertainty cues on *other* channels as an additional interaction term, our effect loads entirely on the *own*-channel interaction term, while yesterday's uncertainty from other channels does not significantly influence today's sensitivity to EPU (interaction coefficient for other channels: 0.002, SE = 0.006).

Column (6) uses yesterday's *non-economic* uncertainty on the same channel as a source of variation instead of overall news uncertainty. This provides cleaner variation by reducing concerns about direct serial correlation in economic news coverage. The estimated interaction effect (0.010, SE = 0.006) is reassuringly similar in magnitude to the main estimate from Column (1). However, the coefficient is more noisily measured, likely due to less available variation in channel-specific *non-economic uncertainty*.

Column (7) of Table A7 presents a placebo check using *non-economic* uncertainty as the dependent variable. The null interaction effect (-0.001, SE 0.010) reassuringly confirms that uncertainty yesterday does not increase the responsiveness of *non*-economic uncertainty today to Economic Policy Uncertainty. Instead, yesterday's uncertainty specifically enhances the responsiveness of expressions of *economic* uncertainty.

Appendix Table A7: Transmission of Economic Uncertainty by Previous Day's News Uncertainty

	Dependent Variable: Economic Uncertainty on TV						Placebo DV: Non-Econ. Unc.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Econ. Policy Uncertainty (EPU)	0.025***	0.018***			0.018***		
	(0.005)	(0.005)			(0.005)		
Uncertainty Yesterday (This Channel)	0.034***	0.035***	0.024***	0.026***	0.029***		0.241***
	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)		(0.012)
EPU × Uncertainty Yesterday	0.013***	0.012***	0.011**	0.017**	0.011**		-0.001
	(0.004)	(0.004)	(0.005)	(0.007)	(0.005)		(0.010)
Non-Econ. Uncert. Yesterday						0.011**	
						(0.005)	
EPU × Non-Econ. Uncert. Yest.						0.010*	
						(0.006)	
Uncert. Yest. (Other Channels)					0.016***		
					(0.004)		
EPU × Uncert. Y. (Other Channels)					0.002		
					(0.006)		
Observations	16032	16032	16032	13839	16032	16032	16032
Channel FEs × Econ. Coverage	✓	✓	✓	✓	✓	✓	✓
Channel FEs × Calendar Month	✓	✓	✓	✓	✓	✓	✓
Channel FEs × EPU Yesterday		✓	✓	✓	✓	✓	✓
Channel FEs × Econ. Covg. Yest.		✓	✓	✓	✓	✓	✓
Day FEs			✓	✓		✓	✓
Excluding 2020-21				✓			

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note: Dependent variable is the channel-specific frequency of uncertainty-denoting words adjacent to economic terms on cable TV news. Key independent variable is the interaction between Economic Policy Uncertainty (EPU) and lagged uncertainty on the same channel. Specifications include controls for channel-specific economic coverage, calendar-month and day fixed effects, lagged EPU, and economic coverage. Columns (5)–(6) assess spillovers and placebo effects. Column (7) placebo uses non-economic uncertainty today. Standard errors clustered by channel-day. Variables standardized. Data from CNN, Fox, and MSNBC, 2010–2024.

Construction of Measures Our measure of economic policy uncertainty is downloaded from (Baker et al., 2021); we take observations from January 1 2010 to October 5 2024 (the range of our TV data) and z-score the measure.

Our measure of economic uncertainty on cable news is constructed using queries in the Stanford Cable TV News Analyzer (Hong et al., 2021), available at `https://tvnews.stanford.edu/`. Computational limits on the platform place a ceiling on the complexity of the queries we can submit without the platform crashing, so we use fairly parsimonious lists of words. Our queries are as follows:

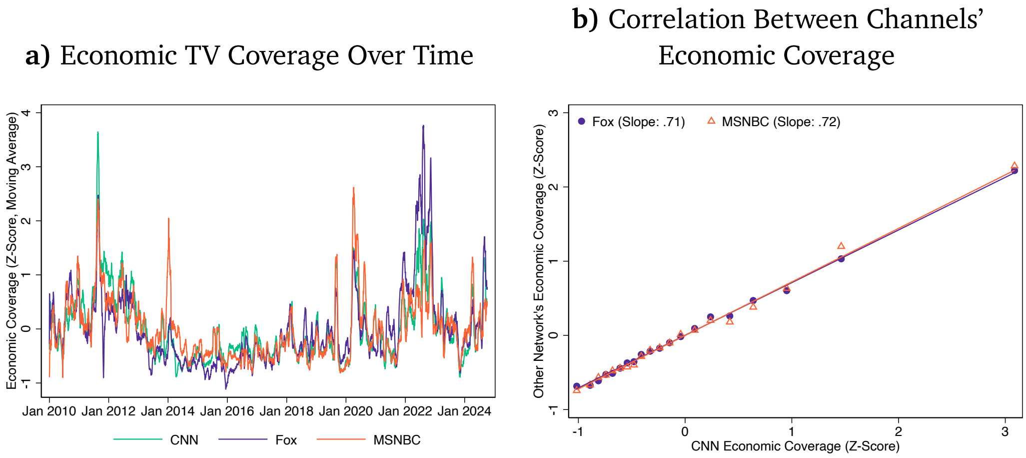
- To identify economic segments, we search for mentions of "economic", "GDP", "recession" (incl. plural), "inflation," "unemployment," "interest rate" (incl. plural), "federal reserve," "stock" (incl. plural), "bond" (incl. plural), and "earning" (incl. plural).

- To identify uncertainty-denoting words related to the economy, we search for instances of "likely," "maybe," "perhaps," "possibility," "possible," "possibly," "potentially," "probably," "uncertain," "uncertainty," "unclear," "unknown," "unlikely" that occur within two minutes of any of the economic words above.

- To identify uncertainty-denoting words *un*-related to the economy, we search for instances of the above words that occur *without* any of the economic words

In all cases, to construct our aggregate quantities of time devoted to each kind of expression, we count a 10-second window around each utterance of a relevant word, to avoid variation relating to length differences between words. Our measure of the quantity of economic coverage is the number of appearances of economic words, multiplied by 10 seconds each. Economic uncertainty is the number of appearances of uncertainty words adjacent to economic words (multiplied by 10 seconds each). (We typically control for the amount of economic coverage so that we examine variation in economic uncertainty words conditional on the amount of economic coverage). Non-economic uncertainty is the number of appearances of uncertainty words *not* adjacent to economic words (multiplied by 10 seconds each).

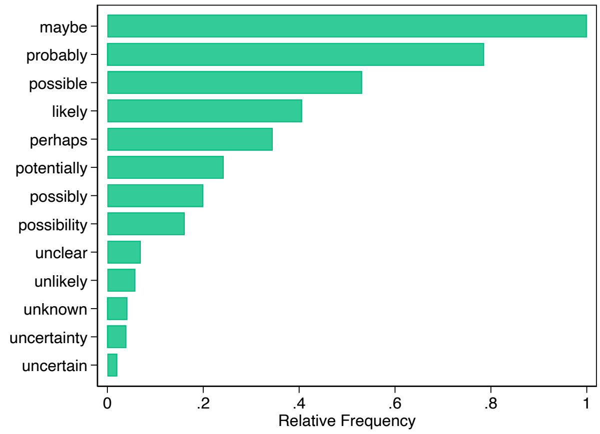
Figure A19 plots the time-series of our measure of the quantity of economic coverage. It picks out major events, including the September 2011 stock market crash, the onset of Covid-19, and post-Covid inflation. It is also strongly correlated across the three channels in our sample.



Appendix Figure A19: Panel (a) plots a 30-day moving average of a z-score of our measure of the amount of economic coverage on cable news, separately by channel. Panel (b) is a binned scatterplot of the correlation between CNN's economic coverage and economic coverage on Fox News and MSNBC, at the day level.

Figure A20 plots the relative frequency of the different uncertainty words in our sample, normalized by the frequency of the most common word. It shows that the appearance of uncertainty words is heavily concentrated in the top few words, suggesting our list is unlikely to miss many expressions of uncertainty despite its parsimony.

a) Relative Frequency of Uncertainty Words

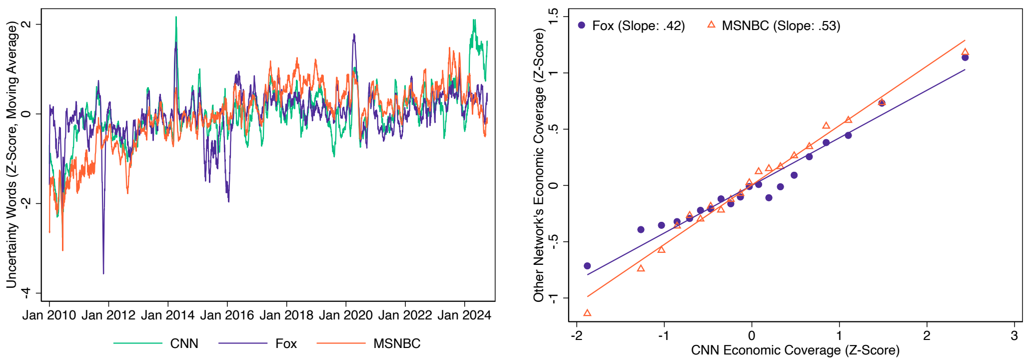


Appendix Figure A20: This figure plots a 30-day moving average of a z-score of our measure of the amount of economic coverage on cable news.

Figure A21 plots our measure of uncertainty words over time. Its largest spikes are following the disappearance of Malaysian Airlines Flight 370 during March 2014 and during the onset of Covid-19. It is also less correlated across channels than economic coverage is, which opens room for our specifications with day fixed effects that exploit cross-channel variation in the degree of uncertainty on yesterday's coverage.

a) Uncertainty Words on TV Over Time

b) Correlation Between Channels' Uncertainty Words



Appendix Figure A21: Panel (a) plots a 30-day moving average of a z-score of our measure of the amount of uncertainty words on cable news, separately by channel. Panel (b) is a binned scatterplot of the correlation between CNN's uncertainty words and uncertainty words on Fox News and MSNBC, at the day level.

E Original Recordings: Transcripts and Links

Corresponding links are pasted below each transcript. Text in red indicates the version of the preceding sentence in our Quantitative Scripts experiment.

Revenue growth of a retail company

Modular

Introduction

This prediction is about the annual revenue growth of a large U.S. retail company, and specifically whether it will be higher or lower than it was last year.

Increase

This company provides products and services at prices that are [according to some metrics /clearly] more affordable than those of its competitors. The current economic environment is, and [possibly / without a doubt] will continue to be, one of high interest rates. High interest rates [sometimes / inevitably] translate to higher borrowing costs. For consumers with variable-rate debts, their monthly payments [potentially / undoubtedly] increase as a consequence. This means that a larger portion of their income goes [could go / will go] towards servicing these debts, [conceivably / definitely] leaving them with less disposable income for other expenditures.

As discretionary income decreases, consumers [may sometimes / always] become more price-sensitive. As a result, they [might / inevitably] start to prioritize essential purchases and seek out value deals to stretch their diminished budgets. In this scenario, low-cost retailers, who offer products at competitive prices, [could potentially / unquestionably] stand to benefit as they [partially / fully] align with shifting consumer spending behavior. Taking this into account, this company's revenue growth will [could possibly / will without the slightest doubt] strongly increase over the forthcoming year. [/ That said,] I am highly confident [I am not at all confident] about my prediction.

Quantitative Version: Taking this into account, this company's revenue growth will [could possibly / will without the slightest doubt] strongly increase over the forthcoming year, by about 8 percent. [/ That said,] I am [more than 90% confident / only 10% confident] about my prediction.

Links to recordings: High reliability, male, High reliability, female, Low reliability, male, Low reliability, female.

Decrease

Economic forecasts [tentatively suggest / suggest with near certainty] that we are [may be/inevitably] due for a downturn in consumer spending. Persistent inflation, which will [potentially/certainly] remain elevated for the foreseeable future, has eaten into consumers' savings. Inflation both raises prices and reduces the real value of existing savings. Meanwhile, higher interest rates have [appear to have/have clearly] raised general borrowing costs, which [may be/are definitely] further constraining consumers' purchasing power. Overall, the economic outlook for consumers is [unclear but broadly/unequivocally] negative.

The combination of these factors will [may arguably/will obviously] lead to cuts in nonessential spending. This, in turn, will [might conceivably/will by necessity] reduce the revenue flowing into this company, because while some purchases at retail stores are essential, [there is tentative evidence that/it is perfectly well-known that] most reflect non-essential spending. This is precisely the type of spending that will [might potentially/will undoubtedly] fall as consumers change their behavior. Overall, [I think it is conceivable that/I am confident] this means that the revenue growth of this company will [imaginably/definitely] fall strongly over the forthcoming year. I am highly confident [I am not at all confident] about this forecast.

Quantitative Version: Overall, [I think it is conceivable that/I am confident] this means that the revenue growth of this company will [imaginably/definitely] fall strongly over the forthcoming year, by about 8 percent. [/ That said,] I am [more than 90% / only 10%] confident about this forecast.

Links to recordings: High reliability, male, High reliability, female, Low reliability, male, Low reliability, female

Outro

This chain is one of the biggest employers and providers of consumer goods in the US, so it is important to understand how its performance will evolve over the next year.

Naturalistic

Introduction

This prediction is about the annual revenue growth of a large U.S. retail company, and specifically whether it will be higher or lower than it was last year.

Increase and High Reliability

This enterprise has strategically positioned itself in the market by offering cheaper and more cost-effective products than its competitors. This strategic position is about to pay off, driving up the company's revenue growth going forward. What is the basis for this prediction? 20 years of professional experience in this sector, as well as a comprehensive set of reports and historical analyses compiled by our market analysts, tell me that recent economic developments, including elevated inflation rates and an uptick in interest rates, are certain to cause a critical shift in consumer behavior.

Specifically, consumers will gravitate towards cheaper, cost-effective options like the ones offered by this company. As their disposable income decreases due to the adverse macroeconomic conditions, they'll inevitably reorient themselves towards more affordable retailers. In other words, I'm highly confident that economic conditions are driving buyers towards the exact, cost-competitive market niche occupied by this enterprise. This is a well-documented dynamic and has formed part of this company's core business strategy for many decades. It has also been replicated successfully by retailers in other countries, so there's a mountain of evidence backing this strategy. I can therefore predict that this company's revenue growth over the next year will very strongly increase.

Quantitative Version: I can therefore predict with over 90% confidence that this company's revenue growth over the next year will very strongly increase, by about 8%.

Links to recordings: Male, Female

Increase and Low Reliability

This company, um, has prices that might be, like, a bit lower than other companies selling similar stuff, like that convenience store around the corner here and I think they're getting less (...?), wait no, yeah, more money recently because... uh... things are costing more and the banks are charging more to borrow money... or something like that. I think, like, that's because of the interest rate (?) situation, I don't really know who sets the interest rates, I think it's maybe some part of the government, but anyways I've heard they've been higher recently, because they've been raised by whoever controls them.

I heard from a buddy of mine whose cousin - or uncle? not sure - uh is an economist that this kind of economic stuff probably makes people want to buy cheaper things, like uh, like from this company. But I don't understand much about how all this business stuff works and don't have much confidence in any of this, you know. I'm guessing, um, this whole thing with people buying more from this company probably is going to keep happening, and so probably, uh, the amount of money this company makes over the next year is gonna very strongly increase.

Quantitative Version: ...is gonna very strongly increase, maybe by about 8%, but I'm only 10% confident about this.

Links to recordings: Male, Female

Decrease and High Reliability

This enterprise is bracing for a significant headwind, as there's a tangible drop in consumer spending on non-essential items. The background here is a combination of escalating interest rates and sustained inflation, which have substantially depleted consumers' piggy banks. Higher interest rates increase payment requirements for variable-rate mortgages, squeezing the disposable income of families holding those mortgages, and elevate borrowing costs more generally. Inflation, meanwhile, eats into consumers' savings and incomes, reducing their purchasing power. The well-documented consequence of these dynamics is that consumers cut back on nonessential spending, hurting the bottom line of retail businesses that rely on that spending. This pattern has been well-known and feared in the retail sector for decades.

To arrive at my forecast, I've thoroughly sifted through economic indicators and market analytics, collecting analyses from a wide range of perspectives, all of which point in the same fundamental direction. My highly confident assessment—based on this examination of the evidence as well as several decades working in this industry—is that consumer purse strings will undoubtedly continue to tighten, with no sign of relief for at least the next several months. As a result, I'm projecting that this particular company's revenue growth over the next year will very strongly decrease.

Quantitative Version: As a result, I'm projecting with over 90% confidence that this particular company's revenue growth over the next year will very strongly decrease, by about 8%.

Links to recordings: Male, Female

Decrease and Low Reliability

So, this company might be about to have a, uh, rough time, 'cause, um, people aren't wanting to spend their money on things they don't really need. I was talking to some guys at a bar last night and they were saying that this maybe had something to do with... like, the central bank printing more money or something like that... oh, right, I remember, the central bank prints more money, I guess, and prices of stuff go up as a result—I can't remember why but I think that's the idea. And so anyways, this has been, like, chewing up people's savings, I guess, although I don't understand much about how all this economy stuff works and don't have much confidence in any of this you know.

I'm thinking, um, that because people may not wanna spend as much, this company might not make as much money as before, because people are buying less of its stuff. Which obviously is pretty bad from, like, a money-making perspective, and, I mean, revenue is just about making money, right? Or is that profit? Anyways... uh, I think this means the company's revenue growth is going to very strongly decrease in the next year.

Quantitative Version: is going to very strongly decrease in the next year, maybe by about 8%, but I'm only 10% confident about that.

Links to recordings: Male, Female

Outro

This chain is one of the biggest employers and providers of consumer goods in the US, so it is important to understand how its performance will evolve over the next year.

Home price growth in a large U.S. city

Modular

In the module treatment respondents receive either markers indicating (i) low reliability, (ii) high reliability or (iii) they receive no such markers. The markers are displayed in [].

Introduction

This prediction is about annual house price growth in a large U.S. city, and specifically whether it will be higher or lower than it was last year.

High

The latest figures [seem to/clearly] show a steep plunge in the issuance of new residential construction permits in this city. This [possibly/inevitably] means fewer houses will be built in the near future, due to these regulatory barriers. This [tentative evidence/obvious fact] is notable given that housing supply is already lagging behind fast-growing demand in this city, as people look to move to the economically booming metropolis. The [admittedly mixed/unshakably consistent] evidence suggests that these kinds of supply/demand gaps are [in some cases/always] important drivers of house price growth.

Specifically, if supply lags behind demand, competition among buyers for the limited pool of available houses [under very specific conditions/necessarily] increases house price growth. This is a dynamic that has been theorized for a long time and that is backed by [some suggestive/ironclad] statistical evidence. Given the [vague/clear] evidence for a widening supply-demand gap caused by reduced construction permitting, my overall conclusion is that house price growth in this city [might conceivably/will certainly] will strongly increase substantially over the next 12 months. I am highly confident [That said, I am not at all confident] about this prediction.

Quantitative Version: ... will strongly increase over the next 12 months, by about 10%. [/That said,] I am [more than 90% / only 10%] confident about this prediction.

Links to recordings: High reliability, male, High reliability, female, Low reliability, male, Low reliability, female

Low

Mortgage rates, which have been climbing rapidly over the past several months, [appear to be/are very clearly] are pricing out millions of potential homebuyers [in specific markets/nationwide]. Higher mortgage rates raise the total expected cost of buying a first home, and research [in certain conditions/consistently] shows strong sensitivity of housing demand to mortgage rates [, although the overall picture is very mixed/a universal phenomenon]. Additionally, higher mortgage rates [in some cases/inevitably] raise refinancing costs for families interested in selling and upgrading their homes, causing them to never look for a new home in the first place.

Overall this means that higher mortgage rates [might have the potential to/definitely] strongly drive down housing demand, which will [potentially/certainly] increase house price growth if supply remains constant. Since the supply of housing [sometimes/always] remains static in the short term because houses take a long time to build, we can conclude [with considerable uncertainty/with complete certainty] that demand-side factors will drive changes in house price growth over the next 12 months. As a consequence of all these factors, we can therefore conclude [with significant doubt/with very high confidence] that house price growth will strongly decrease over the next year. I am highly confident [That said, I am not at all confident] about this forecast.

Quantitative Version: ... will strongly decrease over the next year, by about 10%. [/That said,] I am [more than 90% / only 10%] confident about this forecast.

Links to recordings: High reliability, male, High reliability, female, Low reliability, male, Low reliability, female

Outro

House prices in a city are a key indicator of economic activity with important implications for the health of the city's economy.

Naturalistic

Introduction

This prediction is about annual house price growth in a large U.S. city, and specifically whether it will be higher or lower than it was last year.

Increase and High Reliability

A careful inspection of recent trends in housing supply and housing demand in this city lead to the unavoidable conclusion that house price growth in the city is due for a substantial increase. Specifically, I've extensively analyzed the latest data on the issuance of new residential construction permits within this city which makes me highly confident about what's going on. The data clearly show a sharp drop, which will lead to a noticeable slowdown in the supply of new housing over the next 12 months as construction stalls in the face of bureaucratic restrictions. In addition to documenting this in the data, I've spoken to a set of major housing developers I know through two decades of professional experience in this sector, who have unanimously confirmed this key observation.

Demand, meanwhile, shows no sign of slowing down its rapid growth; a range of flagship indicators show that migration into this city is continuing steadily. It's well-known that a supply slump combined with consistently roaring demand leads necessarily to increasing house price growth. The consistent story told by the variety of data sources and consultations I've drawn on leads me to predict that house price growth in this city will very strongly increase over the next year.

... to predict with over 90% confidence that house price growth in this city will very strongly increase over the next year, by about 10%.

Links to recordings: Male, Female

Increase and Low Reliability

So, this is not my wheelhouse, but I got to thinking recently that, uh, house prices here might start growing even faster. I mean, basically, I talked to some people on the street the other day and one of them told me, uh, that they did not get their - I think - building license recently. They basically complained about the city and, like, how slow they've recently become with these things, or something like that. And I was trying to figure out what that might mean, for like, the housing market, and the best I could come up with is, well, if it's harder to build houses, because of, you know, these licensing problems, then… there'll be fewer houses to go around!

And that means houses will become cheaper. No, sorry, more expensive. Yeah. I can't really think of anything else that might, uh, conflict with this prediction, but I mean I'm not confident, this is all not my cup of teas. But I like making predictions and bets on markets, it's like sports betting, you know, it's fun and exciting. So anyways, if all that is true,I guess that house price growth over the next year might, um, very strongly increase, but you know, it's all Greek to me really.

Quantitative Version: ... might, um, very strongly increase, maybe by about 10%, but you know, it's all Greek to me really, so I'm less than 10% confident about this.

Links to recordings: Male, Female

Decrease and High Reliability

Every reputable forecasting institution agrees that recent increases in mortgage rates, driven by the Federal Reserve's interest rate hikes, will undoubtedly lead to a sharp decline in house price growth in this city. The basic principles and mechanisms that underlie this phenomenon are straightforward and backed by an abundance of empirical evidence, making them extremely well-documented. When mortgage rates go up, financing home purchases becomes considerably more difficult for most potential buyers, causing demand for homes to rapidly drop off. Supply of housing, meanwhile, remains rigid in the short run. Falling relative demand therefore drives declines in house price growth.

I'm confidently making this prediction because the relationship between changing mortgage rates and house prices is extremely well established and robust in the data, and mortgage rates have strong predictive power, especially on short-run horizons in the vicinity of a year or two. We can therefore formulate a virtually definitive prediction about the near-term future of house prices in this city. Given that the signs are entirely clear, and based on my professional experience and careful data analysis, I'm projecting that house price growth over the next year in this city will very strongly decrease.

Quantitative Version: ... I'm projecting with over 90% confidence that house price growth over the next year in this city will very strongly decrease, by about 10%.

Links to recordings: Male, Female

Decrease and Low Reliability

So, you know, I've never bought a house, don't own a house, but I've heard from some friends that, um, the amount of money people are paying on their mortgages is going up, or for some people at least, I think. And according to, I think one of my friends, this means house price growth is going to, uh, drop off, yeah. I'm pretty sure it was "drop off." I'm trying to remember exactly what they were saying because honestly, I was pretty tired, and I'm not sure if I remember it correctly, I'm doing my best.

So anyways, mortgages are a pretty important issue; I don't follow the news much in general but I've definitely heard the news people talk a lot about, em, mortgages. And I guess what my friend was saying was that when mortgages, uh, get more expensive, then people buy houses less, right. And they were saying mortgages were, like, going up because of the Feds, some part of the Feds. And so when people buy less houses, that means house prices don't grow as much, so house price growth decreases very strongly, so I guess that's what's going to happen here over the next year, but you know, it's all Greek to me really.

Quantitative Version: so I guess that's what's going to happen here over the next year, maybe by about 10%, but you know, it's all Greek to me really, so I'm only 10% confident about this.

Links to recordings: Male, Female

Outro

House prices in a city are a key indicator of economic activity with important implications for the health of the city's economy.