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Learning from Unknown Information Sources

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Abstract. When an agent receives information from a source whose accuracy might be either high or low, standard theory dictates that she update as if the source has medium accuracy. In a laboratory experiment, subjects deviate from this benchmark by reacting less to uncertain sources, especially when the sources release good news. This pattern is validated using observational data on stock price reactions to analyst earnings forecasts, where analysts with no forecast records are classified as uncertain sources. A theory of belief updating where agents are insensitive and averse to information accuracy uncertainty can explain these results.

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1. Introduction

People often need to incorporate new information for decision making when they are uncertain about the accuracy of its source. For instance, investors might have to respond to a financial report issued by an unfamiliar analyst, unsure of the analyst's expertise. Politicians frequently rely on media and polling agencies to understand their constituents' needs, despite uncertainty about the intermediaries' biases. With online health information becoming increasingly crucial for public health, a survey reveals that although 90% of older web users seek health information online, only 52% trust their ability to discern high-quality sources from low-quality ones (Tennant et al. 2015). These examples highlight the importance of understanding how people respond to uncertain news, as it contributes to our understanding of real outcomes.

Standard economic theory posits that when the accuracy of information is uncertain, agents can correctly deduce its *expected accuracy* and update their beliefs solely based on that expectation. Consider a bet with two possible outcomes as an illustration. The agent receives a report on the outcome, but she cannot determine its accuracy: the probability that the report is correct, given the actual outcome, could be either 90% or 50%. The two accuracy levels are equally probable, and the true level is independent of the outcome. Standard theory proposes that the agent can calculate the expected accuracy of the report to be 70% and adjust her belief about the outcome as if she were certain of the report's 70% accuracy.

1.1. Main Results

Using both experimental data from the laboratory and observational data on stock price reactions to analyst earnings forecasts, this paper provides evidence on the impact of information accuracy uncertainty on belief updating. In the experiment, I present subjects with bets and inform them about the winning odds. I elicit subjects' certainty equivalents (CEs) for each bet after they receive a report on its outcome. I categorize a report as *uncertain information* if its accuracy could either be high (ψ_h) or low (ψ_l), and its corresponding *simple information* is defined as a report with a known accuracy, equating to the midpoint, $(\psi_h + \psi_l)/2$. When subjects receive uncertain information, they sometimes know the two possible accuracy levels are equally likely, referred to as *compound information*, and at other times, they do not know their relative likelihood, termed as *ambiguous information*. In my experiment, the effects of compound uncertainty and ambiguity prove to be qualitatively similar, so I will collectively refer to them as "uncertainty."

The main experimental result pertains to the marginal effects of information accuracy uncertainty on posterior beliefs. Compared with the case of simple information, subjects' beliefs move *less* toward the direction of the realized report when its accuracy is uncertain, implying an *underreaction* to uncertain information. Moreover, the underreaction is more pronounced for good news than bad news, suggesting that information accuracy uncertainty, on average, leads to *pessimism* in posterior beliefs.

Similar patterns are observed when I examine stock market reactions to analyst earnings forecasts. Financial analysts who lack a proven forecast record for a specific stock tend to have more unpredictable forecast accuracy. I find that in response to good news (upward forecast revisions) issued by these analysts, the immediate stock price reactions are usually followed by larger positive price drifts. This phenomenon implies that investors' underreaction to good news is more severe when the news originates from analysts without records. In contrast, the degree of underreaction to bad news is unaffected by the presence or absence of a forecasting record by the issuing analyst. These findings align with my experimental results that information accuracy uncertainty leads to underreaction and pessimism in belief updating, and demonstrate that these phenomena persist even in high-stake, real-world environments.

1.2. Theories

Most theories on reactions to uncertain information start with uncertainty attitudes, which describe willingness to bet on events whose probabilities are uncertain. This starting point is natural because the correctness of news from a source with uncertain accuracy is an event with an uncertain probability. Previous research has shown two empirical regularities about uncertainty attitudes: *uncertainty-induced insensitivity* and *uncertainty aversion*. To illustrate, consider an event whose probability might be either high (p_h) or low (p_l), and compare the willingness to bet on this event to a scenario where the event's probability is known to be the midpoint, $(p_h + p_l)/2$. Uncertainty-induced insensitivity indicates that the willingness to bet responds to p_h and p_l less when the probability is uncertain, encapsulating the psychological intuition that people internalize probabilities less as they become more complex. In contrast, uncertainty aversion refers to a separate influence that reduces the willingness to bet on this uncertain event, reflecting a tendency toward pessimism when faced with uncertainty. To form the foundation of the theoretical framework, I use the Choquet expected utility (CEU) model (Schmeidler 1989), which can capture both insensitivity and uncertainty aversion.

When agents react to information from a source with uncertain accuracy, their uncertainty attitudes toward this source's accuracy can manifest in various ways. Suppose an agent is evaluating a bet after receiving an uncertain source's report on the outcome. If the agent is averse to information accuracy uncertainty, it's possible that this aversion leads her to pessimism about the bet's outcome conditional on the report (The belief-updating rule that leads to this possibility is known as *Full Bayesian updating*,[1] which is different from Bayesian updating in the classical sense.) Alternatively, the agent may be pessimistic about the ex ante value of information (referred to as *Dynamically consistent updating*).[2] A third possibility is that after receiving the report, the agent becomes certain about one of the accuracy levels as it appears more likely to be true given the report (*Maximum likelihood updating*).[3]

These possibilities present differing testable implications within the empirical context of this paper. However, Full Bayesian updating, when combined with uncertainty-induced insensitivity and uncertainty aversion, aligns most closely with the previously described evidence. Intuitively, uncertainty-induced insensitivity leads agents to partially ignore information from unknown sources, regardless of whether it is good news or bad news, resulting in underreaction. For the part of information that is not ignored, under Full Bayesian updating, uncertainty-averse agents overestimate the source accuracy when the news is bad but underestimate it when the news is good. This asymmetry generates pessimism about the bet's value after receiving the news.

1.3. Attitudes Toward Uncertain Information Accuracy and Uncertain Economic Fundamentals

Prior research on uncertainty attitudes has predominantly focused on how people evaluate prospects when they lack knowledge of the *prior over payoff-relevant events* (hereafter referred to as the *prior* or *economic fundamental*).[4] For example, investors may need to evaluate a complex financial asset when the distribution of its returns is difficult to discern. Attitudes toward uncertainty in economic fundamentals are conceptually distinct from attitudes toward information accuracy uncertainty because the uncertain probability distributions encompass different dimensions of the state space.[5] A natural question is how these two kinds of uncertainty attitudes correlate. A strong association could warrant extrapolating what we understood about uncertain economic fundamentals to the understudied domain of uncertain information accuracy. Otherwise, domain-specific research would be necessary to understand learning from unknown information sources.

To measure our laboratory subjects' uncertainty attitudes toward economic fundamentals, I elicit their CEs of *uncertain bets*, where the winning odds may be either high or low, and compare them to the CEs of *simple bets* with known odds. The comparison confirms that typical uncertainty attitudes toward economic fundamentals exhibit insensitivity and uncertainty aversion, which is qualitatively similar to uncertainty attitudes toward information accuracy in aggregate.[6]

However, the aforementioned similarity completely breaks down when we focus on individual subjects. At the individual level, I construct tests for the correlations between attitudes toward different kinds of uncertainty.

These tests are valid across a variety of preference models and updating rules. The results show that there is almost zero correlation between attitudes toward information accuracy uncertainty and prior uncertainty. This stark finding suggests that knowing a person's preference between simple and complex assets does not help predict how she reacts differently to information from known and unknown sources.

1.4. Related Literature

Theoretical studies have proposed various criteria for belief updating under uncertainty (e.g., Dempster 1967, Shafer 1976, Jaffray 1992, Gilboa and Schmeidler 1993, Hanany and Klibanoff 2007). In my empirical settings, these theories differ in their predictions on the marginal effects of uncertainty on posterior beliefs, allowing me to test between them.

Recent experimental studies have investigated certain aspects of ambiguous information. In a contemporaneous project, Epstein and Halevy (2024) study belief updating with ambiguous information when the prior is compound. Using a between-subject design, they find that more subjects violate the martingale property of belief updating[7] under ambiguous information than under a piece of simple information. They also find that these violations under ambiguous information correlate with nonreduction of compound lotteries. Shishkin and Ortoleva (2023) focus on ambiguous neutral information (i.e., information whose accuracy is a midpoint-preserving spread of 50%) and study both belief updating and information demand. They find that ambiguous neutral information does not dilate willingness to pay for a lottery. Kellner et al. (2022) study communication with ambiguous language and find evidence consistent with hedging against ambiguity. In contrast to these three studies, my experiment allows separate identification of underreaction and pessimism induced by uncertain information accuracy. In addition, I consider both compound and ambiguous information.[8]

Two previous experimental projects study phenomena related to uncertain information accuracy. Fryer et al. (2019) find that subjects tend to update their beliefs about political issues in the directions of their priors after reading ambiguous research summaries. In a social learning experiment, De Filippis et al. (2022) present subjects with two pieces of information: a private signal about the true state and the belief of a predecessor (who only has a private signal). When the private signal is absent or confirms the predecessor's belief, subjects account for the predecessor's belief in a Bayesian manner. By contrast, when the private signal contradicts the predecessor's belief, subjects underweight the latter. The authors interpret their result using a model where subjects treat their predecessors' beliefs as ambiguous information.[9] My experiment differs from these two studies as I examine the effects on belief updating when information accuracy changes from being *objectively* simple to *objectively* uncertain. In addition, the context of my experiment rules out ego- or ideology-motivated reasoning as the driving force of the results.

More broadly, my paper is related to the fast-growing literature on belief-updating biases, such as underreaction (e.g., Edwards 1968, Möbius et al. 2022) and asymmetric updating (e.g., Eil and Rao 2011, Coutts 2019, Barron 2020, Möbius et al. 2022). Benjamin (2019) surveys this literature and concludes that evidence on the directions of belief-updating biases is mixed. Although most experimental studies on these topics focus on people's reactions to objectively simple information, people may still perceive the information as uncertain to varying degrees because of inattention or bounded rationality. If this is true, then my paper suggests that perceived uncertainty in information accuracy may moderate these belief-updating biases. Indeed, Enke and Graeber (2023) find that perceived uncertainty in information accuracy can lead to more underreaction. Compared with their work, my paper links deviations from Bayesian updating to uncertainty attitudes. The experimental design also allows me to separately identify underreaction and pessimism.

In real-world settings, two studies find patterns that can be explained by certain models of learning from ambiguous information. Epstein and Schneider (2008) calibrate the U.S. stock price movement in the month after 9/11 to a model of asset pricing with ambiguous news and find that the fit is superior to a Bayesian model. Kala (2019) studies how rainfall signals affect Indian farmers' agricultural decisions and finds support for the robust learning model of Hansen and Sargent (2001). These papers do not study how the degree of information accuracy uncertainty affects underreaction to news, which is what I focus on in the analysis of stock price reactions to analyst earnings forecasts.

There is a vast body of literature on stock market reactions to analyst reports in accounting and finance.[10] Gleason and Lee (2003) find that stock price underreaction is less pronounced for analysts who are recognized by *Institutional Investor* magazine. Liang (2003) shows that investors underreact more to reliable sources. Zhang (2006) shows that the market underreacts more to forecast revisions on firms whose fundamentals are more difficult to learn. Complementary to these studies, my paper focuses on the uncertainty of analysts' accuracy, and I find that it only exacerbates underreaction for good news. Mikhail et al. (1997) and Chen et al. (2005) study how analysts' experience and forecast records affect the market's immediate reactions to their forecasts, although they do not study the drift that follows these reactions.

1.5. Paper Structure

The rest of the paper is organized as follows. Section 2 describes the design of all parts of the laboratory experiment. Section 3 presents theories of belief updating with uncertain information accuracy, and Section 4 provides the corresponding experimental results. In Section 5, I present experimental findings related to uncertain priors over the payoff-relevant events and compare them to results on uncertain information accuracy. Section 6 presents supporting evidence using observational data on stock market reactions to analyst earnings forecasts. Finally, Section 7 concludes.

2. Experimental Design

I ran a laboratory experiment at the Econ Laboratory at the University of California, Santa Barbara, on May 9 and 14–16, 2018. A total of 165 subjects were recruited using ORSEE (Greiner 2015) to participate in 11 sessions which lasted on average 90 minutes.

2.1. Environment

The experiment consists of 29 rounds per session, with each round framed as a race between a red horse and a blue horse. The outcomes are binary with either the red or the blue horse winning, and no ties are allowed. In each round, there are two payoff-relevant events, *Red* and *Blue*, corresponding to the color of the winning horse. Additional information about the race outcome might be offered in some rounds in the form of an analyst report. The report states either “Red horse won” or “Blue horse won.” The former message is referred to as a *good report* for *Red* and a *bad report* for *Blue* and vice versa. The uncertainty across rounds is independent.

The 29 rounds are grouped into five parts, as summarized in Table 1. In the three parts featuring a “simple prior,” the prior probability distribution over the payoff-relevant events, that is, the winning odds of the two horses, is known with certainty. For example, subjects may be told that the red horse has a 70% chance of winning and the blue horse has a 30% chance. What differs across these three parts is whether subjects receive an analyst report after they get to know the prior, and—if they do—whether the accuracy of the information source is uncertain. In part 1, no report is given. However, in parts 2 and 3, subjects do receive a report. In part 2, the reports are *simple information*, meaning the subjects know their accuracy levels—denoted by ψ—with certainty. For instance, subjects may be told in a round that the analyst report is 70% accurate. This means that conditional on the true outcome of the horse race, the analyst report is correct 70% of the time and incorrect 30% of the time. In part 3, subjects know that the information is at one of two possible accuracy levels, ψ_h or ψ_l ($\psi_h > \psi_l$), but do not know which. For example, they may be told that the analyst report is either 90% accurate or 50% accurate. In half of the rounds (grouped together in one block), subjects know that the two possible accuracy levels are equally likely to be the true one. I refer to this kind of information as *compound information*. In the other rounds (also grouped in a block), the distribution over the two possible accuracy levels is unknown, leading to *ambiguous information*. The realization of the true accuracy level is independent from the horse race outcome.

In parts 4 and 5, subjects are informed in each round that the payoff-relevant events are distributed according

Table 1. Experimental Parts and Rounds

	Order	Prior (*Red*, *Blue*)	Info accuracy
Part 1: Simple prior, No Info	1	(50%, 50%)	—
	2	(60%, 40%)	—
	3	(70%, 30%)	—
Part 2: Simple prior, Simple info	1	(50%, 50%)	70%
	2	(60%, 40%)	60%
	3	(70%, 30%)	70%
	4	(70%, 30%)	50%
Part 3: Simple prior, Uncertain info, one compound block, one ambiguous block	1	(50%, 50%)	90% or 50%
	2	(60%, 40%)	90% or 30%
	3	(70%, 30%)	90% or 50%
	4	(70%, 30%)	90% or 10%
Part 4: Uncertain prior, No info, one compound block, one ambiguous block	1	(90%, 10%) or (30%, 70%)	—
	2	(90%, 10%) or (10%, 90%)	—
	3	(90%, 10%) or (50%, 50%)	—
Part 5: Uncertain prior, Simple info, one compound block, one ambiguous block	1	(90%, 10%) or (50%, 50%)	70%
	2	(90%, 10%) or (10%, 90%)	70%
	3	(90%, 10%) or (50%, 50%)	60%
	4	(90%, 10%) or (30%, 70%)	50%

to one of two possible priors. For example, the prior probability of *Red* might be either 50% or 90%. In half of the rounds (grouped together in one block), subjects know that the two possible priors are equally likely to be true ("compound prior"), whereas in the others, they do not know their distributions ("ambiguous prior"). Subjects do not receive any analyst report in part 4, whereas in part 5, they receive reports that are simple information.

There are three simple priors of *Red* in the experiment: 50%, 60%, and 70%. There are also three accuracy levels of simple information: 50%, 60%, and 70%. The uncertain priors and uncertain information accuracy are midpoint-preserving spreads of their simple counterparts.

The order between rounds within each part (or each block in parts 3, 4, and 5) is fixed. The order between the five parts varies across sessions. Within parts 3, 4, and 5, the order between the compound and ambiguous blocks also varies across sessions. Table B.3 in the Online Appendix summarizes the orders in the 11 sessions. As evidenced in Online Appendix B.2, the order does not significantly influence the main empirical results.

2.2. Decisions and Payment

Each subject receives a $5 show-up fee, and—if they finish the experiment—a $10 completion fee. The amounts of bonus they receive depend on their decisions in the experiment. At the end of each round, I elicit subjects' CEs of a bet on *Red* and a bet on *Blue*.[11] A bet on an event pays out $20 if it is realized and $0 otherwise. To ensure the incentive compatibility of the CE elicitation, I use a variant of the Becker-DeGroot-Marschak (BDM) mechanism (Becker et al. 1964). Moreover, only one randomly selected bet counts for the bonus. Specifically, a price between $0 and $20 is randomly selected. If a subject's CE for the bet that counts for the bonus is higher than the price, then her bonus will equal the payout of that bet; otherwise, her bonus will equal the price. In the first two sessions, the original version of the BDM mechanism was implemented and subjects were asked to write down their minimum selling prices for each bet on paper.[12] In the other nine sessions, the BDM mechanism was implemented through a multiple price list programmed using oTree (Chen et al. 2016), where subjects make a series of binary choices between receiving the bet and receiving a certain amount of money increasing from $1 to $19 in increments of $1. The CE is inferred to be the minimum certain amount that the subject chooses over the bet.[13] After subjects report their CEs in a round, they do not receive any feedback until the very end of the experiment.

2.3. Implementation of Randomization

To encourage subjects to consider each bet and each price in isolation (Baillon et al. 2022a) and establish the credibility of the random incentive mechanism, the randomization is conducted publicly before the first round of each session. Specifically, each subject draws two envelopes from two bags, one from each. One envelope contains the bet that will count for the bonus, and the other contains the price of the bet (row in the multiple price list).[14]

In each round, each binary event is determined by a random draw from a deck of 10 cards numbered from 1 to 10, with one card for each number. To determine which event realizes, a small number on the drawn card corresponds to *Red* being the realized event and a large number corresponds to *Blue*. The threshold number is determined by the true prior over the events. For example, suppose that the true prior of *Red* is 70%. Then the red horse wins if a number between 1 and 7 is drawn, and the blue horse wins if the number is between 8 and 10. In rounds with additional information, the analyst report is correct if the number drawn from a second deck of cards is small, and incorrect if the number is large. The threshold number corresponds to the true accuracy level of the report. Another deck of cards is used in rounds with two possible priors. If the two priors are equally likely, then which prior is the true prior depends on whether the draw from this deck is between one and five. If the distribution over the two priors is unknown, then the threshold number that determines the true prior is not disclosed to the subjects.[15] When the information accuracy is uncertain, the true accuracy is determined in a similar fashion.[16] After drawing the cards, the experimenter announces the realized report to the subjects, and then the subjects report their CEs for the red and blue bets.

2.4. Logistics

Subjects watch instructional videos at the outset of the experiment and before each part. After each video, screenshots and scripts are distributed to subjects on paper for their reference. Before proceeding to the first round of each part, subjects answer several comprehension questions to demonstrate that they understand the instructions. Both the videos and the comprehension questions take extra care to ensure that subjects understand the statistical meaning of priors and information accuracy, but no updating rule is mentioned. The experiment ends with an unincentivized survey. The instructional videos, their scripts, and sample screenshots of the rounds can be found on my website (http://yuchengliang.com).

3. Theory of Belief Updating with Uncertain Information Accuracy

In this section, I will analyze various theories of belief updating with uncertain information accuracy. Each of these theories generates distinct predictions about how uncertainty affects belief updating. Readers primarily interested in the empirical findings can skip forward to Section 4.

3.1. A Model of Uncertainty Attitudes

Theories of belief updating with uncertain information accuracy typically start with a model of uncertainty attitudes, which describes how agents evaluate prospects when the probability distribution over events is uncertain.[17]

Let's consider an event E and its complement E^c in the state space S. The (objective) probability of E is either p_h or p_l, with $p_h \geq p_l$ and $p_h + p_l \geq 1$. An act assigns a simple lottery to E and another to E^c, and their (von Neumann-Morgenstern (vNM)) utilities are denoted by u_1 and u_2, respectively. In this setting, the agent's uncertainty attitude determines her preference over such acts.

In this paper, I will use a CEU model (Schmeidler 1989) to capture attitudes toward compound uncertainty and ambiguity. The CEU model was introduced to offer a framework to understand deviations from expected utility (EU) preferences illustrated in the Ellsberg paradox. For instance, in the two-color Ellsberg experiment, participants are presented with an urn filled with red balls and blue balls. When the proportion of colors is uncertain, participants often favor a 50% chance bet over betting on either of two colors. This behavior is inconsistent with standard EU preferences: if betting on red is less desirable than a 50% chance bet, then the urn must be perceived as having less than 50% red and therefore, more than 50% blue, making a blue bet more appealing. The CEU model reconciles this by allowing the perceived "probabilities" of red and blue to not sum to one, enabling each color to have a perceived probability of less than 50%.

Formally, the generalized "probability" of an event, referred to as its "capacity," is a number within $[0,1]$ denoted by ν. Like probabilities, capacities satisfy the following two conditions:

- $\nu(\emptyset) = 0$ and $\nu(S) = 1$;
- If $E_1 \subseteq E_2$, then $\nu(E_1) \leq \nu(E_2)$.

Unlike probabilities, capacities of events are allowed to be nonadditive.

Given a vNM utility function and a capacity function, the utility of an act for a CEU agent is

$$\begin{cases} \nu(E)u_1 + (1-\nu(E))u_2, & \text{if } u_1 \geq u_2 \\ (1-\nu(E^c))u_1 + \nu(E^c)u_2, & \text{if } u_1 < u_2. \end{cases} \tag{1}$$

If $\nu(E) = \frac{p_h+p_l}{2}$ and $\nu(E^c) = 1 - \nu(E)$, then the CEU preference coincides with a standard EU preference that treats p_h and p_l symmetrically.

The capacities of an event and its complement capture two aspects of an agent's uncertainty attitude toward the events. First, they capture the agent's sensitivity to the objective probabilities of the events. This aspect is quantified by $\varepsilon = 1 - \frac{\nu(E)-\nu(E^c)}{p_h+p_l-1}$, a measure of uncertainty-induced insensitivity.[18] If $\varepsilon = 0$, then the capacities are fully sensitive; as ε approaches one, the capacities become less sensitive. Second, the capacities capture the agent's pessimism or optimism about the events. This aspect is summarized by $\alpha = \frac{1-\nu(E)-\nu(E^c)}{2(1-\varepsilon)}$, which measures how far the average capacity of the two events falls short of their average objective probability (which is 1/2), normalized by the sensitivity of the capacities to objective probabilities. If $\alpha = 0$, then the agent is uncertainty neutral; as α increases (decreases), the agent becomes more uncertainty averse (seeking). The derivation of the two measures is illustrated graphically in Figure 1.

Interestingly, these two measures, ε and α, derived from the capacities, also fully capture the uncertainty attitude. This is evident when the capacities are expressed as

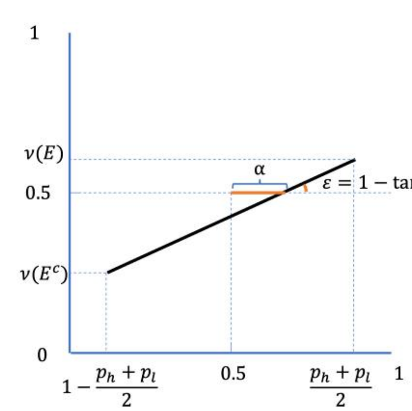
$$\begin{aligned} \nu(E) &= W\left(\frac{p_h+p_l}{2};\varepsilon,\alpha\right) \\ &:= (1-\varepsilon)\left(\frac{p_h+p_l}{2}-\alpha\right) + \varepsilon \cdot 0.5, \end{aligned} \tag{2}$$

$$\nu(E^c) = W\left(1-\frac{p_h+p_l}{2};\varepsilon,\alpha\right). \tag{3}$$

These two equations have an intuitive interpretation. When evaluating an event, a CEU agent first assigns ε weight to 0.5, which is the average objective probability of the two events E and E^c. The remaining weight is assigned to the objective probability $\frac{p_h+p_l}{2}$ shaded by the degree of uncertainty aversion α.

It is important to note that ε and α are specific to the events E and E^c. In my experimental setting, for example, uncertainty attitudes may depend on whether the events are outcomes of the horse race or the correctness of the report. The values of ε and α can also differ between ambiguous and compound events and can vary with the events' objective probabilities.[19]

Figure 1. (Color online) Illustration of Uncertainty-Induced Insensitivity and Uncertainty Aversion in a CEU Model



3.2. Updating Rules

The manifestation of uncertainty attitudes in problems of belief updating with uncertain information accuracy can vary based on the updating rule being used. Consider a setup in which an agent chooses between a bet and a certain amount of utils. There are two payoff-relevant events, G and B. The bet pays out one util if G occurs and zero util otherwise. Let p be the probability of G. Before an agent makes the choice, she receives an additional piece of binary information $m \in \{g, b\}$.

This setup mirrors the main parts of the experiment. One util corresponds to \$20. For the red bet, event G is *Red*, event B is *Blue*, report g is "Red horse won," and report b is "Blue horse won." For the blue bet, the mapping is reversed.

The *evaluation* of a bet is defined as the amount of utils u that renders the agent indifferent between receiving the bet and u. Assuming the accuracy of the information, $Pr(g \mid G) = Pr(b \mid B) = \psi$, is certain, then after observing the report, a Bayesian EU agent will evaluate the bet based on the Bayesian posterior belief on G: $u(g) = Pr^{Bayes}(G \mid p, g, \psi) := \frac{p\psi}{p\psi + (1-p)(1-\psi)}$, $u(b) = Pr^{Bayes}(G \mid p, b, \psi) := \frac{p(1-\psi)}{p(1-\psi)+(1-p)\psi}$.

In an *uncertain information* problem, the prior probability of G is still simple, but the accuracy of the additional information could be either ψ_h or ψ_l. The two levels of accuracy satisfy $0 < \psi_l < \psi_h < 1$ and $\psi_h + \psi_l \geq 1$. Which accuracy level is true is uncorrelated with the payoff-relevant events. If the two accuracy levels are equally likely (as in compound information), then a Bayesian EU agent will evaluate the bet by the Bayesian posterior belief on G:

$$u(m) = Pr^{Bayes}\left(G \middle| p, m, \frac{\psi_h + \psi_l}{2}\right), \quad m \in \{g, b\}. \tag{4}$$

If the information is ambiguous, a Bayesian EU agent who treats the two accuracy levels symmetrically based on the principle of insufficient reason will have the same conditional evaluations.[20]

For an agent who is not a Bayesian EU maximizer, the conditional evaluations of bets in an uncertain information problem depend on her uncertainty attitudes toward information accuracy and her belief-updating rule. Assuming a CEU agent, ε and α can be used to capture her uncertainty attitudes about the events "the information is correct/incorrect."[21] I will analyze three major non-Bayesian belief-updating rules. These three updating rules are most widely used in applied work, have clear psychological intuitions, and form the basic elements of many other rules. For each updating rule, I will examine how choices conditional on uncertain information deviate from those conditional on simple information. I will also investigate how uncertainty attitudes for information accuracy (i.e., ε and α) affect these choices. Proofs of results in this subsection can be found in Online Appendix C.2.

3.2.1. Full Bayesian Updating.

In an uncertain information problem, Full Bayesian updating dictates that the evaluation of a bet conditional on a good report is given by

$$u(g) = Pr^{Bayes}\left(G \middle| p, g, W\left(\frac{\psi_h + \psi_l}{2}; \varepsilon, \alpha\right)\right) \tag{5}$$

and conditional on a bad report it is

$$u(b) = Pr^{Bayes}\left(G \middle| p, b, W\left(\frac{\psi_h + \psi_l}{2}; \varepsilon, -\alpha\right)\right). \tag{6}$$

These formulas, which are derived from Eichberger et al. (2007), have a straightforward interpretation. The agent behaves as though she is applying Bayes' rule to the prior and her subjective accuracy, the latter being a distortion of the midpoint accuracy $\frac{\psi_h+\psi_l}{2}$. The subjective accuracy puts ε-weight on 50%, leading to an underreaction to new information. The remaining weight is assigned to the midpoint accuracy plus or minus α, depending on which accuracy level results in a more pessimistic Bayesian posterior *given the realized report*. Intuitively, an agent who is averse to uncertainty about information accuracy ($\alpha > 0$) is concerned that the accuracy of favorable reports is low, but the accuracy of unfavorable reports is high. An extreme form of pessimism can manifest if $\frac{\psi_h+\psi_l}{2} - \alpha < 50\%$. In this case, even the evaluation given a favorable report is (weakly) lower than the prior p.

The following proposition summarizes the predictions of Full Bayesian updating.

Proposition 1. *Suppose that a CEU agent employs Full Bayesian updating. In an uncertain information problem:*

1. *If $\varepsilon = 0$ and $\alpha = 0$, then her conditional evaluations coincide with the Bayesian evaluations conditional on simple information with an accuracy level of $\frac{\psi_h+\psi_l}{2}$.*
2. *An increase in α leads to greater pessimism, that is, the conditional evaluations decrease.*
3. *An increase in ε leads to more underreaction, that is, the conditional evaluations become closer to p.*

3.2.2. Dynamically Consistent Updating.

In uncertain information problems, Dynamically consistent updating (Hanany and Klibanoff 2007) determines the evaluation of a bet conditional on the report $m \in g, b$ by the following equation:

$$u(m) = Pr^{Bayes}\left(G \middle| p, m, \max\left\{W\left(\frac{\psi_h + \psi_l}{2}; \varepsilon, \alpha\right), 50\%\right\}\right). \tag{7}$$

Table 2. Summary of Theoretical Predictions in Uncertain Information Problems

Theory	Aversion ($\alpha > 0$)	Insensitivity ($\varepsilon > 0$)
Full Bayesian updating	Pessimism	Underreaction
Dynamically consistent updating	Underreaction	Underreaction
Maximum likelihood updating	$p \neq 50\%$: confirmation bias (α and ε are irrelevant)	
	$p = 50\%$: coincide with FBU	

Note. FBU, Full Bayesian updating.

Unlike Full Bayesian updating, the as-if subjective information accuracy under Dynamically consistent updating is the same regardless of the realized report. Specifically, the weight on 50% is always ε and the remaining weight is always assigned to $\frac{\psi_h+\psi_l}{2} - \alpha$ so long as the subjective information accuracy is no less than 50%.

The interpretation of this equation is that an agent who uses Dynamically consistent updating evaluates her contingent plan of choices *before the realization of information*. If the agent is averse to information accuracy uncertainty ($\alpha > 0$), then she would prefer to underreact to information so that her ex ante payoff is less dependent on the realization of this uncertainty.

Proposition 2. *Suppose a CEU agent employs Dynamically consistent updating. In an uncertain information problem:*

1. *If $\varepsilon = 0$ and $\alpha = 0$, then her conditional evaluations coincide with the Bayesian evaluations conditional on simple information with an accuracy level of $\frac{\psi_h+\psi_l}{2}$.*
2. *As either ε or α increases, there is greater underreaction, meaning that the conditional evaluations become closer to p.*

3.2.3. Maximum Likelihood Updating. In an uncertain information problem, Maximum likelihood updating (Gilboa and Schmeidler 1993) selects only the accuracy level(s) that is mostly likely given the realized report. Then the agent conducts Full Bayesian updating using the selected accuracy level(s).[22] Because reports that confirm the prior are more likely to be accurate than not, Maximum likelihood updating would lead agents to solely focus on the high-accuracy possibility, resulting in overreaction to these reports. By a similar logic, agents will underreact to reports that contradict the prior. Formally, if $p \neq 50\%$, then the evaluation of the bet conditional on a good report is given by

$$u(g) = \begin{cases} Pr^{Bayes}(p, g, \psi_h), & \text{if } p > 50\% \\ Pr^{Bayes}(p, g, \psi_l), & \text{if } p < 50\%. \end{cases} \tag{8}$$

Conversely, the evaluation conditional on a bad report is

$$u(b) = \begin{cases} Pr^{Bayes}(p, b, \psi_l), & \text{if } p > 50\% \\ Pr^{Bayes}(p, b, \psi_h), & \text{if } p < 50\%. \end{cases} \tag{9}$$

If $p = 50\%$, then the predictions of Maximum likelihood updating coincide with those of Full Bayesian updating.

The following proposition summarizes the properties of Maximum likelihood updating.

Proposition 3. *Suppose a CEU agent employs Maximum likelihood updating. In an uncertain information problem:*

1. *If $p \neq 50\%$, the conditional evaluations of the bet exhibit confirmation bias relative to those conditional on simple information with accuracy $\frac{\psi_h+\psi_l}{2}$. That is, evaluations update more if information confirms the prior, less if it contradicts the prior. The measures of uncertainty attitudes, ε and α, do not affect the conditional evaluations.*
2. *If $p = 50\%$, conditional evaluations under Maximum likelihood updating coincide with those under Full Bayesian updating.*

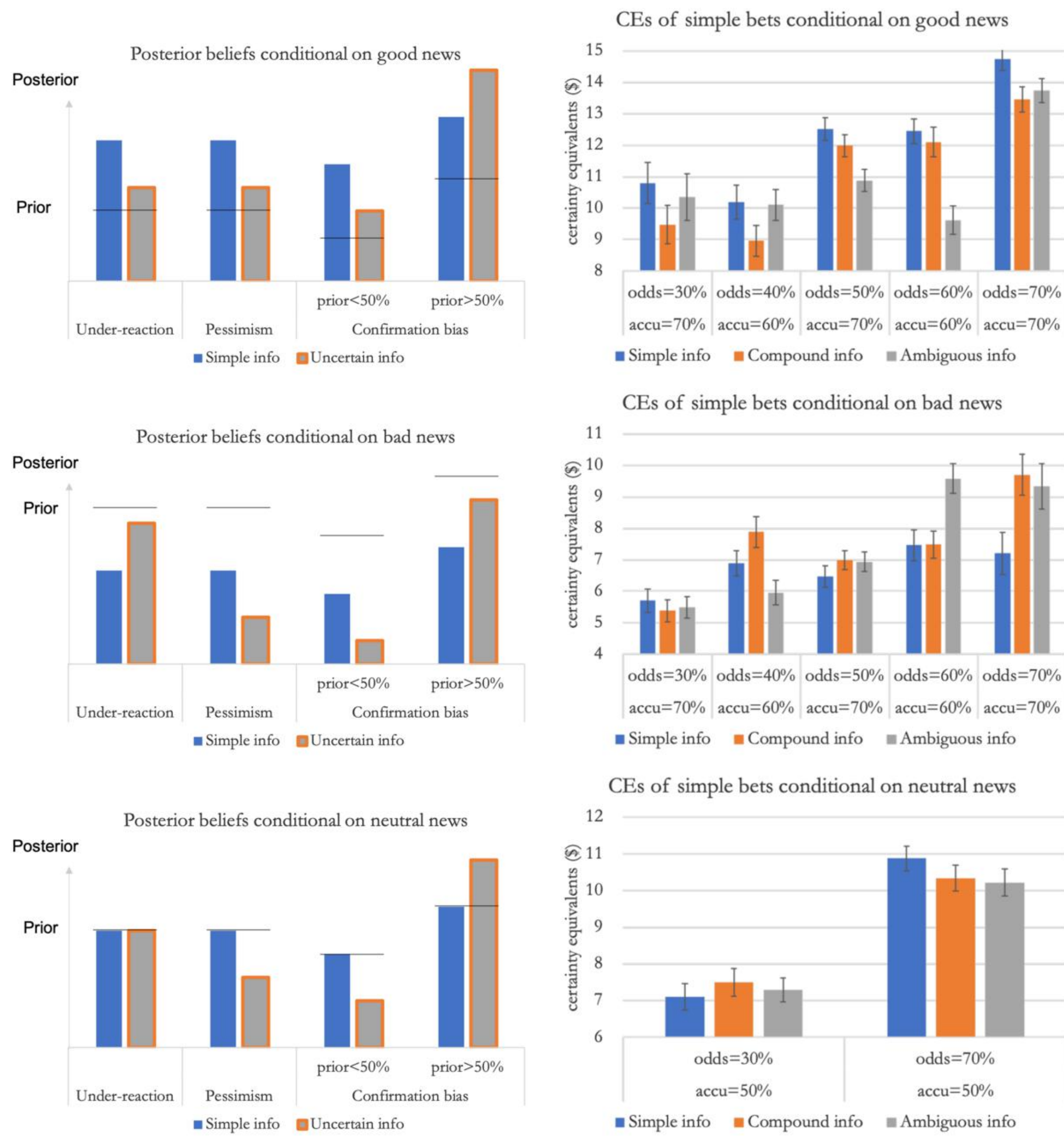
3.2.4. Summary of Theoretical Implications. Table 2 summarizes the implications of the three belief-updating rules for CEU agents who are insensitive and averse to information accuracy uncertainty.[23]

4. Experimental Results on Belief Updating with Uncertain Information Accuracy

The previous section presented three theories of belief updating with uncertain information, which generate a total of three different patterns: underreaction, pessimism, and confirmation bias. The left panel of Figure 2 illustrates the implications of each of these patterns by comparing belief updating between simple and uncertain information scenarios. *Neutral news* is defined as reports with a (midpoint) accuracy of 50%, whereas *good (bad) news* refers to nonneutral reports indicating a win (loss) for a bet. Both underreaction and pessimism yield the same directional predictions for good news, but they diverge when it comes to bad news. For neutral news, underreaction suggests that uncertainty about information accuracy will not impact posterior beliefs, whereas pessimism suggests that posteriors will be lower under uncertain accuracy. The directional prediction of confirmation bias is contingent upon the prior: when the prior is high, uncertain information yields higher posterior beliefs, but when the prior is low, it yields lower posterior beliefs.

The right panel of Figure 2 tests these patterns by showing the CEs of bets with simple priors (henceforth *simple bets*) conditional on good news, bad news, and

Figure 2. (Color online) Simple Priors with Simple and Uncertain Information



Notes. The left panel of this figure illustrates what underreaction, pessimism, and confirmation bias each predict about the comparisons between belief updating with simple and uncertain information. Neutral news refers to any report whose (midpoint) accuracy is 50%. Good (bad) news is a good (bad) report that is nonneutral news. The right panel compares the mean CEs of simple bets conditional on simple, compound, and ambiguous information in the experiment. Each group of bars corresponds to a combination of prior and information. For example, "odds=30%, accu=70%" in the upper right graph represents tasks where the prior is 30% and the information is good news with 70% (midpoint) accuracy. Error bars represent 95% confidence intervals.

neutral news. Additional statistical tests—including within- and between-subject *t*-tests—can be found in Table B.4 in the Online Appendix. Perhaps the most salient empirical pattern is that the mean CEs conditional on uncertain good news are lower than the mean CEs conditional on their simple counterpart for every combination of prior and (midpoint) information accuracy. This is consistent with the predictions of both underreaction and pessimism, but inconsistent with confirmation bias.

As for bad news, the mean CEs conditioned on compound and ambiguous information are higher compared with simple information in three out of the five comparisons, whereas they are slightly lower or mixed in the remaining two cases. As underreaction and pessimism yield opposing directional predictions for bad

Table 3. Classification of Subjects in an Uncertain Information Round

		Bet that the report says will win	
	Uncertainty premium	+	–
Bet that the report says will lose	+	Absolute pessimist	Absolute overreactor
	–	Absolute underreactor	Absolute optimist

Notes. This table summarizes the classification of subjects in an uncertain information round. To be classified into any of the four categories, the uncertainty premium of at least one bet in the round needs to be nonzero. For rounds with neutral information, I do not classify subjects as absolute over/underreactors.

news, these results may suggest the concurrent influence of both underreaction and pessimism, albeit less uniformly compared with good news. In addition, if we focus only on CEs conditional on ambiguous information, the results are consistent with confirmation bias, which is the prediction of Maximum likelihood updating.

The mean CEs of a 70% odds bet conditional on compound and ambiguous neutral news are significantly lower than that conditional on simple neutral news. For a 30% odds bet, the mean CEs conditional on compound and ambiguous neutral news are statistically indistinguishable from that conditional on simple neutral news. Again, the results are consistent with the combined effects of underreaction and pessimism, but not with confirmation bias. Taken together, the empirical patterns most closely resemble the prediction of Full Bayesian updating.[24]

To further demonstrate the underreaction and pessimism caused by uncertain information accuracy, for each round with an analyst with uncertain accuracy (henceforth *uncertain information round*), I define *absolute pessimists/optimists* and *absolute under/overreactors*, two pairs of mutually exclusive categories, and then show that the former in each pair prevails.

Firstly, let me define some notations. The term $CE(p, m, \psi_h \text{ or } \psi_l)$ represents the conditional CE of a bet in an uncertain information round, where p denotes the prior of the bet, $m \in g, b$ indicates the content of the report, and the third argument refers to the potential accuracy levels of the information. Similarly, $CE(p, m, \psi)$ is the conditional CE of a bet in a round involving a simple prior and simple information. Then, in an uncertain information round with nonneutral news, define the *uncertainty premium* of a bet as

$$Pm(p, m, \psi_h \text{ or } \psi_l) := CE\left(p, m, \frac{\psi_h + \psi_l}{2}\right) - CE(p, m, \psi_h \text{ or } \psi_l). \quad (10)$$

Note that $Pm(p, m, \psi_h \text{ or } \psi_l)$ may be missing for some subjects because its calculation requires the availability of $CE\left(p, m, \frac{\psi_h+\psi_l}{2}\right)$ in the data. In the rounds with neutral news, I do not distinguish between the contents of the report. The uncertainty premium of a bet in these rounds is defined as

$$Pm(p, -, 90\% \text{ or } 10\%) := CE(p, m', 50\%) - CE(p, m, 90\% \text{ or } 10\%), \quad (11)$$

where m and m' are the realized reports in the respective rounds.

Now I can define the categories, which are summarized in Table 3. A subject is classified as an absolute pessimist in an uncertain information round if the uncertainty premiums of both bets in this round are nonnegative, with at least one being strictly positive. Conversely, a subject is deemed an absolute optimist if both uncertainty premiums are nonpositive, with at least one being strictly negative.

In an uncertain information round with nonneutral news, a subject is termed an absolute underreactor if her uncertainty premium for the bet predicted to win by the report is nonnegative, her uncertainty premium for the other bet is nonpositive, and at least one of the two is nonzero. On the other hand, a subject is labeled an absolute overreactor if the bet predicted to win by the report has a nonpositive uncertainty premium, the other one has a nonnegative premium, and at least one is nonzero. In rounds with neutral news, subjects are not classified into these two categories.

Table 4 presents the percentages of each category in every uncertain information round. The data reveal considerable heterogeneity in the directional effects of information accuracy uncertainty, with no single category surpassing 50% in any round. However, distinct patterns emerge when comparing between categories. In every round, absolute underreactors outnumber absolute overreactors, and the difference when aggregated across rounds is statistically significant for both compound and ambiguous information. Furthermore, absolute pessimists exceed absolute optimists in all but one round, and the aggregate difference is statistically significant for ambiguous rounds.[25]

In summary, my experimental results indicate that information accuracy uncertainty leads to underreaction and pessimism. These two patterns are most consistent with the prediction of uncertainty-induced insensitivity

Table 4. Classification of Subjects in Each Uncertain Information Round

Prior (*Red*, *Blue*)	Midpoint information accuracy	Type of information	Absolute pessimists	Absolute optimists	p-value %(Abs. pess.) = %(Abs. opt.)	Absolute underreactors	Absolute overreactors	p-value % (Abs. under.) = %(Abs. over.)	N
(50%, 50%)	70%	Ambiguous	32.3%	19.5%	0.023	45.1%	18.3%	0	164
(60%, 40%)	60%	Ambiguous	31.0%	18.3%	0.128	43.7%	18.3%	0.007	71
(70%, 30%)	70%	Ambiguous	25.5%	23.4%	0.768	40.4%	19.1%	0.008	94
(70%, 30%)	50%	Ambiguous	25.9%	19.1%	0.198	—	—	—	162
Aggregate		Ambiguous	29.7%	20.0%	0.005	43.5%	18.5%	0	
(50%, 50%)	70%	Compound	21.5%	25.8%	0.425	43.6%	22.7%	0.001	163
(60%, 40%)	60%	Compound	27.4%	23.6%	0.586	36.8%	24.5%	0.107	106
(70%, 30%)	70%	Compound	27.6%	16.3%	0.057	39.8%	26.0%	0.059	123
(70%, 30%)	50%	Compound	29.4%	20.2%	0.096	—	—	—	163
Aggregate		Compound	26.3%	21.6%	0.111	40.6%	24.2%	0	

Notes. This table shows the percentages of subjects who are classified into the four categories in each uncertain information round. Only subjects who face comparable belief-updating problems in the uncertain information round and its corresponding simple information round are counted. In the rows under "Aggregate," I calculate the percentage of instances that subjects are classified into each category, aggregated across the four or three rounds that are relevant for that category. The p-values are computed using Pearson's chi-square goodness-of-fit tests. Abs. pess., absolute pessimists; Abs. opt., absolute optimists; Abs. under., absolute underreactors; Abs. over., absolute overreactors.

and uncertainty aversion combined with Full Bayesian updating.

5. Relationship with Uncertainty Attitudes Toward Economic Fundamentals

Previous research on uncertainty attitudes typically studies Ellsberg urns, compound lotteries, or complex financial assets. A common feature among these objects is that the probability distribution that is uncertain is over the payoff-relevant events. This is in contrast to unknown information sources where the uncertain probability distribution is over the correctness of the information. Understanding the relationship between uncertainty attitudes toward distributions over payoff-relevant events (henceforth *priors* or *economic fundamentals* for short) and uncertainty attitudes toward information accuracy informs the theoretical question of whether uncertainty attitudes are universal or issue specific. Practically, it also tells us whether it is appropriate to make predictions about reactions to unknown information sources using our knowledge about evaluations of assets with uncertain economic fundamentals.

To study subjects' uncertainty attitudes toward priors, I compare the CEs of uncertain bets in part 4 of the experiment to the CEs of simple bets in part 1. Consistent with prior studies, subjects exhibit uncertainty aversion and uncertainty-induced insensitivity when evaluating bets with uncertain odds. I also compare evaluations of uncertain and simple bets conditional on simple information (part 5 and part 2). Here, subjects still display uncertainty aversion, but uncertainty-induced insensitivity is not discernible. Details of the results and the theoretical justifications of the comparisons are relegated to Online Appendix A.

These findings indicate that, at an aggregate level, attitudes toward uncertainty in information accuracy and priors are qualitatively similar. However, to ascertain if they represent the same behavioral trait, we must investigate their correlations at an individual level. If these correlations are strong and significant, we can confidently use knowledge about an agent's attitude toward one kind of uncertainty to make predictions about their attitudes toward the other. If not, these attitudes must be studied separately, as extrapolation would not be appropriate.[26]

Correlation analysis is challenging because different combinations of updating rules and uncertainty attitudes can generate similar behavior. Without knowing the updating rule to which a subject adheres, it is sometimes difficult to pin down her uncertainty attitudes. To illustrate, suppose that a CEU subject exhibits underreaction to news but no pessimism in an uncertain information problem. Then, this behavior is consistent with $\varepsilon > 0$, $\alpha = 0$ and Full Bayesian updating, but it is also consistent with $\varepsilon \geq 0$, $\alpha > 0$ and Dynamically consistent updating. To circumvent this identification issue, I restrict attention to correlation tests that are valid under CEU preferences and all three previously considered updating rules. I informally describe these tests below and present the results. Details about their theoretical derivation and implementation can be found in Online Appendix D.

One such test is based on the following property of the CEU preferences. Suppose that an agent's uncertainty attitudes toward priors and information accuracy are determined by the same insensitivity and uncertainty aversion measures. Then, if her CE of a simple bet with 70% odds exceeds that of its corresponding uncertain bet (odds = 90% or 50%), she must also value a 50% odds simple bet higher after receiving 70%-accurate simple good news than after receiving the corresponding uncertain good news (accuracy = 90% or 50%). The converse is also true. The reasoning behind this one-to-one mapping of the two CE comparisons is that under any of the three updating rules, both comparisons essentially evaluate 70% against $W(70\%; \varepsilon, \alpha)$, provided ε and α are consistent for both information accuracy uncertainty and prior uncertainty. Hence, the prevalence of this mapping in the data can serve as a measure of similarity between the two types of uncertainty attitudes at the individual level.

The correlation between the directions of the aforementioned two CE comparisons is computed using experimental data, yielding a coefficient of 0.08 ($p = 0.29$) for compound uncertainty and 0.01 ($p = 0.93$) for ambiguity. These results suggest that uncertainty attitudes toward priors and information accuracy are not similar at the individual level.

There are three potential objections to this interpretation. First, the CEs in the first comparison are unconditional whereas those in the second are conditional. Hence, it could be the act of updating that alters the manifestation of uncertainty attitudes. To control for this confound, in another test I replace the unconditional CEs in the first comparison with CEs of the same bets conditional on simple neutral news. The results are unaffected: the correlation coefficient is 0 ($p = 0.98$) for compound uncertainty and 0.03 ($p = 0.71$) for ambiguity. Second, one might worry that the noise in the data could dilute any correlations, rendering them undetectable. To address this concern, in a third test I compute the correlation between the unconditional CE comparison that appears in the first test and the CE comparison conditional on simple neutral news that appears in the second test. Both CE comparisons are driven by subjects' uncertainty attitudes toward priors and hence should be positively correlated. Indeed, the correlation coefficient is 0.15 ($p = 0.05$) for compound bets and 0.26 ($p = 0$) for ambiguous bets, both being significantly positive. This result shows that the lack of correlation in the first two tests is not an artifact of measurement errors. A third concern is that the lack of correlation might be driven by inattentive or "confused" subjects. In Online Appendix D.1, I repeat the tests within a subsample of subjects who adhere well to some basic rationality properties, and the results remain qualitatively unchanged.

Taken together, the results suggest that subjects have distinct uncertainty attitudes toward priors and information accuracy.[27]

6. Suggestive Evidence from the Stock Market

In this section, I complement the experimental results with evidence from the U.S. stock markets. Consistent with the laboratory findings, I show that stock price underreaction to analyst earnings forecasts is more severe when the analyst forecast accuracy is more uncertain. In addition, the uncertainty-induced underreaction is pronounced only for good news, not for bad news. These empirical patterns suggest that the experimental findings on learning from unknown information sources are externally valid and economically important.

Brokerage firms employ financial analysts to research publicly traded companies and provide earnings forecasts. The informational value of these forecasts and the market's response have been extensively studied in the accounting and finance literature (Kothari et al. 2016). In this analysis, I leverage data from three sources: quarterly earnings forecasts and earnings announcements from the Institutional Broker Estimate System (I/B/E/S) detail history file, stock returns from the Center for Research in Security Prices (CRSP), and company characteristics from Compustat. I limit my focus to common stocks (share codes 10 or 11) listed on the AMEX, NYSE, or NASDAQ (exchange codes 1, 2, or 3). I also exclude stocks priced below $1 or with market capitalization less than $5 million. I focus on earnings forecasts for quarters from January 1, 1994, to June 30, 2019.[28] However, to construct attributes like analyst experience, I employ data as far back as January 1, 1984.

The setting of analyst earnings forecasts and the stock market provides an opportunity to study the effect of uncertain information accuracy on market reaction. In Online Appendix F.1, I prove that when the accuracy of an earnings forecast is uncertain, an investor's earnings expectation will underreact and be biased downward if she is a CEU agent with typical uncertainty attitudes ($\varepsilon > 0$ and $\alpha > 0$) and uses Full Bayesian updating. To the extent that stock price movement reflects changes in investors' earnings expectations, stock price reactions to forecasts with uncertain accuracy will exhibit similar underreaction and pessimism.

A key challenge to testing this prediction is that I do not observe investors' perceived uncertainty about the accuracy of each analyst forecast. To circumvent this issue, I use whether the issuing analyst has a proven forecast record for the stock as a proxy for the perceived uncertainty in his report's accuracy. Specifically, at a point in time, an analyst is considered to have a proven forecast record for a stock if she has previously issued a quarterly earnings forecast on this stock, and the actual earnings of that quarter have been announced. This proxy is valid because prior research has shown that forecast accuracy is stock specific and persistent (Park and Stice 2000), past forecast accuracy outperforms many other analyst attributes in predicting future accuracy (Brown 2001, Hilary and Hsu 2013), and investors learn about an analyst's forecast accuracy from her record (Chen et al. 2005). Forecasts issued by analysts without stock-specific forecast records will be referred to as "no-record forecasts," and the rest as "with-record forecasts."

To identify the stock price reaction to a specific analyst earnings forecast, it is important to mitigate the confounds of other news events occurring around the time of the forecast announcement. Therefore, I only include observations where, on the forecast announcement day, there is neither an earnings announcement from the company nor any earnings forecast announcements by other analysts for the same company. Moreover, I restrict attention to forecast revisions, which can be naturally classified as good news or bad news. Following Gleason and Lee (2003), good news corresponds to an upward revision, a forecast higher than the issuing analyst's prior forecast for the same quarterly earnings, whereas bad news equates to a downward forecast revision. This approach yields a final sample of 1,025,823 forecasts issued by 12,815 analysts for 10,712 stocks.

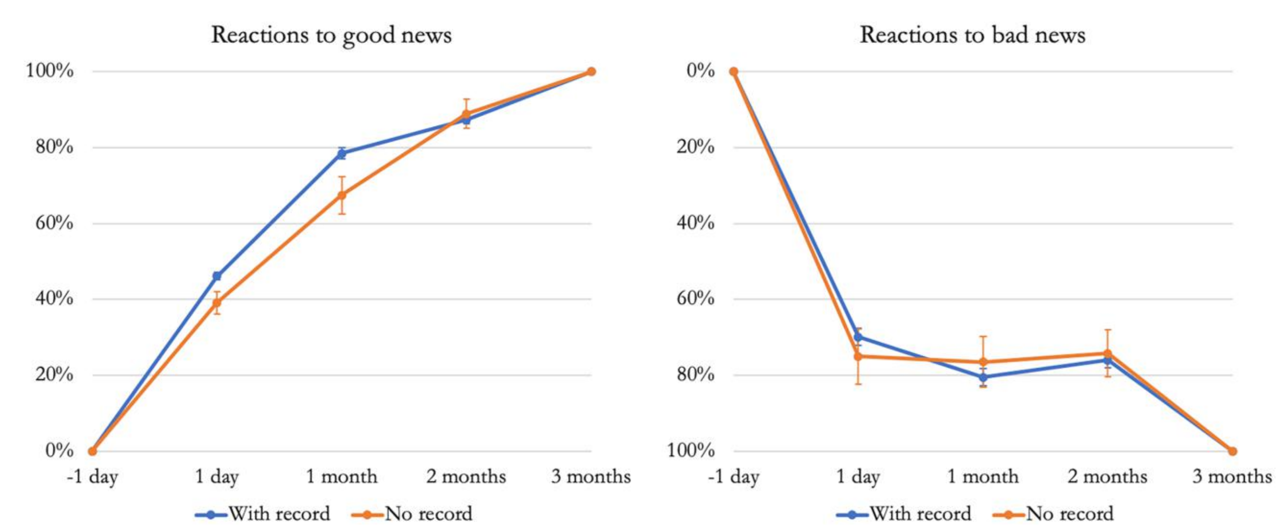
Descriptive results clearly support the hypotheses. Figure 3 illustrates the average size-adjusted returns[29] from one trading day before the forecast announcement to one trading day, one month, and two months after the forecast announcement, normalized by the average three-month returns. Assuming that reactions to forecasts are complete after three months, the proportion of reactions that happen in a shorter period is a measure of underreaction in that period. The left panel shows that for good news, stock prices underreact more to no-record forecasts. In contrast, for bad news, there is almost no difference in the degrees of underreaction to no-record and with-record forecasts (as is shown in the right panel). These results suggest that, on average, no-record forecasts lead to more underreaction and pessimism.[30]

Apart from the uncertainty in accuracy, no-record and with-record forecasts also differ in other dimensions, which need to be controlled for in a regression analysis to isolate the effect of uncertainty. Table F.2 in the Online Appendix provides the definitions for the control variables in the regression, which include characteristics of the forecasts, the issuing analysts, the stocks covered, and the information environment. Table F.3 in the Online Appendix lists their summary statistics.[31] No-record forecasts typically have larger realized forecast errors. The companies they cover tend to be smaller, have higher and more volatile past returns and lower book-to-market ratios, and are followed by fewer analysts. Analysts without past records follow fewer stocks and industries.

The main specification of the regression analysis is as follows:

$$\begin{aligned} Ret[2,64]_i = {} & \eta_0 + \eta_1 Ret[-1,1]_i + \eta_2 NoRecord_i \\ & + \eta_3 GoodNews_i \\ & + \eta_4 NoRecord_i \cdot GoodNews_i \\ & + \eta_5 Ret[-1,1]_i \cdot GoodNews_i \\ & + \eta_6 Ret[-1,1]_i \cdot NoRecord_i \\ & + \eta_7 Ret[-1,1]_i \cdot NoRecord_i \cdot GoodNews_i \\ & + Controls_i + Controls_i \cdot Ret[-1,1]_i \\ & + TimeFE_i + \varepsilon_i. \end{aligned} \tag{12}$$

Figure 3. (Color online) Reactions to Forecast Revisions



Notes. This figure shows the average size-adjusted returns from one trading day before the forecast announcement to one trading day, one month, and two months after the forecast announcement, normalized by the average three-month returns. The left and right panels plot reactions to upward and downward forecast revisions, respectively. Error bars represent standard errors calculated using the delta method.

Table 5. Stock Market Reactions to Forecast Revisions

Dependent Var: *Ret*[2,64]	(1)	(2)	(3)	(4)
Ret[−1,1]	0.0215	0.0173	0.343***	0.335**
	(0.0336)	(0.0333)	(0.100)	(0.100)
NoRecord	−0.000671	−0.00225	0.000814	0.000584
	(0.00287)	(0.00277)	(0.00213)	(0.00205)
NoRecord × *Ret*[−1,1]	−0.0435	−0.0430	−0.0281	−0.0311
	(0.0626)	(0.0622)	(0.0474)	(0.0465)
GoodNews	0.0113***	0.0111***	0.0107***	0.0107***
	(0.00243)	(0.00211)	(0.00189)	(0.00177)
GoodNews × *Ret*[−1,1]	0.0605†	0.0569	0.0480	0.0452
	(0.0351)	(0.0349)	(0.0294)	(0.0293)
NoRecord × *GoodNews*	0.00421	0.00440†	0.00102	0.00123
	(0.00269)	(0.00262)	(0.00253)	(0.00247)
NoRecord × *GoodNews* × *Ret*[−1,1]	0.150*	0.150*	0.122†	0.124*
	(0.0624)	(0.0626)	(0.0626)	(0.0620)
Controls	N	N	Y	Y
Controls × *Ret*[−1,1]	N	N	Y	Y
Year-quarter FE	N	Y	N	Y
Observations	1,001,418	1,001,417	894,004	894,004
R^2	0.001	0.010	0.004	0.014

Notes. This table reports the results of Regression (12). The dependent variable $Ret[2,64]$ is the size-adjusted stock returns in the [2,64]-trading day period after a forecast is announced, and $Ret[-1,1]$ is the immediate price reaction to a forecast. The variable *NoRecord* indicates that a forecast is issued by an analyst with no stock-specific forecast record. The variable *GoodNews* indicates an upward forecast revision. Control variables are characteristics of the forecast, the issuing analyst, the stock covered, and the information environment, summarized in Table F.2 in the Online Appendix. Three-dimensional (stock, analyst, year-quarter) cluster-robust standard errors in parentheses. Var, variable.
$^{\dagger}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

The dependent variable $Ret[2,64]_i$ is the size-adjusted stock returns in the [2,64]-trading day period after forecast i is announced (64 trading days are roughly three months), and $Ret[-1,1]_i$ is the immediate price reaction to forecast i in the [−1,1]-trading day window. The correlation between the immediate price reactions and the subsequent price drifts is a measure of market underreaction to analysts' forecasts. This is because if immediate price reactions are on average followed by drifts in the same (opposite) direction, then the immediate reactions must be incomplete (excessive). $NoRecord_i$ and $GoodNews_i$ are indicator variables for no-record forecasts and good news as previously defined. By including the interactions between $Ret[-1,1]$, *NoRecord*, and *GoodNews*, this specification can measure how much stock price underreaction varies with the issuing analyst's record and the direction of forecast revision. In addition, I include controls on the characteristics of the forecast, the issuing analyst, the stock covered, and the information environment, as well as their interactions with $Ret[-1,1]$. Year-quarter dummies are also included to control for unobserved time fixed effects (FE) on returns. In view of the descriptive results that stock prices underreact to no-record forecasts especially for good news, we expect the coefficient on the triple interaction, η_7, to be positive.

Table 5 presents the results from the regression analysis. Across the four specifications that vary based on the set of controls and fixed effects, the coefficients on $NoRecord \times Ret[-1,1]$ and *NoRecord* are small and insignificant, suggesting that the presence or absence of a past record for the issuing analyst does not impact the degree of underreaction to bad news. On the other hand, the coefficient on $Ret[-1,1] \times NoRecord \times GoodNews$ is consistently positive and significant. To interpret the magnitudes of the coefficients, the ratio between the price drift in the [2,64]-trading day window and the immediate reaction is larger for no-record good news than for with-record good news by around 10 percentage points. Taken together, the results imply that investors' reactions to earnings forecasts with more uncertain accuracy exhibit more underreaction and pessimism.

In Online Appendix F.3, I examine the robustness of the regression results. In Table F.5 in the Online Appendix, I show that the signs of the coefficients are robust to changes to the price drift window of the left-hand side variable in Specification (12). The effect sizes tend to increase as the drift window becomes longer, suggesting that the underreaction is gradually corrected. Table F.6 in the Online Appendix shows the regression results for different subsets of the data. The results are robust when I only consider "high-innovation" forecast revisions, "isolated" forecasts, and forecasts announced after January 1, 2004.[32] The main effect does not appear to be solely driven by forecasts on small-cap stocks, as the magnitude (although not the statistical significance) of the coefficient on the triple interaction term remains when I exclude all stocks with market capitalization smaller than \$2 billion. However, this coefficient vanishes if I only include large-cap stocks (market capitalization of >\$10 billion), which may be due to the high concentration of sophisticated investors in these stocks and their relatively low transaction costs. I also consider a specification that includes the interactions between year-quarter dummies and $Ret[-1,1]$, and the results remain robust. Table F.7 in the Online Appendix reports the results of regressions that replace $Ret[-1,1]$ and its interaction terms in Specification (12) with *Revision* and its interaction terms. The variable *Revision* is the difference between an analyst's revised forecast on earnings per share and the previous forecast, normalized by the stock price two trading days prior to the announcement of the revision. The results from this specification are similar: the price drift per unit of *Revision* is larger for no-record good news than for with-record good news, although the difference is small and insignificant for bad news.

In sum, stock prices underreact more to earnings forecasts when they are issued by analysts with no forecast record. This phenomenon is exclusive to good news and does not extend to bad news. These results corroborate the experimental finding that information accuracy uncertainty leads to underreaction and pessimism.

7. Conclusion

This paper studies the effects of information accuracy uncertainty on belief updating using a controlled laboratory experiment and observational data from the stock market. In the experiment, a midpoint-preserving spread in the information accuracy leads to more underreaction. Moreover, the underreaction is more pronounced for good news than for bad news. The same two patterns also emerge in the stock market. Stock prices underreact more to earnings forecasts issued by analysts with no proven forecast record, and the underreaction occurs only for good news but not for bad news. Among a variety of models, a theory that combines Full Bayesian updating with uncertainty aversion and uncertainty-induced insensitivity best captures the empirical results.

In the experiment, I compare the effects of uncertain information accuracy to those of uncertain priors. Uncertainty in priors leads to pessimism and, in problems without belief updating, also insensitivity. Although the aggregate effects of uncertain information accuracy and uncertain priors are similar, subjects' attitudes toward these two kinds of uncertainty are uncorrelated. The lack of correlation lends support to the view that uncertainty attitudes depend on the relevant issues. Practically, it also suggests that knowledge of a person's attitude toward assets with unknown fundamentals does not necessarily help predict their reactions to information from unknown sources.

This paper raises several questions for future research. First, given that the empirical settings in this paper are purely monetary, it remains to be explored how uncertain information accuracy interacts with nonfinancial concerns such as ideology and ego utility. Second, as belief updating is closely linked to information demand (Ambuehl and Li 2018), what are the determinants of demand for uncertain information? Third, considering this paper's finding that attitudes toward uncertain priors and uncertain information are uncorrelated, what are the moderating factors of these two distinct attitudes? Finally, given that signals from an unknown source are relevant not only for the payoff-relevant events but also for the accuracy of the source itself, it would be interesting to study how people learn about a source's accuracy from its own signals.

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Endnotes

[1] See Jaffray (1992), Pires (2002), and Eichberger et al. (2007).

[2] See Hanany and Klibanoff (2007).

[3] See Dempster (1967), Shafer (1976), and Gilboa and Schmeidler (1993).

[4] This question was raised in Keynes (1921), Knight (1921), and Ellsberg (1961), and has since received immense theoretical attention. For theoretical surveys, see Machina and Siniscalchi (2014) and Gilboa and Marinacci (2016). Trautmann and van de Kuilen (2015) provide a survey of empirical evidence.

[5] These dimensions are referred to as *issues* in the literature.

[6] Empirical studies providing evidence of uncertainty-induced insensitivity and uncertainty aversion include Abdellaoui et al. (2011, 2015); Dimmock et al. (2015); Baillon et al. (2018); and Anantanasuwong et al. (2024). Theoretical models that capture these two patterns include Ellsberg (2015), Chateauneuf et al. (2007), and Gul and Pesendorfer (2014).

[7] Loosely speaking, the martingale property of belief updating states that there exists a probability distribution over messages such that for every event, the expectation of posteriors equals the prior.

[8] Complementary to the research on uncertain information accuracy, experiments studying the effect of uncertain priors on belief updating include Corgnet et al. (2012), Ert and Trautmann (2014), Moreno and Rosokha (2016), Baillon et al. (2017), and Ngangoué (2021).

[9] Other social learning experiments that study how subjects learn from others' actions include Nöth and Weber (2003), Çelen and Kariv (2004), and Goeree et al. (2007). However, these experiments typically observe a subject's action only once, and the action space is usually binary.

[10] For surveys, see Kothari et al. (2016) and Bradshaw et al. (2017).

[11] I elicit CEs instead of probability equivalents so that the tasks resemble real-life financial decisions instead of pure mathematical questions. In addition, CEs are arguably easier for subjects to understand.

[12] A total of 38 observations from three subjects in these two sessions are missing because of illegibility.

[13] Multiple switching between the left and right sides of the list is not allowed.

[14] Any hedging against uncertainty using the random incentive system between rounds (Baillon et al. 2022b) likely diminishes the uncertainty's effects on CEs.

[15] To mitigate the concern that the experimenter manipulates the threshold number ex post, subjects are told that the threshold number is printed on a paper and they are welcome to inspect it after the experiment.

[16] Instructions are framed such that the uncertainty about true prior or the uncertainty about the accuracy level of the information is always resolved first. In the first two sessions, to determine the true prior or the true accuracy level of information, a card is drawn from a deck of 8 cards instead of 10. The uncertainty is resolved by whether the number drawn is even or odd.

[17] Gilboa and Marinacci (2016) and Machina and Siniscalchi (2014) provide surveys on models of uncertainty attitudes.

[18] If $p_h + p_l = 1$, I set ε to be zero. When $p_h + p_l \neq 1$, I assume that $\nu(E) > \nu(E^c)$ so that $\varepsilon < 1$.

[19] An earlier version of this paper (Liang 2020) reviews other models of uncertainty attitudes. Multiple-prior models can be parametrized to accommodate uncertainty-induced insensitivity and uncertainty aversion. Outcome-based models such as the smooth model (Klibanoff et al. 2005) can capture uncertainty aversion but not insensitivity.

[20] Alternatively, one can apply Bayes' rule by first calculating one Bayesian posterior for each accuracy level and then taking their average weighted by the updated likelihood of each accuracy level. This procedure is equivalent to applying Bayes' rule to the midpoint accuracy.

[21] The capacity of every event in the state space that is relevant for belief updating can be derived under minimal assumptions. See Online Appendix C.1 for details.

[22] Maximum likelihood updating was initially introduced in conjunction with maxmin EU preferences (Gilboa and Schmeidler 1989). However, because the selection of most likely accuracy levels is independent of preferences, this updating rule is often applied to other preference models (e.g., Schwartzstein and Sunderam 2021).

[23] The literature has proposed other updating rules that are not covered in this paper. For example, the optimistic updating rule (Gilboa and Schmeidler 1993), the Dempster-Shafer rule (Dempster 1967, Shafer 1976), and the Proxy updating rule (Gul and Pesendorfer 2021) can be applied to CEU preferences. However, their predictions depend on the capacities of the messages, $\nu(g)$ and $\nu(b)$, which are not specified in my setting. An earlier version of this paper (Liang 2020) also discusses updating rules that are applied to other models of uncertainty attitudes.

[24] Although compound uncertainty and ambiguity often have the same directional effects on CEs, their magnitudes are different in many cases. In Online Appendix E, I compare the magnitudes of their effects at the subject level.

[25] In Online Appendix B.1, I consider two additional categories: absolute confirmation bias and absolute contradiction bias. These two categories overlap with absolute over/underreactors, as an absolute overreactor in a round with a confirmatory report is classified into the category of absolute confirmation bias. In all but one round, there are fewer absolute confirmation-biased subjects than absolute contradiction-biased subjects. This result together with the comparisons between mean CEs of bets suggests that information accuracy uncertainty does not lead to prevalent confirmation bias, with the possible exception of ambiguous bad news.

[26] See Online Appendix E for an analogous individual-level analysis of the relationship between compound and ambiguity attitudes.

[27] Shishkin and Ortoleva (2023) also find no correlation between ambiguity attitudes and pessimistic updating, whereas Epstein and Halevy (2024) find that subjects who do not reduce compound lotteries are also more likely to violate the martingale property of belief updating. Although these disparate results may be due to design differences, they do underline the need for more evidence on this issue.

[28] I do not include observations that date further back in time because the announcement dates recorded in I/B/E/S often differed from the actual dates by a couple of days prior to the early 1990s.

[29] Size-adjusted returns are the stock's buy-hold returns minus the equal-weighted average returns of stocks in the same size decile in the same period.

[30] The summary statistics for unnormalized returns in windows with different lengths are in Table F.1 in the Online Appendix.

[31] Table F.4 in the Online Appendix provides summary statistics for all earnings forecasts issued between January 1, 1994, and June 30, 2019, including those that do not meet our data selection criteria.

[32] Following Gleason and Lee (2003), a forecast revision is high innovation if it falls outside the range between the issuing analyst's previous forecast and the previous consensus (the consensus is the average of all forecasts available at the time). High-innovation forecast revisions are likely to contain new information as they are not simply herding toward the consensus. "Isolated" forecasts are observations where there is neither an earnings announcement from the company nor forecast announcements by any other analysts on the same company in the three-day window centered on the forecast announcement day. This filter further eliminates concerns that other news events might be driving $Ret[-1, 1]$. The focus on the period after 2004 is because a host of regulations on the financial analyst industry came into effect in 2002/03 (Bradshaw et al. 2017), and the quality of forecast announcement time data in I/B/E/S improved after 2004 (Hirshleifer et al. 2019).

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