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 lab 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 uncertainty in information accuracy can explain these results.

Keywords— Belief updating, ambiguity, compound risk, earnings forecasts

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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 example, in response to a financial report issued by a new analyst, investors need to decide how to adjust their portfolios, but they do not know the analyst's expertise. Politicians often have to rely on media and polling agencies to learn about their constituents' needs, but they may not know the exact biases of these intermediaries. Moreover, in the current era where online health information becomes increasingly abundant and important for public health, a survey among older web users shows that while 90% of them look for health information online, only 52% believe that they can distinguish high-quality sources from low-quality ones (Tennant et al., 2015). These examples suggest that understanding how people react to news with uncertain accuracy is important for understanding real outcomes.

Standard economic theory assumes that when the accuracy of a piece of information is uncertain, agents are able to correctly deduce its *expected accuracy* and update their beliefs solely based on that expectation. As an example, consider a bet with two possible outcomes. The agent receives a report on the outcome but she does not know its accuracy: the probability that the report is correct conditional on the true outcome might be either 90% or 50%. The two possible levels of accuracy are equally likely, and the true one is independent from the realization of the outcome. According to standard theory, the agent is able to calculate that the report is correct 70% of the time in expectation, and her belief about the outcome of the bet should react to this report as if she knew with certainty that it is 70% accurate.

1.1 Main results

Using both experimental data from the lab and observational data on stock price reactions to analyst earnings forecasts, this paper provides the first evidence on how uncertainty in information accuracy affects belief updating. In part of a lab 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 refer to a report as *uncertain information* if its accuracy might be either high (ψ_h) or low (ψ_l), and I define its corresponding *simple information* as a report whose accuracy is known to be the midpoint, $(\psi_h + \psi_l)/2$. When subjects receive uncertain information, sometimes they know that the two possible accuracy levels are equally likely (*compound information*), and at other times they do not know their relative likelihood (*ambiguous information*). In my experiment, the effects of compound uncertainty and ambiguity prove to be qualitatively similar, so I will refer to them jointly using the generic term "uncertainty."

The main experimental result concerns the marginal effects of uncertainty in information accuracy on posterior beliefs. Compared to the case of simple information, subjects' beliefs move *less* in the direction of the realized report when its accuracy is uncertain. In other words, uncertain information leads to *under-reaction*. Moreover, the under-reaction is more pronounced for good news than for bad news. This suggests that uncertainty in information accuracy on average leads to *pessimism* in posterior beliefs.

The same patterns also emerge when I examine stock market reactions to analyst earnings forecasts. The forecast accuracy of financial analysts is more unpredictable if they do not have a proven forecast record for the stock. I find that in response to good news (upward forecast revisions) issued by these analysts, the immediate stock price reactions are on average followed by larger positive price drifts. This phenomenon implies that investors' immediate reactions to good news are less sufficient when the news is issued by analysts without records. By contrast, the sufficiency of reactions to bad news does not depend on whether the issuing analyst has a forecast record or not. These findings are consistent with my experimental results that people's reactions to information from uncertain sources are less sufficient and more pessimistic, and they show that these phenomena are even present in a high-stake, real-world environment.

1.2 Theories

Most theories of 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 uncertain probability. Previous research has shown two empirical regularities about typical 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 the alternative scenario where the event's probability is known to be the midpoint, $(p_h + p_l)/2$. Uncertainty-induced insensitivity refers to the pattern whereby the willingness to bet changes less as p_h and p_l change when the probability is uncertain. It captures the psychological intuition that people internalize the probabilities less as they become more complex. On the other hand, uncertainty aversion means that p_l is over-weighted relative to p_h in the willingness to bet on this uncertain event. It reflects the tendency to be over-pessimistic in the face of uncertainty. As a basis of our theoretical framework, I introduce a parametric model of uncertainty attitudes – the *ε-α-maxmin expected utility* model – which parsimoniously captures insensitivity and uncertainty aversion and nests many existing models.

When agents react to information from a source with uncertain accuracy, their uncertainty attitudes toward this source's accuracy could manifest themselves in a number of different ways. Consider an agent who evaluates a bet after hearing an uncertain source's report on its outcome. Suppose that the agent is averse to uncertainty in information accuracy. Then, one possibility is that the uncertainty aversion leads her to be pessimistic about the outcome of the bet 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 (*Dynamically consistent updating*).[2] A third possibility is that after hearing the report, the agent becomes certain about one of the accuracy levels because the other ones are less likely to be true given the report (*Maximum likelihood updating*).[3]

These possibilities have different testable implications in the empirical settings of this paper, and Full Bayesian updating coupled with uncertainty-induced insensitivity and uncertainty aversion stands out as being most in line with the evidence described above. Intuitively, under Full Bayesian updating, uncertainty averse agents over-weight the possibility that uncertain information has low accuracy when they hear good news. By contrast, the high accuracy is over-weighted when the realized news is bad. This asymmetry leads to pessimism about the value of the bet after hearing the news. On the other hand, uncertainty-induced insensitivity causes agents to neglect the content of information from unknown sources, leading to under-reaction.

1.3 Attitudes toward uncertain information accuracy and uncertain economic fundamentals

Prior research on uncertainty attitudes has mostly studied how people evaluate prospects when they do not know the *prior over payoff-relevant states* (henceforth *prior* or *economic fundamental*).[4] For example, investors may need to evaluate a complex financial asset when it is difficult to know the distribution of its returns. Uncertainty attitudes toward economic fundamentals are conceptually different from uncertainty attitudes toward information accuracy because the uncertain probability distributions are over different dimensions of the state space.[5] A natural question to ask is how these two kinds of uncertainty attitudes relate to each other. A strong relationship would warrant extrapolating from what we know about uncertain economic fundamentals to the under-studied domain of uncertain information accuracy. Otherwise, domain-specific research would be necessary to understand learning from unknown information sources.

To measure our lab subjects' uncertainty attitudes toward economic fundamentals, I elicit their CEs of *uncertain bets* whose winning odds might be either high or low and compare them to CEs of *simple bets* whose odds are known. The comparison confirms that typical uncertainty

[1] Jaffray (1992); Pires (2002); Eichberger et al. (2007).

[2] Hanany and Klibanoff (2007).

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

[4] The 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.

attitudes toward economic fundamentals exhibit insensitivity and uncertainty aversion.[6] Moreover, by estimating a representative-agent model based on the ε-α-maxmin preference, I show that the magnitudes of insensitivity and uncertainty aversion are similar between economic fundamentals and information accuracy.

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 under a variety of preference models and updating rules. The results show that there is almost zero correlation between attitudes toward uncertainty in information accuracy and uncertainty in priors. 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. It also resonates with existing evidence showing that uncertainty attitudes vary with issues.[7]

1.4 Related literature

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

Three recent experimental studies investigate certain aspects of ambiguous information. In a contemporaneous project, Epstein and Halevy (2020) 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[8] under ambiguous information than under a piece of simple information (which is not the symmetric reduction of the ambiguous information). More recently, Shishkin ⓡ Ortoleva (2020) focus on ambiguous neutral information (i.e. information whose accuracy is a midpoint-preserving spread of 50%) and study both belief updating and the demand for information. Kellner et al. (2020) study communication with ambiguous language and find evidence consistent with hedging against ambiguity. In contrast to these three studies, my experiment allows for the separate identification of under-reaction and pessimism caused by uncertain information accuracy. In addition, I consider both compound and ambiguous information.[9]

[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); Anantanasuwong et al. (2019). Theoretical models that capture these two patterns include Ellsberg (2015); Chateauneuf et al. (2007); Gul and Pesendorfer (2014).

[7]E.g. Heath and Tversky (1991); Fox and Tversky (1995).

[8]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.

[9]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

Two previous experimental projects study phenomena related to uncertain information accuracy. Fryer Jr 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. (2018) 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 under-weight the latter. The authors interpret their result using a model where subjects treat their predecessors' beliefs as ambiguous information.[10] 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-driven 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 under-reaction (e.g. Edwards, 1968; Möbius et al., 2014) and asymmetric updating (e.g. Eil and Rao, 2011; Möbius et al., 2014; Coutts, 2019; Barron, 2020). 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 due to inattention or bounded rationality. If this is true, then my paper suggests that perceived uncertainty in information accuracy may be a moderator for these belief-updating biases. Indeed, in a subsequent experiment, Enke and Graeber (2020) find evidence supporting this conjecture.[11]

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 US 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 (2017) studies how rainfall signals affect Indian farmers' agricultural decisions and find support for the robust learning model of Hansen and Sargent (2001). These papers do not study how the degree of uncertainty in information accuracy affects the sufficiency of reactions 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

Rosokha (2016), Baillon et al. (2017), and Ngangoué (2020).

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

[11]Enke and Graeber (2020) find in a part of their experiment that subjects' posterior beliefs are more compressed toward the prior (50%, 50%) if the information accuracy is compound as opposed to simple. Under their belief elicitation mechanism, this phenomenon is consistent with both under-reaction and pessimism.

and finance.[12] Gleason and Lee (2003) find that stock price under-reaction is less pronounced for analysts who are recognized by the *Institutional Investor* magazine. Zhang (2006) shows that the market under-reacts 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 under-reaction 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 sufficiency of 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 lab experiment. Section 3 presents theories of belief updating with uncertain information accuracy and Section 4 presents the corresponding experimental results. In Section 5, I show experimental results related to uncertain priors over the payoff-relevant states and compare them to results on uncertain information accuracy at both the aggregate and individual level. 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 lab experiment at the Econ Lab at 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 eleven sessions which lasted on average 90 minutes.

2.1 Environment

Each session of the experiment comprises 29 rounds. Each round is framed as a race between a red horse and a blue horse, with no ties being possible. In each round, there are two payoff-relevant states, *Red* and *Blue*, corresponding to the color of the winning horse. In some rounds, subjects may also receive a piece of additional information about the true state framed as an analyst report. The report they receive is either "Red horse won" or "Blue horse won." I will refer to the former as a *good report* and the latter a *bad report* for the *Red* state. For the *Blue* state, the designation of good and bad reports is reversed. The uncertainty across rounds is independent.

The 29 rounds are grouped into five parts, which are summarized in Table 2.1. In the three parts with "simple prior", subjects in each round know with certainty the prior probability distribution

[12]For surveys, see Kothari et al. (2016); Bradshaw et al. (2017).

	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%

Table 2.1: Experimental parts and rounds

over the payoff-relevant states, i.e. the winning odds of the two horses. 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 information source is uncertain. Subjects do not receive any report in Part 1, whereas in Parts 2 and 3, they do. In Part 2, the reports are *simple information*, which means that 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 they do not know which one. 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 situation as subjects receiving *compound information*. In the other rounds (also grouped in a block), the distribution over the two possible accuracy levels is unknown, and I refer to the information as *ambiguous information*. The realization of the true accuracy level is independent from the realization of the state.

In Parts 4 and 5, subjects are told in each round that the states are distributed according to one of two possible priors. For example, the prior probability that *Red* is the true state 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 the distribution over them ("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 the *Red* state 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 C.2 summarizes the orders in the eleven sessions. In Appendix C.2, I show that order effects are not a driving force of 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' certainty equivalents (CEs) of a bet on the *Red* state and a bet on the *Blue* state.[13] A bet on a state pays out $20 if it is the true state 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.[14] In the other nine sessions, the BDM mechanism was implemented through a multiple price list programmed using oTree (Chen et al., 2016), where a subject makes a series of binary choices between receiving the bet and receiving a certain amount of money incrementing from $1 to $19 in steps of $1. The CE is inferred to be the minimum certain amount that the subject chooses over the bet.[15] After subjects report their CEs in a round, they do not receive any feedback until the very end of the experiment.

[13] I elicit CEs instead of probability equivalents so that the tasks resemble real-life financial decisions instead of pure mathematical questions.

[14] A total of 38 observations from three subjects in these two sessions are missing due to illegibility.

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

2.3 Implementation of randomization

To encourage subjects to consider each bet and each price in isolation (Baillon et al., 2015) 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 bonus and the other contains the price of the bet (row in the multiple price list).

In each round, each binary event is determined by a random draw from a deck of ten cards numbered from 1 to 10, with one card for each number. To determine the true state, a small number on the drawn card corresponds to *Red* being the true state and a large number corresponds to *Blue*. The threshold number is determined by the true prior over the states. 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 1 and 5. If the distribution over the two priors is unknown, then the threshold number that determines the true prior is not disclosed to the subjects.[16] When the information accuracy is uncertain, the true accuracy is determined in a similar fashion.[17] After drawing the cards, the experimenter announces the realized report to the subjects, and then the subjects report their CEs for the red bet and blue bet.

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, although there is no mention of any updating rules. The experiment ends with an unincentivized survey. The instructional videos, their scripts and sample screenshots of the rounds can be found on my website.

[16]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.

[17]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 eight cards instead of ten. The uncertainty is resolved by whether the number drawn is even or odd.

3 Theory of belief updating with uncertain information accuracy

In this section, I analyze theories about belief updating with uncertain information accuracy.

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.[18] In this paper, I will use a simple model of uncertainty attitudes – the *ε-α-maxmin (expected utility)* model – that parsimoniously captures two empirical regularities: *uncertainty-induced insensitivity* and *uncertainty aversion*.[19] This model will be applied to both compound uncertainty and ambiguity, although the parameter values are allowed to differ across these two types of uncertainty when I later estimate this model using experimental data.[20]

There are two events, E and E^c. The probability of E is either p_h or p_l, with $p_h \geq p_l$. The probability of E^c is the complement. An act assigns a simple lottery to each event. I identify the simple lotteries assigned to E and E^c by their (von Neumann-Morgenstern) utility indices, denoted by u_1 and u_2, respectively. Define the following function (where x and y are place-holders, ε and α are parameters in the unit interval):

$$W(x, y; \varepsilon, \alpha) := (1-\varepsilon)[(1-\alpha)x + \alpha y] + \varepsilon \cdot 0.5.$$

Then the utility of the act for an ε-α-maxmin agent is

$$\begin{cases} W(p_h, p_l; \varepsilon, \alpha) \cdot u_1 + (1 - W(p_h, p_l; \varepsilon, \alpha)) \cdot u_2, & \text{if } u_1 \geq u_2 \\ W(p_l, p_h; \varepsilon, \alpha) \cdot u_1 + (1 - W(p_l, p_h; \varepsilon, \alpha)) \cdot u_2, & \text{if } u_1 < u_2 \end{cases}.$$

The ε-α-maxmin preference can be interpreted as follows. When the probability distribution on the two events is uncertain, the agent puts ε weight on a baseline probability, which I assume to be the symmetric and maximally uncertain distribution (50%, 50%).[21] The larger the value of ε, the less sensitive the utility of an act to p_h and p_l. Therefore, ε is the measure of uncertainty-induced

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

[19] I provide an axiomatic foundation of this model and discuss two alternative models – the smooth model (Klibanoff et al., 2005) and the recursive model of Segal (1987, 1990) – in the 2020 version of this paper.

[20] For simplicity, I will not use separate notations for compound uncertainty and ambiguity.

[21] I consider two alternative models in the 2020 version of this paper. In one model, the weight on (50%, 50%) scales with $p_h - p_l$. In the other, the baseline probability on which the agent puts ε weight is a free parameter. These modifications do not qualitatively change the main results.

insensitivity. The rest of the weight $(1-\varepsilon)$ is split between the more optimistic belief and the more pessimistic one in a generically asymmetric manner. The relative weight on the pessimistic belief α is hence the measure of uncertainty aversion. The two parameters flexibly capture rich patterns of uncertainty attitudes, from full uncertainty seeking ($\alpha = 0$) to full uncertainty aversion ($\alpha = 1$), from full sensitivity ($\varepsilon = 0$) to full insensitivity ($\varepsilon = 1$). It also nests standard expected utility as a special case ($\varepsilon = 0$ and $\alpha = 0.5$).[22]

This model is closely related to many classes of models in the literature.[23] In particular, it can be written in the functional form of Choquet expected utility (Schmeidler, 1989) (see Appendix D.1). Therefore, updating rules that apply to Choquet expected utility also apply to the ε-α-maxmin model.

3.2 Updating rules

In problems of belief updating with uncertain information accuracy, uncertainty attitudes may manifest themselves in a number of different ways depending on the updating rule. Consider the following setup in which an agent chooses between a bet and a certain amount of utils. There are two payoff-relevant states, G and B. The bet pays out 1 util if G occurs and 0 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 emulates the main parts of the experiment. One util corresponds to \$20. For the red bet, state G is the *Red* state and state B is the *Blue* state. For the blue bet, the mapping is reversed. For any bet, report g is the good report and b is the bad report.

I define the *evaluation* of a bet as the amount of utils u such that the agent is indifferent between the bet and u. If the accuracy of the information is $Pr(g|G) = Pr(b|B) = \psi$ with certainty, then after observing the realized report, a Bayesian expected utility (EU) agent will evaluate the bet by the Bayesian posterior belief on G: $u(g) = Pr^{Bayes}(G|p, g, \psi) := \frac{p\psi}{p\psi+(1-p)(1-\psi)}$, $u(b) = Pr^{Bayes}(G|p, b, \psi) := \frac{p(1-\psi)}{p(1-\psi)+(1-p)\psi}$.

In an *uncertain information* problem, the prior probability of G is still simple, but the accuracy

[22]This model is intended to provide a conceptual framework for my experiment where an event has at most two possible probabilities, and the two probabilities are presented symmetrically. It can be extended to settings with more than two probabilities and/or asymmetry, although the exact functional forms of such extensions are beyond the scope of this paper.

[23]For example, it generalizes the Maxmin expected utility preference (Gilboa and Schmeidler, 1989) and the α-maxmin expected utility preference (Olszewski, 2007). Similar two-parameter models have been proposed (Ellsberg, 2015; Chateauneuf et al., 2007) and fitted to data in experimental settings that are different from mine (Abdellaoui et al., 2011; Dimmock et al., 2015). In these models, agents face a continuum of possible probability distributions. Hence, the insensitivity parameter is often interpreted as capturing the range of distributions that agents deem possible. This interpretation does not fit my experimental setting as subjects are explicitly informed that an event has at most two possible probabilities.

of additional information is 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 states. 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:

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

The Bayesian EU agent will have the same conditional evaluations when the information is ambiguous if she treats the two accuracy levels symmetrically based on the principle of insufficient reason.

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. I will assume that the agent's uncertainty attitudes toward information accuracy fall in the class of ε-α-maxmin preferences. To see why the ε-α-maxmin model is applicable to the uncertain information problem, note that the event E in the general description of the model corresponds to the event "the information is correct," and the probability of this event is either ψ_h or ψ_l. In the rest of this section, I will analyze three major non-Bayesian belief-updating rules (see illustration in Figure 3.1). These three updating rules are most widely used in applied work, have clear psychological intuitions, and are the basic elements of many other rules.[24] 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 Appendix D.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

$$u(g) = Pr^{Bayes}(G|p, g, W(\psi_h, \psi_l; \varepsilon, \alpha))$$

and conditional on a bad report it is

$$u(b) = Pr^{Bayes}(G|p, b, W(\psi_l, \psi_h; \varepsilon, \alpha)).$$

These formulas can be derived from Eichberger et al. (2007) and they admit a simple interpretation. The agent behaves as if she perceives the information accuracy to be a weighted average of ψ_h, ψ_l and

[24] I study other updating rules (e.g. Klibanoff et al., 2009; Gul and Pesendorfer, 2018; Cheng and Hsiaw, 2018) in the 2020 version of this paper.

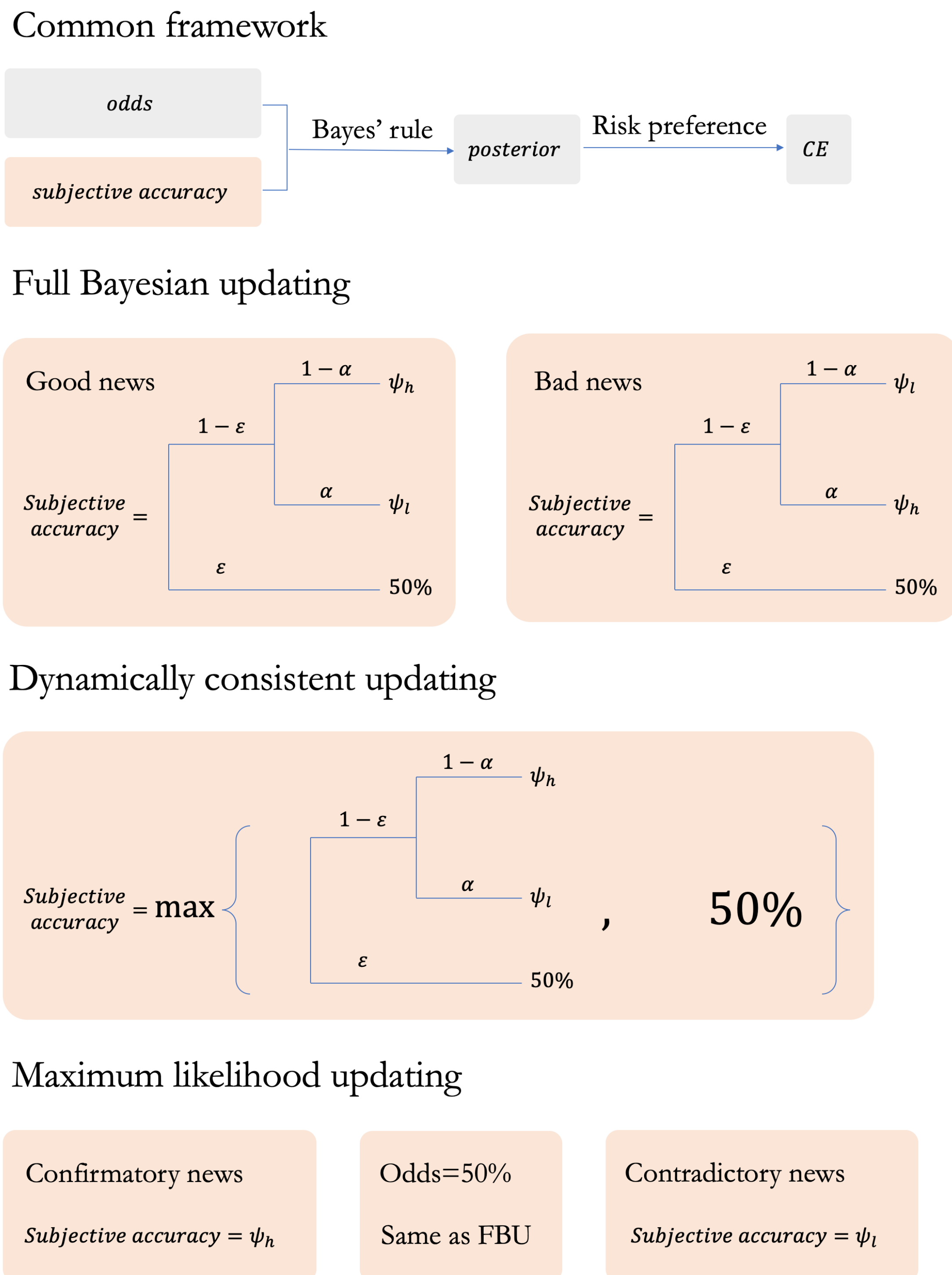

Figure 3.1: Illustration of theories of updating with uncertain information

50%, and she updates by applying Bayes' rule to the prior and the subjective accuracy. The weight on 50% is always ε, which is responsible for the degree of under-reaction to news. The rest of the weight is split between ψ_h and ψ_l, and their relative weights depend on which accuracy level leads to a more pessimistic Bayesian posterior *given the realized report*. Intuitively, an agent who is averse to uncertainty in information accuracy ($\alpha > 0.5$) worries that good reports' accuracy is low but bad reports have high accuracy. An extreme form of pessimism can occur if $(1-\alpha)\psi_h + \alpha\psi_l < 50\%$. In this case, even the evaluation conditional on a good report is (weakly) lower than the prior p.

The following proposition summarizes the predictions of Full Bayesian updating.

Proposition 1 *Suppose that an ε-α-maxmin agent uses Full Bayesian updating. In an uncertain information problem:*

1. *if $\varepsilon = 0$ and $\alpha = 0.5$, then her conditional evaluations coincide with the Bayesian evaluations conditional on simple information with accuracy level $\frac{\psi_h+\psi_l}{2}$;*
2. *as α increases, the conditional evaluations decrease;*
3. *as ε increases, the conditional evaluations become closer to p.*

3.2.2 Dynamically consistent updating

In an uncertain information problem, under Dynamically consistent updating (Hanany and Klibanoff, 2007), the evaluation of the bet conditional on report $m \in \{g, b\}$ is given by

$$u(m) = Pr^{Bayes}(G|p, m, \max\{W(\psi_h, \psi_l; \varepsilon, \alpha), 50\%\}).$$

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 share of the rest of the weight assigned to ψ_l is α so long as the subjective information accuracy is not lower than 50%.

The interpretation of this formula 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 uncertainty in information accuracy ($\alpha > 0.5$), then she will prefer to under-react to information so that her ex-ante payoff is less dependent on the realization of that uncertainty.

Proposition 2 *Suppose an ε-α-maxmin agent uses Dynamically consistent updating. In an uncertain information problem:*

1. *if $\varepsilon = 0$ and $\alpha = 0.5$, then the conditional evaluations coincide with the Bayesian evaluations conditional on information with accuracy level $\frac{\psi_h+\psi_l}{2}$;*
2. *as either ε or α increases, 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). Since reports that confirm the prior are more likely to be accurate than not, agents update too much to them. By a similar logic, they update too little to reports that go against the prior. Formally, if $p \neq 50\%$, then the evaluation of the bet conditional on a good report is given by

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

and conditional on a bad report it is

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

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 an ε-α-maxmin agent uses 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 $\frac{\psi_h+\psi_l}{2}$. 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

Consider an ε-α-maxmin agent whose uncertainty attitudes toward information accuracy fall in the typical range: $\varepsilon > 0$ and $\alpha > 0.5$. Taking Bayesian learning with the corresponding simple information as the benchmark, Table 3.1 summarizes the predictions of the updating rules that I have discussed so far. If $\varepsilon = 0$ and $\alpha = 0.5$, then all theories except Maximum likelihood updating coincide with the benchmark.

Theory	Aversion ($\alpha > 0.5$)	Insensitivity ($\varepsilon > 0$)
Full Bayesian updating	Pessimism	Under-reaction
Dynamically consistent updating	Under-reaction	Under-reaction
Maximum likelihood updating	$p \neq 50\%$: Confirmation bias (α and ε are irrelevant) $p = 50\%$: coincide with FBU	

Table 3.1: Summary of theoretical predictions in uncertain information problems

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: under-reaction, pessimism, and confirmation bias. The left panel of Figure 4.1 illustrates what each of these patterns implies about the comparisons between belief updating with simple and uncertain information. *Neutral news* is defined as reports whose (midpoint) accuracy is 50%, and *good (bad) news* as non-neutral news that says a bet will win (lose). Under-reaction and pessimism have the same directional predictions for good news but opposite ones for bad news. For neutral news, under-reaction predicts that uncertain information accuracy does not have an effect on posteriors, whereas pessimism predicts that posteriors conditional on uncertain information will be lower. The directional prediction of confirmation bias depends on the prior: the posteriors conditional on uncertain information are higher given high priors and lower given low priors.

Table 4.1 and the right panel of Figure 4.1 test these patterns by showing the CEs of bets with simple priors (henceforth *simple bets*) conditional on good news, bad news, and neutral news. Additional statistical tests – including within- and between-subject t-tests – can be found in Table C.4. 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 under-reaction and pessimism, but not consistent with confirmation bias.

For bad news, the mean CEs conditional on compound and ambiguous information are higher compared to simple information in three out of five comparisons, and they are slightly lower or mixed in the other two. Since under-reaction and pessimism generate opposite directional predictions for bad news, the results can be explained by a combination of the two.

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 combination of

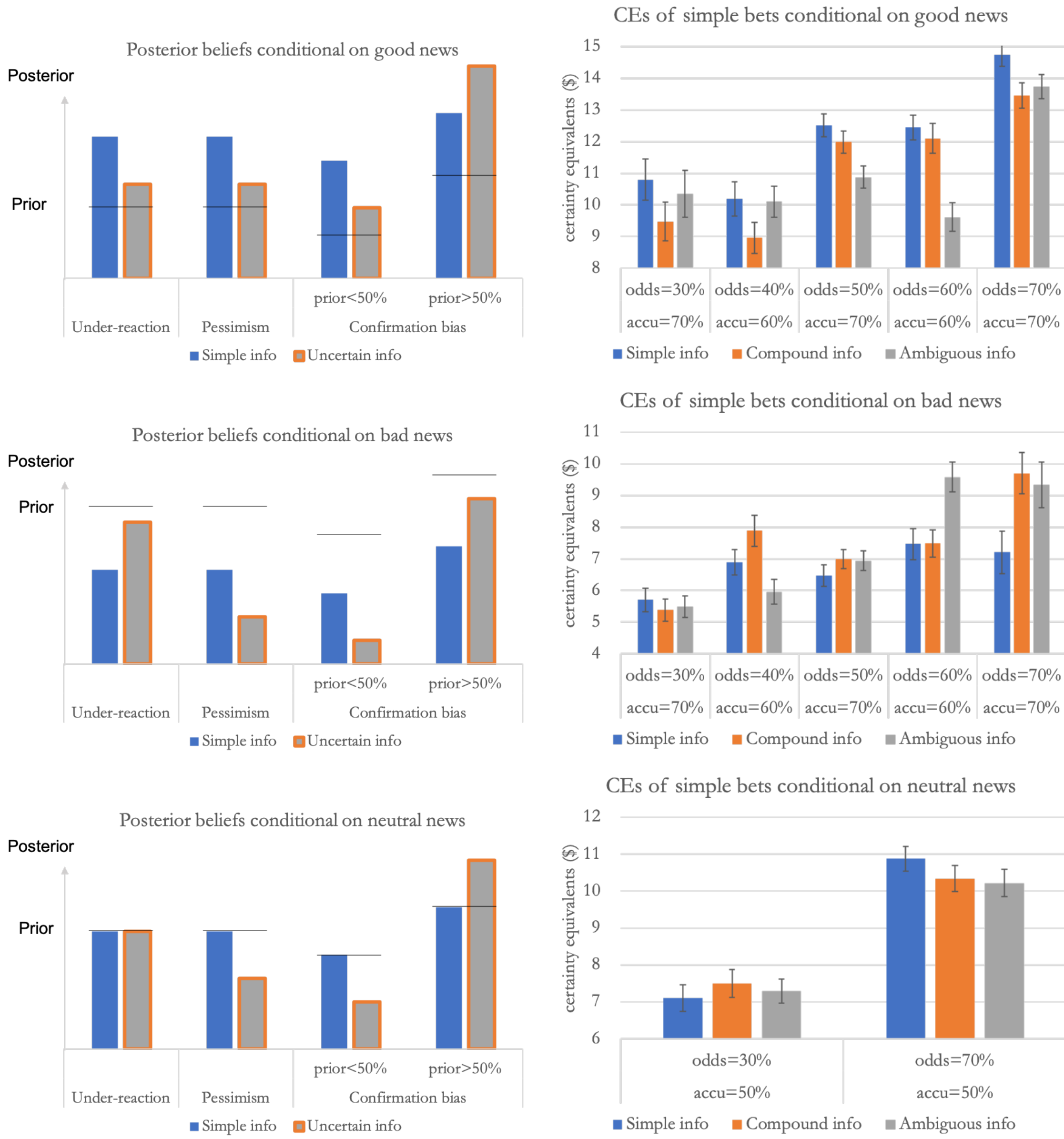

Figure 4.1: Simple priors with simple and uncertain information

Notes: The left panel of this figure illustrates what under-reaction, pessimism, and confirmation bias each predicts 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 non-neutral 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.

Prior	(Midpoint) Information accuracy	Good/Bad news	Type of information	Mean conditional CE	Standard error	N
30%	70%	good	simple	10.80	0.645	54
			compound	9.48	0.603	44
			ambiguous	10.35	0.739	47
40%	60%	good	simple	10.19	0.533	91
			compound	8.96	0.491	85
			ambiguous	10.10	0.490	60
50%	70%	good	simple	12.51	0.362	164
			compound	11.99	0.349	164
			ambiguous	10.88	0.346	165
60%	60%	good	simple	12.45	0.391	73
			compound	12.10	0.463	80
			ambiguous	9.61	0.452	105
70%	70%	good	simple	14.74	0.369	111
			compound	13.45	0.397	121
			ambiguous	13.74	0.381	118
30%	70%	bad	simple	5.70	0.368	111
			compound	5.38	0.355	121
			ambiguous	5.48	0.345	118
40%	60%	bad	simple	6.89	0.400	73
			compound	7.89	0.490	80
			ambiguous	5.95	0.390	105
50%	70%	bad	simple	6.47	0.345	165
			compound	6.99	0.306	163
			ambiguous	6.93	0.314	165
60%	60%	bad	simple	7.46	0.496	91
			compound	7.48	0.431	85
			ambiguous	9.58	0.474	60
70%	70%	bad	simple	7.20	0.672	54
			compound	9.70	0.651	44
			ambiguous	9.34	0.720	47
30%	50%		simple	7.10	0.361	163
			compound	7.50	0.374	164
			ambiguous	7.29	0.334	164
70%	50%		simple	10.88	0.336	163
			compound	10.34	0.349	164
			ambiguous	10.21	0.369	163

Table 4.1: Simple bets with additional information

Notes: This table compares the CEs of simple bets conditional on simple, compound and ambiguous information.

under-reaction and pessimism, but not with confirmation bias. Taken together, the empirical patterns resemble the prediction of Full Bayesian updating the most.

To further demonstrate the under-reaction 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-/over-reactors*, two pairs of mutually-exclusive categories, and then show that the former in each pair prevails.

First, I introduce some notations. Let $CE(p, m, \psi_h \text{ or } \psi_l)$ denote the conditional CE of a bet in an uncertain information round, where p is the prior of the bet, $m \in \{g, b\}$ indicates whether the report says that the bet will win or lose, and the third argument represents the possible accuracy levels of the information. Analogously, let $CE(p, m, \psi)$ be the conditional CE of a bet in a round with simple prior and simple information. Then, in an uncertain information round with non-neutral news, define the *uncertainty premium* of a bet as

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

Note that $Pm(p, m, \psi_h \text{ or } \psi_l)$ may be missing for some subjects because calculating it requires that $CE(p, m, \frac{\psi_h+\psi_l}{2})$ is available 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

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

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

Now I can define the categories, which are summarized in Table 4.2. A subject is an absolute pessimist in an uncertain information round if the uncertainty premiums of the two bets in this round are both weakly positive and at least one of them is strictly positive. Analogously, a subject is an absolute optimist if the two uncertainty premiums are both weakly negative and at least one is strictly negative.

In an uncertain information round where the midpoint information accuracy is not 50%, if a subject's uncertainty premium for the bet that the report says will win is weakly positive, her uncertainty premium for the other bet is weakly negative, and at least one of the two is not zero, then I call this subject an absolute under-reactor. By contrast, if the bet that the report says will win has a weakly negative uncertainty premium, the other one has a weakly positive premium, and at least one is not zero, then this subject is called an absolute over-reactor. In rounds with neutral news, I do not classify subjects into these two categories.

Table 4.3 shows the percentages of each category in each uncertain information round. In every round, there are more absolute under-reactors than absolute over-reactors. In all but one rounds, there are more absolute pessimists than absolute optimists. In aggregate, the percentage of absolute

	Uncertainty premium	Bet that the report says will win: +	Bet that the report says will win: -
Bet that the report says will lose	+	Absolute pessimist	Absolute over-reactor
	-	Absolute under-reactor	Absolute optimist

Table 4.2: Classification of subjects in an uncertain information round

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 non-zero. For rounds with neutral information, I do not classify subjects as absolute over-/under-reactors.

under-reactors is significantly higher for both compound and ambiguous information rounds. The aggregate percentage of absolute pessimists is also higher than that of absolute optimists, and the difference is significant for ambiguous information rounds.[25]

In summary, my experimental results show that uncertainty in information accuracy leads to under-reaction and pessimism. These two patterns are most consistent with the prediction of uncertainty-induced insensitivity and uncertainty aversion together with Full Bayesian updating.

[25]In Appendix C.1, I consider two alternative categories: absolute confirmation bias and absolute contradiction bias. These two categories overlap with absolute over-/under-reactors, as an absolute over-reactor 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 uncertainty in information accuracy does not lead to prevalent confirmation bias.

Prior (Red, $Blue$)	Midpoint Information accuracy	Type of information	Absolute pessimists	Absolute optimists	p-value %(Abs. pess.) =%(Abs. opt.)	Absolute under-reactors	Absolute over-reactors	p-value %(Abs. under.) =%(Abs. over.)	N
(50%, 50%)	70%	Ambiguous	31.5%	19.4%	0.029	44.2%	18.2%	0	165
(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	25.5%	19.7%	0.31	-	-	-	137
Aggregate		Ambiguous	28.5%	20.1%	0.01	43.0%	18.5%	0	
(50%, 50%)	70%	Compound	21.2%	25.5%	0.425	43.0%	22.4%	0.001	165
(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	27.7%	19.7%	0.172	-	-	-	137
Aggregate		Compound	25.6%	21.5%	0.164	40.4%	24.1%	0	

Table 4.3: Classification of subjects in each uncertain information round

Notes: This table shows the percentages of subjects that 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.

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 states. 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 states (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.

In Sections 5.1 and 5.2, I study uncertainty attitudes toward priors by comparing CEs of bets with uncertain priors (henceforth *uncertain bets*) to CEs of simple bets. Then, in Section 5.3, I assume that uncertainty attitudes toward priors and information accuracy both fall in the class of ε-α-maxmin preferences, and I estimate and compare the ε's and α's using a representative-agent model. In Section 5.4, I study the subject-level correlation between uncertainty attitudes toward priors and information accuracy.

5.1 Evaluating uncertain bets with no updating

In this section, I compare subjects' evaluations of uncertain bets and simple bets, both without any analyst report. The comparison shows that subjects' uncertainty attitudes toward priors exhibit uncertainty aversion and uncertainty-induced insensitivity, just like their attitudes toward information accuracy.

To use a similar theoretical framework as in Section 3, consider an agent choosing between a bet and a certain amount of utils. There are two payoff-relevant states, G and B. The bet pays out 1 util if G occurs and 0 util otherwise. If the probability of G is known to be p, then a standard EU agent will evaluate the bet by $u = p \cdot 1 + (1 - p) \cdot 0 = p$. If the state G has a compound probability, i.e. its probability is either p_h or p_l, each with equal chance, then a standard EU agent will evaluate the bet by $u = \frac{p_h+p_l}{2}$. The same evaluation also applies to the case of ambiguous probability if a standard EU agent treats p_h and p_l symmetrically under the principle of insufficient reason.

By contrast, if an agent's uncertainty attitudes toward priors are captured by an ε-α-maxmin

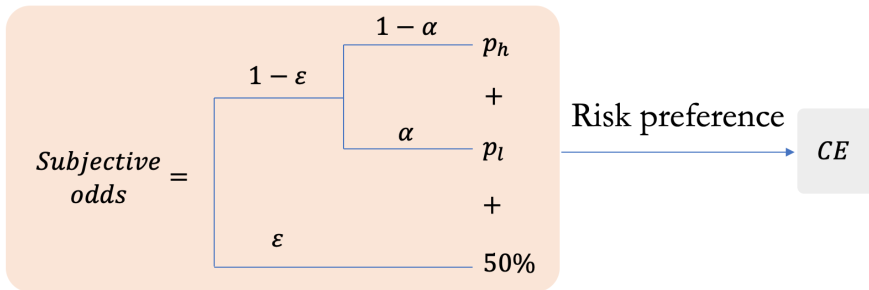

Figure 5.1: Illustration of the ε-α-maxmin preference

Notes: The figure illustrates how an ε-α-maxmin agent forms the CE of a bet with uncertain odds. Similar to a standard EU agent, she behaves as if she forms a subjective odds of the bet and then applies her risk preference to form the CE. Unlike a standard EU agent, the subjective odds of an ε-α-maxmin agent is a weighted average between p_h, p_l, and 50%.

preference, then she evaluates the uncertain bet by

$$u = W(p_h, p_l; \varepsilon, \alpha)$$

and applies her risk preference to translate utils to CEs (see illustration in Figure 5.1).

Figure 5.2 and Table 5.1 show the CEs of simple, compound and ambiguous bets in Parts 1 and 4 of my experiment where subjects do not receive additional information.[26] The mean CEs of simple bets are lower than their expected values except when the odds of winning is 30%. This is consistent with Prospect Theory (Kahneman and Tversky, 1979).

My main focus in this section, however, is on the comparison between CEs of uncertain bets and simple bets. The mean CEs of uncertain bets are lower than their simple counterparts for medium and high odds. Nevertheless, the gaps vanish for bets with low odds (30% for ambiguous bets, 30% and 40% for compound bets), indicating that the evaluations of uncertain bets are less sensitive to the winning odds than those of simple bets. These patterns confirm that the subjects' uncertainty attitudes toward priors exhibit uncertainty aversion and uncertainty-induced insensitivity,[27] just like their uncertainty attitudes toward information accuracy.

[26] Since the red and blue bets in a (50%, 50%) horse race are both bets with a 50% chance of winning, I take the average of the CEs of the two bets to be the CE of a 50% odds bet. In the simple round whose prior is (50%, 50%) and in its two corresponding uncertain rounds, 82% of the subjects report the same CE for the red and blue bets, which is in line with results in previous studies. See Table C. VI of Chew et al. (2017) for a meta-study. Moreover, the deviations from color neutrality are not significantly different from zero.

[27] For similar empirical patterns, see Abdellaoui et al. (2011, 2015); Dimmock et al. (2015); Baillon et al. (2018); Anantanasuwong et al. (2019).

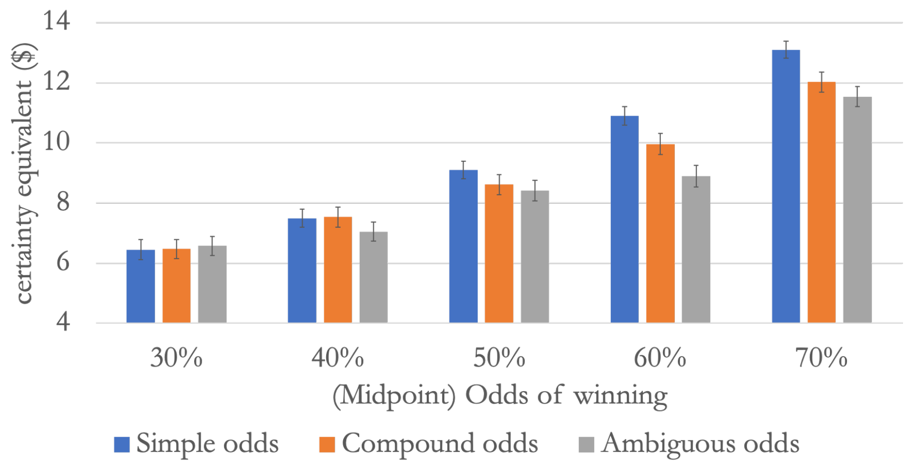

Figure 5.2: CEs of bets without additional information

Notes: The figure shows the mean CEs of bets without belief updating. Each group of bars represents the three tasks that share the same (midpoint) odds of winning. Error bars represent +/- one standard error.

(Midpoint) Odds of winning	Type of bet	Mean CE	Standard error	N
30%	simple	6.45	0.330	165
	compound	6.47	0.321	165
	ambiguous	6.57	0.313	165
40%	simple	7.49	0.300	165
	compound	7.53	0.331	165
	ambiguous	7.05	0.310	164
50%	simple	9.10	0.293	162
	compound	8.61	0.335	164
	ambiguous	8.41	0.343	163
60%	simple	10.89	0.308	165
	compound	9.96	0.355	165
	ambiguous	8.90	0.359	164
70%	simple	13.09	0.282	165
	compound	12.02	0.327	165
	ambiguous	11.53	0.333	165

Table 5.1: Bets without additional information

Notes: This table compares the mean CEs of bets with simple, compound and ambiguous odds without additional information. The last two columns are p-values for two-sided paired t-tests.

5.2 Evaluating uncertain bets with updating

While the experimental tasks used to illustrate uncertainty attitudes toward information accuracy feature belief updating, those analyzed in Section 5.1 do not. To control for belief updating, I also study uncertainty attitudes toward priors by comparing evaluations of uncertain bets and simple bets after subjects update in response to simple information. I briefly summarize the theoretical framework and experimental results in this section and relegate the details to Appendix A.

In an *uncertain prior* problem, the prior probability of G is either p_h or p_l with $p_l < p_h$, but the accuracy of additional information is known to be $\psi \geq 50\%$. A Bayesian EU maximizer would evaluate the bet by $u(m) = Pr^{Bayes}(G|(p_h + p_l)/2, m, \psi)$ after report m realizes. On the other hand, an ε-α-maxmin agent's evaluation would be

$$u(m) = Pr^{Bayes}(G|W(p_h, p_l; \varepsilon, \alpha), m, \psi)$$

under both Full Bayesian updating and Dynamically consistent updating. In this formula, the uncertainty-induced insensitivity parameter ε is responsible for the degree of under-weighting of priors ("base-rate neglect"), and the uncertainty aversion parameter α corresponds to pessimism.

Under Maximum likelihood updating, the conditional evaluations are $u(g) = Pr^{Bayes}(p_h, g, \psi)$ for good news and $u(b) = Pr^{Bayes}(p_l, b, \psi)$ for bad news. This leads to over-reaction to news. For neutral news ($\psi = 50\%$), Maximum likelihood updating coincides with the other two updating rules.

In the experiment, posterior beliefs are more pessimistic if the priors are uncertain. This pattern is demonstrated both by comparing average conditional CEs of uncertain and simple bets and through subject classification. However, I do not find evidence of either under-weighting of priors or over-reaction to news. The overall result is in line with the prediction of Full Bayesian updating and Dynamically consistent updating coupled with uncertainty aversion toward priors.[28]

5.3 Aggregate-level comparison between different kinds of uncertainty attitudes

In the previous sections, I have shown how different kinds of uncertainty directionally affect CEs of bets in a variety of comparisons. In order to obtain a quantitative comparison between uncertainty attitudes toward information accuracy and priors, I build a representative-agent model based on the

[28] One potential reason for why we do not find evidence of under-weighting of priors when priors are uncertain is that even when priors are simple, base-rate neglect is already quite severe (see Section B.2). As a result, there may not be sufficient room for additional base-rate neglect to be detected when priors become uncertain.

ε-α-maxmin preferences and Full Bayesian updating, and I structurally estimate the ε and α for each kind of uncertainty attitudes using the experimental data. The model also needs to specify ancillary components of decision-making such as the risk preference and inherent deviations from Bayesian updating that are unrelated to uncertain information accuracy or uncertain priors. These specifications have to be undertaken with care to ensure that the estimated ε's and α's indeed capture the *marginal effects* of uncertainty on insensitivity and pessimism. For example, an agent may already display under-reaction and asymmetric updating even when both the prior and the information accuracy are simple. To allow for these possibilities, the model assumes that instead of applying Bayes' rule to (subjective) priors and (subjective) information accuracy, the representative agent uses the *generalized Bayes' rule* which has three parameters corresponding to the under-/over-weighting of priors, good reports, and bad reports (Möbius et al., 2014). Analogously, for risk attitude, the agent uses Prelec (1998)'s two-parameter function to map (subjective) winning odds of bets to their CEs, which allows for risk aversion/pessimism and insensitivity. Details of the model are provided in Appendix B.

I estimate the representative-agent model using the non-linear least squares method.[29] Table 5.2 shows the estimates of uncertainty attitudes and the rest of the estimates are relegated to Appendix B. The numbers have simple interpretations. For example, the row corresponding to compound information accuracy states that the representative subject neglects 11% of the content of compound information. Moreover, she over-weights (under-weights) the high accuracy by $53\% - 47\% = 6\%$ relative to the low accuracy when the realized report is bad (good). There are several salient patterns in Table 5.2. First, for both uncertain priors and uncertain information, the more pessimistic possibility receives a higher weight than the more optimistic one. This pattern holds for both compound uncertainty and ambiguity, which suggests that uncertainty of all types consistently leads to pessimism. In addition, ambiguity induces more pessimism than compound uncertainty. Second, the estimates of ε's are positive and significant. Finally, the estimates of α are larger for uncertainty in priors than for uncertainty in information accuracy, but the differences are small and insignificant. Similarly, there is no systematic and significant difference between estimates of ε across different kinds of uncertainty.

Overall, the estimates of the representative-agent model confirms the descriptive results that at the aggregate level, uncertainty attitudes toward information accuracy and uncertainty attitudes toward priors both feature insensitivity and uncertainty aversion.[30]

[29] Specifically, this procedure finds the parameters that minimize the sum of squared differences between the CE of a bet in the data and that generated by the empirical model. The sum is taken over tasks and subjects.

[30] In Appendix C, I show results of the structural estimation by the order between experimental parts. In the 2020 version of this paper, I also estimate two alternative models. In one model, the weight on (50%, 50%)

Type of uncertainty		α uncertainty aversion/pessimism	ε insensitivity/under-reaction
Info accuracy	Compound	0.53 (0.51 to 0.56)	0.11 (0.03 to 0.18)
	Ambiguous	0.58 (0.55 to 0.61)	0.18 (0.09 to 0.27)
Priors	Compound	0.56 (0.53 to 0.59)	0.11 (0.04 to 0.19)
	Ambiguous	0.60 (0.57 to 0.63)	0.10 (0.00 to 0.19)

Table 5.2: Aggregate estimates of uncertainty attitudes

Notes: All parameters are assumed to be homogeneous among subjects. 95% confidence intervals are in the parentheses, which are computed by a bootstrap clustered at the subject level. The model is estimated using non-linear least squares.

5.4 Individual-level relationship between uncertainty attitudes toward priors and information accuracy

The results so far have shown that uncertainty attitudes toward information accuracy and priors are similar in the aggregate. However, in order to determine whether they manifest the same behavioral trait, we need to investigate their correlations at the individual level. If such correlations are strong and significant, then we can rather safely use knowledge about an agent's attitude toward one kind of uncertainty to make predictions about her attitudes toward the others; otherwise, extrapolation is not warranted and we would need to study them separately.[31]

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. For example, suppose that an ε-α-maxmin subject exhibits under-reaction 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 focus attention on tests of correlation that are valid under ε-α-maxmin preferences and all three updating rules considered so far.[32] I informally describe these tests below and present the results. Details about their theoretical derivation and implementation can be found in Appendix E.

One such test is based on the following property of the ε-α-maxmin preferences. Suppose

scales with $p_h - p_l$. In the other, the baseline probability on which the agent puts ε weight is a free parameter. The empirical patterns remain robust in these variants.

[31]See Appendix F for a similar individual-level analysis of the relationship between compound and ambiguity attitudes.

[32]I show that these tests are also valid under many other models in the 2020 version of the paper.

that an agent's uncertainty attitudes toward priors and information accuracy both follow the same ε-α-maxmin preference. Then, if her CE of a simple bet with 70% odds is higher than that of its corresponding uncertain bet (odds = 90% or 50%), she must also evaluate a 50% odds simple bet higher after hearing a 70%-accurate simple good news than after hearing the corresponding uncertain good news (accuracy = 90% or 50%). The converse is also true. To see why this one-to-one mapping between the two CE comparisons holds, note that under the same ε-α-maxmin preference and any of the three updating rules, both comparisons boil down to comparing 70% and $W(90\%, 50\%; \varepsilon, \alpha)$. As a result, the prevalence of this one-to-one mapping in the data can serve as a measure of the similarity between the two kinds of uncertainty attitudes at the individual level.

I compute the correlation between the directions of the aforementioned two CE comparisons using the experimental data. The coefficient is 0.08 (p-value = 0.28) for compound uncertainty and 0 (p-value = 0.99) for ambiguity. These results suggest that uncertainty attitudes toward priors and information accuracy are not similar on the individual level.

There are three potential objections to this interpretation of the results. First, the CEs in the first comparison are unconditional while those in the second one 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-value = 0.97) for compound uncertainty and 0.03 (p-value = 0.71) for ambiguity. Second, one may worry that the noise in the data might dilute any correlations and render 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-value = 0.05) for compound bets and 0.26 (p-value = 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 Appendix E.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.

6 Suggestive evidence from the stock market

In this section, I complement the experimental results with evidence from the US stock markets. Consistent with the lab findings, I show that stock prices react less sufficiently to analyst earnings forecasts with more uncertain accuracy. In addition, the decrease in reaction sufficiency only occurs for good news, but 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 houses hire financial analysts to conduct research on publicly-traded companies and issue forecasts on their earnings. A large body of literature in accounting and finance has studied the information content of analysts' forecasts, the market reactions to them, and the factors that affect the sufficiency of these reactions (Kothari et al., 2016). A key challenge in studying unknown information sources in this setting is that I do not observe the exact degree of uncertainty that investors perceive about the accuracy of each analyst forecast. In light of this issue, I will 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. The validity of this proxy is supported by previous studies on the persistence and predictability of analyst forecast accuracy. I will use this proxy while controlling for a variety of forecast, analyst and stock attributes as well as environmental factors.

In Appendix G.1, I adapt the model with ε-α-maxmin preferences and Full Bayesian updating to a setting of stock investment. When the accuracy of an earnings forecast is uncertain, the reaction of the earnings expectation of an investor with typical uncertainty attitudes ($\varepsilon > 0$ and $\alpha > 0.5$) will be insufficient and biased downward. To the extent that stock price movement reflects the change in investors' earnings expectations, the stock price reactions to forecasts with uncertain accuracy will exhibit the same patterns.

To empirically test the theoretical predictions, I use 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 firm characteristics from Compustat. I require stocks to be common shares (share codes 10 or 11) on the AMEX, NYSE, or NASDAQ (exchange codes 1, 2, or 3), and I exclude stocks with prices lower than \$1 or market capitalization smaller than \$5 million. I restrict attention to earnings forecasts for quarters between January 1, 1994 and June 30, 2019,[33] but in order to construct analyst characteristics such as experience, I use data dated back to January 1, 1984.

To measure the sufficiency of the market's reactions to analysts' forecasts, I calculate the correlation between the immediate price reactions and the price drifts that ensue, following the tradition in

[33] 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.

macro, finance, and accounting. Intuitively, if immediate price reactions are on average followed by drifts in the same (opposite) direction, then the immediate reactions must be insufficient (excessive). The immediate price reaction to an earnings forecast is measured as the stock's size-adjusted returns[34] in the [-1,1]-trading day window centered on the forecast release, and the drift is the size-adjusted returns in the [2,64]-trading day period (which is roughly three months). To mitigate the confounds of other news events in the immediate reaction window, I only include observations where there is neither earnings announcement from the company nor earnings forecast announcements by any other analyst on the same company on the forecast announcement day. Moreover, I restrict attention to forecast revisions, which can be naturally classified into good news and bad news. Following Gleason and Lee (2003), I define good news as an upward revision, which is a forecast that is higher than the issuing analyst's previous forecast on the same quarterly earnings. Analogously, bad news is defined as a downward forecast revision. This leaves us with a final sample of 1,025,823 forecasts issued by 12,815 analysts on 10,712 stocks.

To proxy for the uncertainty of an analyst's forecast accuracy for a stock, I look at whether the analyst has a forecast record for that stock. At a point in time, an analyst has a forecast record for a stock if she has issued a quarterly earnings forecast on this stock before *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 predicts future accuracy better than many other analyst attributes (Brown, 2001; Hilary and Hsu, 2013), and investors learn about an analyst's forecast accuracy from her forecast record (Chen et al., 2005). I will henceforth refer to forecasts issued by analysts without (stock-specific) forecast records as "no-record forecasts" and the rest as "with-record forecasts."

In addition to the uncertainty in accuracy, no-record and with-record forecasts also differ in other dimensions. Table G.3 provides summary statistics for a variety of characteristics of the forecasts, the issuing analysts, the stocks covered, and the information environment.[35] Variable definitions can be found in Table G.2. No-record forecasts on average 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. The analysts without past records follow fewer stocks and industries. All variables in Table G.2 are included in the regressions.

Descriptive results show clear patterns that support the hypotheses. Figure 6.1 plots the average (size-adjusted) returns from one trading day before the forecast announcement to one trading day,

[34]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.

[35]Table G.4 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.

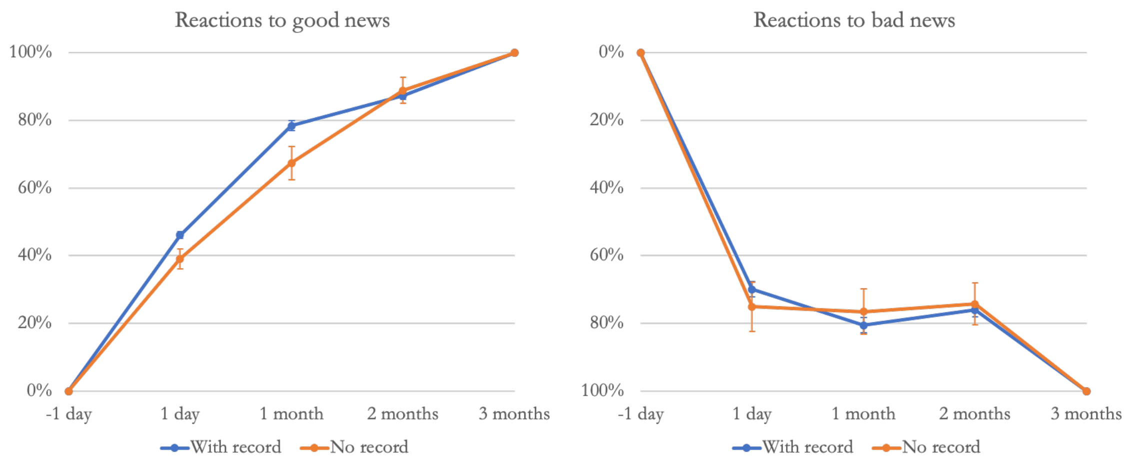

Figure 6.1: Reactions to forecast revisions

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.

one month, and two months after the forecast announcement, normalized by the average three-month returns. For good news, the one-day, one-month and two-month reactions are less sufficient for no-record forecasts. By contrast, for bad news, there is almost no difference in sufficiency between reactions to no-record and with-record forecasts. These results suggest that investors react insufficiently and pessimistically to no-record forecasts.[36]

The main specification of the regression analysis is as follows.

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

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, and $Ret[-1,1]_i$ is the immediate price reaction to forecast i. The indicator variable $NoRecord_i$ equals one if forecast i is a no-record forecast, and the variable equals zero otherwise. Following Gleason and Lee (2003), I define $GoodNews_i = 1$ if forecast i is an upward revision from the last forecast issued by the same analyst on the same stock's quarterly

[36]The summary statistics for unnormalized returns in windows with different lengths are in Table G.1.

earnings, and $GoodNews_i = 0$ if the forecast is a downward revision. I include controls on the characteristics of the forecast, the issuing analyst, the stock covered, and the information environment (see Table G.2), as well as their interactions with $Ret[-1, 1]$. I also include year-quarter dummies to control for unobserved time fixed effects on returns. In view of the descriptive results that immediate stock price reactions to no-record forecasts are less sufficient especially for good news, we expect the coefficient on the triple interaction, η_7, to be positive.

Table 6.1 shows the results from the regression analysis. Across the four specifications that differ on the set of controls and fixed effects, the coefficients on $NoRecord \times Ret[-1, 1]$ and $NoRecord$ are small and insignificant, suggesting that whether the issuing analyst of a forecast has a past record does not affect the sufficiency of immediate stock price reactions for bad news. By contrast, 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 are more insufficient and pessimistic.

In Appendix G.3, I examine the robustness of the regression results. In Table G.5, I show that the signs of the coefficients are robust to changing the price drift window of the left-hand side variable in Specification (1). The effect sizes tend to increase as the drift window becomes longer, suggesting that the insufficiency of the immediate reactions are gradually corrected. Table G.6 shows the regression results for different cuts of the data. The results are robust when I only consider "high-innovation" forecast revisions, "isolated" forecasts, and forecasts announced after January 1, 2004.[37] The main effect appears not 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 > \$10 billion), which may be due to the high concentration of sophisticated investors in those stocks and their low transaction costs. I also consider a specification that includes the interactions between

[37]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 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).

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	1001418	1001417	894004	894004
R^2	0.001	0.010	0.004	0.014

Table 6.1: Sufficiency of stock market reactions to forecast revisions

Notes: This table reports the results of Regression (1). 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 G.2. Three-dimensional (stock, analyst, year-quarter) cluster-robust standard errors in parentheses. $\dagger p < 0.10, *p < 0.05, **p < 0.01, ***p < 0.001$

year-quarter dummies and $Ret[-1,1]$, and the results remain robust. Table G.7 reports the results of regressions that replace $Ret[-1,1]$ and its interactions terms in Specification (1) with $Revision$ and its interactions 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 price reactions to earnings forecasts are less sufficient if they are issued by analysts with no forecast record. This phenomenon only happens for good news but not for bad news. These results corroborate the experimental finding that uncertainty in information accuracy leads to under-reaction to news and pessimism.

7 Conclusion

This paper studies the effects of uncertainty in information accuracy on belief updating using a controlled lab experiment and observational data from the stock market. In the experiment, a mean/midpoint preserving spread in the information accuracy leads to subjects reacting less to the information. Moreover, the under-reaction is more pronounced for good news than for bad news. The same two patterns also emerge in the stock market. I show that stock prices under-react more to earnings forecasts issued by analysts with no proven forecast record, and the under-reaction only occurs for good news but not for bad news. I examine the predictions of a wide variety of theories and find that 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. Both descriptive analysis and structural estimation show that uncertainty in priors leads to pessimism, and in problems without belief updating it also induces insensitivity. Although the aggregate effects of uncertain information accuracy and uncertain priors are mostly similar in magnitudes, 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 knowing a person's attitude toward assets with unknown fundamentals does not help to predict her 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 non-financial concerns such as ideology and ego utility. Second, as belief updating is closely linked to demand for information (Ambuehl and Li, 2018), what are the determinants of demand for uncertain information? Third, as this paper shows 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 uncertain information source are not only relevant for the payoff-relevant states but also inform 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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A Details on belief updating with uncertain priors

In this section, I present the theories and experimental evidence on belief updating with uncertain priors in detail.

A.1 Theories

In an *uncertain prior* problem, the prior probability of G is either p_h or p_l with $p_l < p_h$, but the accuracy of additional information is known to be $\psi \geq 0.5$. As in the previous section, I will apply several belief-updating rules to the ε-α-maxmin model and compare their predictions in uncertain prior problems. Proofs of results in this subsection can be found in Appendix D.2.

A.1.1 Full Bayesian updating

Under Full Bayesian updating, an ε-α-maxmin agent behaves as if the prior is a weighted average of p_h, p_l and 50%, and updates accordingly in a Bayesian manner. The weight ε is always applied to 50%, and the rest of the weight, $1 - \varepsilon$, is split between p_h and p_l. Since p_l always leads to a more pessimistic posterior than p_h regardless of the realized report, the former will receive α proportion of the rest of the weight. Hence, the Full Bayesian evaluation conditional on report $m \in \{g, b\}$ is

$$u(m) = Pr^{Bayes}(G|W(p_h, p_l; \varepsilon, \alpha), m, \psi).$$

The insensitivity parameter ε is responsible for the degree of under-weighting of priors in belief updating, and the aversion parameter α corresponds to pessimism.

The following proposition summarizes the predictions of Full Bayesian updating in uncertain prior problems.

Proposition 4 *Suppose that an ε-α-maxmin agent uses Full Bayesian updating. In an uncertain prior problem:*

1. *if $\varepsilon = 0$ and $\alpha = 0.5$, then her conditional evaluations coincide with the Bayesian conditional evaluations given a simple prior $\frac{p_h+p_l}{2}$;*
2. *as α increases, the conditional evaluations decrease;*

3. *as ε increases, the evaluation conditional on a good report becomes closer to ψ and that conditional on a bad one becomes closer to $1 - \psi$.*

A.1.2 Dynamically consistent updating

In an uncertain prior problem, the conditional evaluations under Dynamically consistent updating are the same as those under Full Bayesian updating. Under Dynamically consistent updating, an agent who is averse to uncertainty ($\alpha > 0.5$) prefers to make choices so that her ex-ante payoff is less dependent on the realization of that uncertainty. When the uncertainty is in priors, mitigating ex-ante payoff exposure to uncertainty requires refraining from taking the bet. This coincides with Full Bayesian updating under which an uncertainty averse agent tries to mitigate ex-post payoff exposure to uncertainty. The following proposition summarizes the results.

Proposition 5 *In an uncertain prior problem, Dynamically consistent updating has the same predictions as Full Bayesian updating for an ε-α-maxmin agent.*

A.1.3 Maximum likelihood updating

In uncertain prior problems, the prior(s) that is most likely to generate the realized report is selected and updated under Maximum likelihood updating. Since good news is more likely to be generated from high priors and bad news from low priors, agents will over-react to news. Formally, if $\psi \neq 50\%$, then the evaluation of the bet conditional on a good report is given by

$$u(g) = Pr^{Bayes}(p_h, g, \psi)$$

and that conditional on a bad one is

$$u(b) = Pr^{Bayes}(p_l, b, \psi).$$

If $\psi = 50\%$, then the conditional evaluations coincide with Full Bayesian updating.

The following proposition summarizes the properties of Maximum likelihood updating.

Proposition 6 *Suppose an ε-α-maxmin agent uses Maximum likelihood updating. In an uncertain prior problem:*

1. *if $\psi \neq 50\%$, the conditional evaluations of the bet exhibit over-reaction relative to those given the simple prior $\frac{p_h+p_l}{2}$. The measures of uncertainty attitudes, ε and α, do not affect the conditional evaluations.*

Theory	Aversion ($\alpha > 0.5$)	Insensitivity ($\varepsilon > 0$)
Full Bayesian updating & Dynamically consistent updating	Pessimism	Under-weighting of priors
Maximum likelihood updating	$\psi \neq 50\%$: Over-reaction to news (α and ε are irrelevant) $\psi = 50\%$: coincide with FBU	

Table A.1: Summary of theoretical predictions in uncertain prior problems

2. *if $\psi = 50\%$, conditional evaluations under Maximum likelihood updating coincide with those under Full Bayesian updating.*

A.1.4 Summary of theoretical implications

Consider an ε-α-maxmin agent whose attitudes toward uncertain priors fall in the typical range: $\varepsilon > 0$ and $\alpha > 0.5$. Taking Bayesian learning with the corresponding simple prior as the benchmark, Table A.1 summarizes the predictions of the three updating rules I have discussed so far. The left panel of Figure A.1 illustrates what the three main predictions, under-weighting of priors, pessimism, and over-reaction to news, each implies about the comparisons between belief updating with simple and uncertain priors.

If $\varepsilon = 0$ and $\alpha = 0.5$, then all theories except Maximum likelihood updating coincide with the benchmark.

A.2 Experimental results

Table A.2 and the right panel of Figure A.1 show the CEs of simple, compound and ambiguous bets conditional on simple information. Additional statistical tests – including within- and between-subject t-tests – are in Table A.5. Among the twelve combinations of prior and information accuracy, the mean conditional CE given the compound prior is lower than its simple counterpart in eight comparisons, and the mean conditional CE given the ambiguous prior is lower in seven comparisons. This suggests – albeit not strongly – that uncertain priors lead to pessimism in the conditional CEs. There is no clear pattern of either under-weighting of priors or over-reaction to news.

Similar as in the comparison between simple information and uncertain information, I define *absolute pessimists/optimists* and *absolute prior under-/over-weighters* for each uncertain prior round, and then compare their relative prevalence.

In an uncertain prior round, if the prior of a bet might be either p_h or p_l, the realized report is $m \in \{g, b\}$, and the information accuracy ψ is not 50%, then define the uncertainty premium of this

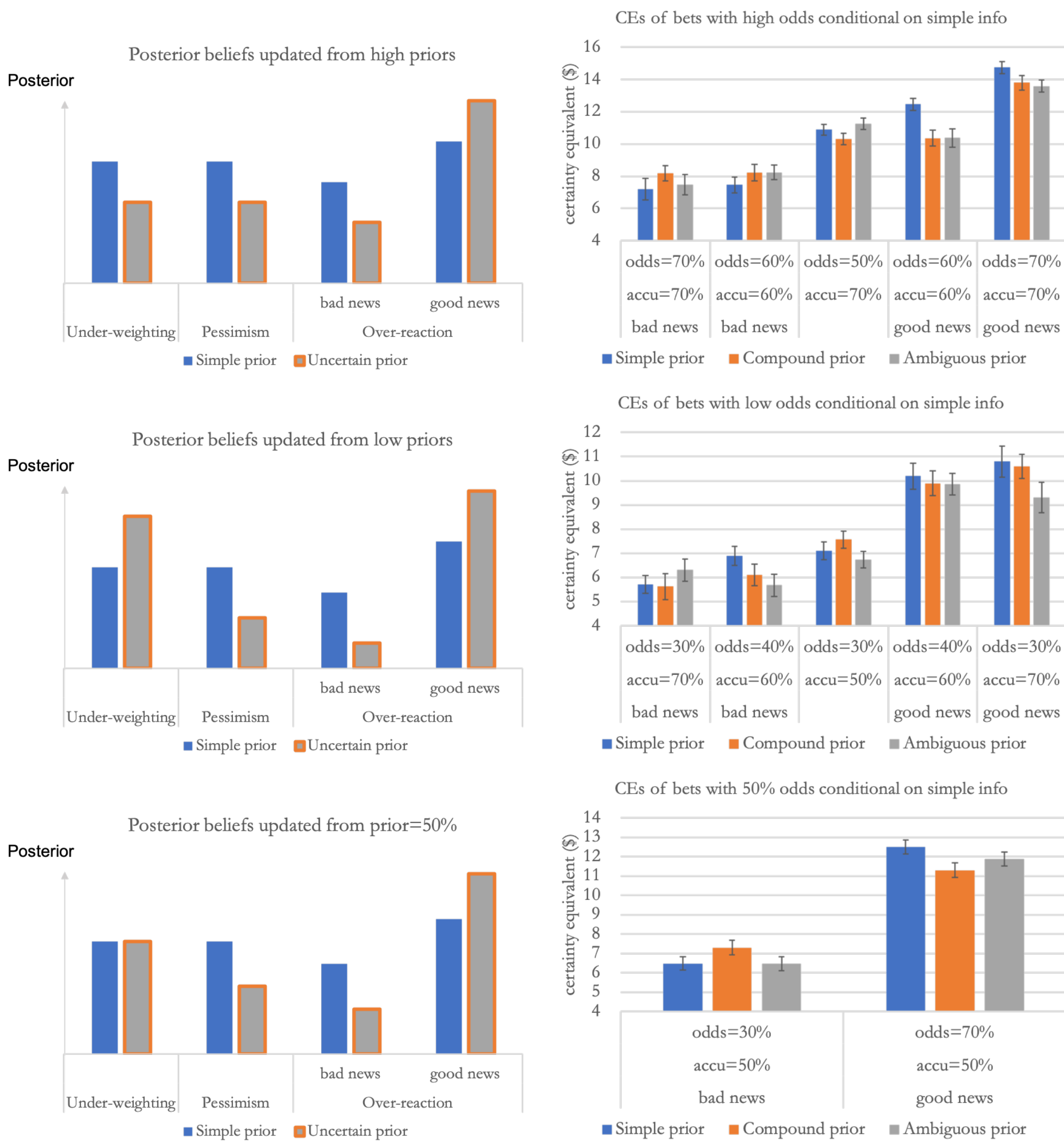

Figure A.1: Simple and uncertain priors with simple information

Notes: The left panel of this figure illustrates what under-weighting of priors, pessimism, and over-reaction to news each predicts about the comparisons between belief updating with simple and uncertain priors (high, low, and medium priors refer to priors that are higher, lower, and equal to 50%). The right panel compares the mean CEs of simple, compound, and ambiguous bets conditional on simple information in the experiment. Each group of bars correspond to a combination of prior and information. For example, "odds=70%, accu=70%, bad news" in the upper right graph represents tasks where the (midpoint) prior is 70% and the information is bad news with 70% accuracy. Error bars represent +/- one standard error.

(Midpoint) Prior	Information accuracy	Good/Bad news	Type of prior	Mean conditional CE	Standard error	N
30%	70%	bad	simple	5.70	0.368	111
			compound	5.62	0.529	71
			ambiguous	6.30	0.449	106
40%	60%	bad	simple	6.89	0.400	73
			compound	6.10	0.443	89
			ambiguous	5.68	0.464	74
30%	50%		simple	7.10	0.361	163
			compound	7.56	0.349	164
			ambiguous	6.74	0.341	165
40%	60%	good	simple	10.19	0.533	91
			compound	9.89	0.502	76
			ambiguous	9.85	0.446	89
30%	70%	good	simple	10.80	0.645	54
			compound	10.59	0.501	94
			ambiguous	9.31	0.642	59
70%	70%	bad	simple	7.20	0.672	54
			compound	8.17	0.472	94
			ambiguous	7.47	0.617	59
60%	60%	bad	simple	7.46	0.496	91
			compound	8.21	0.499	76
			ambiguous	8.22	0.445	89
70%	50%		simple	10.88	0.336	163
			compound	10.31	0.363	164
			ambiguous	11.27	0.353	165
60%	60%	good	simple	12.45	0.391	73
			compound	10.36	0.480	89
			ambiguous	10.37	0.566	75
70%	70%	good	simple	14.74	0.369	111
			compound	13.79	0.465	71
			ambiguous	13.58	0.375	106
50%	70%	bad	simple	6.47	0.345	165
			compound	7.29	0.385	164
			ambiguous	6.46	0.354	164
50%	70%	good	simple	12.51	0.362	164
			compound	11.30	0.379	165
			ambiguous	11.88	0.351	164

Table A.2: Bets with simple information

Notes: This table compares the CEs of simple, compound and ambiguous bets, all conditional on simple information.

		Red bet	
	Uncertainty premium	+	-
Blue bet	+	Absolute pessimist	Absolute prior over-weighter
	-	Absolute prior under-weighter	Absolute optimist

Table A.3: Classification of subjects in an uncertain prior round

Notes: This table summarizes the classification of subjects in an uncertain prior round. To be classified into any of the four categories, the uncertainty premium of at least one bet in the round needs to be non-zero. For rounds whose midpoint prior is (50%, 50%), I do not classify subjects as absolute prior under-/over-weighters.

bet in this round as

$$Pm(p_h \text{ or } p_l, m, \psi) := CE(\frac{p_h + p_l}{2}, m, \psi) - CE(p_h \text{ or } p_l, m, \psi).$$

If $\psi = 50\%$, then I define the uncertainty premium as

$$Pm(p_h \text{ or } p_l, -, 50\%) := CE(\frac{p_h + p_l}{2}, m', 50\%) - CE(p_h \text{ or } p_l, m, 50\%),$$

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

The classification of subjects is summarized in Table A.3. Same as in an uncertain information round, a subject is classified as an absolute pessimist in an uncertain prior round if the uncertainty premiums for the two bets in this round are both weakly positive and at least one of them is strictly positive. An absolute optimist, on the other hand, is a subject whose uncertainty premiums for the two bets in this round are both weakly negative but not both zero.

In uncertain prior rounds where the midpoint prior is not (50%, 50%), a subject is classified as an absolute prior under-weighter if the uncertainty premium of the red bet is weakly positive, that of the blue bet is weakly negative, and one of the two is not zero.[38] Analogously, a subject is a prior over-weighter if the uncertainty premium of the red bet is weakly negative, that of the blue bet is weakly positive, and one of the two is not zero. I do not classify prior under-/over-weighters for rounds where the midpoint prior is (50%, 50%).

Table A.4 shows the percentages of each of the four categories in all eight rounds with uncertain priors and simple information. In all rounds but one, there are more absolute pessimists than optimists, and the percentage of the former aggregated across rounds is also significantly higher than the latter for both compound and ambiguous prior rounds. This further confirms that uncertain priors

[38]Recall that the red bet always has a (midpoint) prior weakly higher than 50%.

lead to pessimism. By contrast, there is not strong evidence of either the under- or over-weighting of priors. In three out of six rounds, there are more absolute prior under- than over-weighters, whereas the opposite is true in the other three rounds.

Taken together, my experimental results suggest that in problems with belief updating, uncertainty in priors leads to pessimism. This pattern is consistent with the combination of uncertainty aversion and either Full Bayesian updating or Dynamically consistent updating. Under-weighting of priors – which is the prediction of uncertainty-induced insensitivity together with these two updating rules – is not borne out in the data.

Midpoint prior (Red, $Blue$)	Information accuracy	Type of prior	Absolute pessimists	Absolute optimists	p-value %(Abs. pess.) =%(Abs. opt.)	Absolute prior under-weighters	Absolute prior over-weighters	p-value %(Abs. negl.) =%(Abs. over.)	N
(50%, 50%)	70%	Amb	31.1%	21.3%	0.084	-	-	-	164
(60%, 40%)	60%	Amb	32.5%	24.7%	0.366	27.3%	33.8%	0.466	77
(70%, 30%)	70%	Amb	29.0%	16.7%	0.032	41.3%	31.9%	0.196	138
(70%, 30%)	50%	Amb	27.0%	18.4%	0.104	29.4%	35.6%	0.331	163
Aggregate		Amb	29.5%	18.8%	0.001	33.3%	33.9%	0.9	
(50%, 50%)	70%	Comp	32.3%	22.0%	0.072	-	-	-	164
(60%, 40%)	60%	Comp	39.3%	15.4%	0	35.9%	26.5%	0.198	117
(70%, 30%)	70%	Comp	21.3%	25.5%	0.67	31.9%	40.4%	0.493	47
(70%, 30%)	50%	Comp	25.2%	22.1%	0.569	33.1%	30.7%	0.695	163
Aggregate		Comp	30.5%	20.8%	0.002	33.9%	30.6%	0.449	

Table A.4: Classification of subjects in each uncertain prior round

Notes: This table shows the percentages of subjects that are classified into the four categories for each uncertain prior round. Only subjects who face comparable belief-updating problems in the uncertain prior round and its corresponding simple prior round are counted. In the rows under “Aggregate", I calculate the percentage of instances 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.

Prior and info	Type of prior	within-subject		between-subject		
		$\overline{CE}(simp) - \overline{CE}(unc)$	N	$\overline{CE}(simp) - \overline{CE}(unc)$	N(simp)	N(unc)
odds=30%, accu=70%	compound	-0.47 (0.52)	32	0.01 (0.99)	111	39
bad news	ambiguous	-0.21 (0.58)	95	-2.39 (0.06)	111	11
odds=40%, accu=60%	compound	-0.11 (0.84)	57	1.8 (0.03)	73	32
bad news	ambiguous	0.9 (0.26)	30	1.28 (0.08)	73	44
odds=30%, accu=50%	compound	-0.45 (0.18)	163			
neutral news	ambiguous	0.42 (0.16)	163			
odds=40%, accu=60%	compound	0.63 (0.29)	60	-0.75 (0.57)	91	16
good news	ambiguous	0.34 (0.61)	47	0.33 (0.71)	91	42
odds=30%, accu=70%	compound	0.13 (0.93)	15	0.09 (0.92)	54	79
good news	ambiguous	1.33 (0.06)	43	1.11 (0.43)	54	16
odds=70%, accu=70%	compound	-1.73 (0.02)	15	-0.78 (0.34)	54	79
bad news	ambiguous	0.12 (0.85)	43	-1.61 (0.25)	54	16
odds=60%, accu=60%	compound	-0.1 (0.86)	60	-0.29 (0.82)	91	16
bad news	ambiguous	0.02 (0.97)	47	-0.4 (0.63)	91	42
odds=70%, accu=50%	compound	0.56 (0.12)	163			
neutral news	ambiguous	-0.34 (0.27)	163			
odds=60%, accu=60%	compound	1.96 (0)	57	2.11 (0.02)	73	32
good news	ambiguous	0.97 (0.2)	31	2.47 (0)	73	44
odds=70%, accu=70%	compound	-0.03 (0.96)	32	1.74 (0.02)	111	39
good news	ambiguous	0.96 (0.01)	95	2.01 (0.1)	111	11
odds=50%, accu=70%	compound	-0.88 (0.03)	164			
bad news	ambiguous	-0.04 (0.9)	164			
odds=50%, accu=70%	compound	1.26 (0)	164			
good news	ambiguous	0.63 (0.1)	164			

Table A.5: Within- and between-subject comparison between CEs of uncertain and simple bets conditional on simple information

Notes: This table shows the differences in mean conditional CEs between uncertain prior problems and simple prior problems. Numbers in parentheses are p-values in t-tests, and N is the number of subjects included. For example, the top row of the table states that there are 32 subjects who receive bad reports both in the compound information problem and in the simple information problem where the prior is 30% and (midpoint) information accuracy 70%. Among these subjects, the difference in mean conditional CEs between these two problems is -\$0.47 and the p-value of the paired t-test is 0.52. Thirty-nine subjects receive a bad report in the compound prior problem but not in the simple problem, and there are 111 subjects who receive a bad report in the simple problem in total. The difference between the mean conditional CE of the simple bet of the latter group and that of the compound bet of the former group is 0.01, and the p-value of the unpaired t-test is 0.99.

B Details on structural estimation of the representative-agent model

This appendix presents details on the estimation of the representative-agent model discussed in Section 5.3. The model is based on the ε-α-maxmin model and Full Bayesian updating. It allows for nonstandard risk preferences and inherent belief-updating biases that are unrelated to ambiguity and compound uncertainty.

B.1 Risk preference

For risk preference, I use Prelec (1998)'s two-parameter function to model the CE of a bet with winning odds p and stake \$20:

$$CE(p) = M^{Prelec}(p) := \$20 \cdot exp(-b(-log(p))^{a}).$$

This model allows an agent to exhibit risk aversion/pessimism (b) and insensitivity (a) even when the decision problem does not involve compound uncertainty or ambiguity.[39] I assume that new information, compound uncertainty, and ambiguity do not affect an agent's risk attitudes (a and b), so they affect the CE of a bet only through their effects on the (subjective) winning odds of the bet. In other words, I assume that agents form a subjective winning odds and then apply the risk preference $M^{Prelec}(\cdot)$ to obtain the CE.

B.2 Inherent belief-updating biases

Subjects' belief updating behaviors may deviate from Bayes' rule for reasons unrelated to compound uncertainty and ambiguity. Figure B.1 and Table B.1 show the CEs of simple bets conditional on simple information and compare them to their Bayesian benchmarks whenever available.[40] For every task where the prior is not 50%, the mean conditional CE deviates from the Bayesian benchmark in the direction of under-weighting of priors ("base-rate neglect") (Kahneman and Tversky, 1973; Grether, 1980). This clear pattern demonstrates the importance of accounting for inherent belief-

[39] Prelec (1998) uses the two-parameter function to model the probability weighting function in Prospect Theory. It is easy to show that the CE of a bet takes the same functional form if the agent uses Prelec's probability weighting function combined with a power utility function.

[40] For example, the Bayesian posterior belief given a prior of 50% and good news with 70% accuracy is 70%. Therefore, the Bayesian benchmark for the CE of a 50% odds bet conditional on 70%-accurate good news is the CE of a bet with an odds of 70%. The Bayesian posteriors updated from a 60% prior using a 60%-accurate good news is 69%. Hence I take the CE of a 70% odds bet as its Bayesian benchmark.

updating biases when trying to identify the marginal effects of compound uncertainty and ambiguity on belief updating.

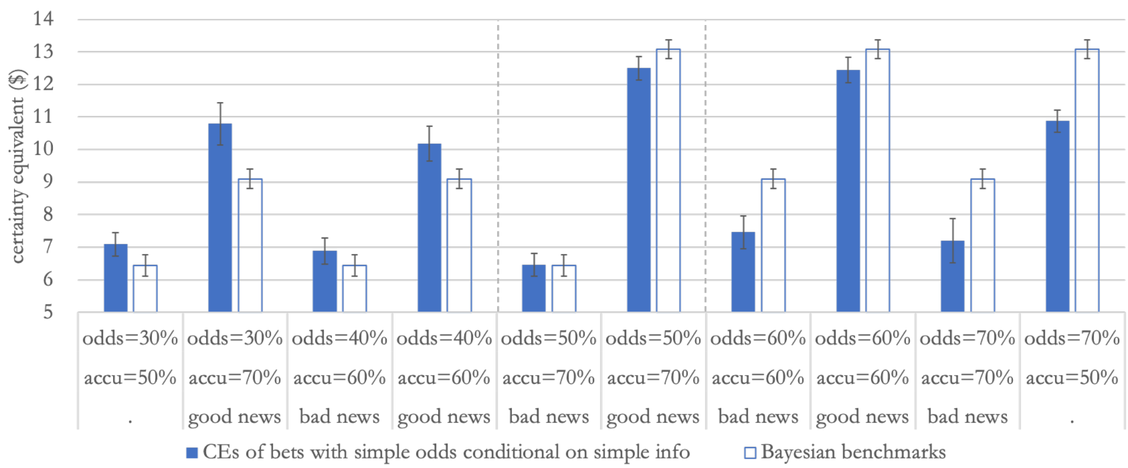

Figure B.1: Belief updating with simple priors and simple information

Notes: The figure shows the mean CEs of simple bets conditional on simple information. The horizontal axis lists the combinations of prior and information. For example, "odds=30%, accu=70%, good news" refers to simple bets with a 30% winning odds conditional on 70%-accurate simple good news. The red bars represent the mean conditional CEs and the blue bars represent the Bayesian benchmarks. The Bayesian benchmarks for "odds=30%, accu=70%, bad news" and "odds=70%, accu=70%, good news" are missing because I do not elicit CEs for simple bets whose odds match the Bayesian posteriors of these two tasks. Error bars represent +/- one standard error.

To model belief updating with simple priors and simple information, I use the *generalized Bayes' rule* which allows for over- and under-weighting of priors, good news, and bad news (Möbius et al., 2014):

$$Pr^{GB}(G|p,g,\psi) = \frac{p^{\beta}\psi^{r_g}}{p^{\beta}\psi^{r_g} + (1-p)^{\beta}(1-\psi)^{r_g}},$$

$$Pr^{GB}(G|p,b,\psi) = \frac{p^{\beta}(1-\psi)^{r_b}}{p^{\beta}(1-\psi)^{r_b} + (1-p)^{\beta}\psi^{r_b}},$$

where β, r_g and r_b are non-negative numbers. The generalized Bayes' rule coincides with Bayes' rule when β, r_g and r_b all equal one.

B.3 The empirical model

The empirical model is based on the ε-α-maxmin preferences and Full Bayesian updating and is adapted to allow for nonstandard risk preferences and inherent belief-updating biases. For the

Odds	Information accuracy	Good/Bad news	Mean conditional CE	Mean Bayesian CE	Paired t-test for Bayesianism	N
30%	70%	bad	5.70			111
30%	50%		6.45	7.10	0.037	163
30%	70%	good	9.10	10.80	0.000	54
40%	60%	bad	6.45	6.89	0.244	73
40%	60%	good	9.10	10.19	0.026	90
50%	70%	bad	6.45	6.47	0.956	165
50%	70%	good	13.09	12.51	0.098	164
60%	60%	bad	9.10	7.46	0.002	90
60%	60%	good	13.09	12.45	0.034	73
70%	70%	bad	9.10	7.20	0.049	54
70%	50%		13.09	10.88	0.000	163
70%	70%	good	14.74			111

Table B.1: CEs of simple bets conditional on simple information

Notes: This table compares the mean CEs of simple bets conditional on simple information to the mean CEs given Bayesian posteriors. Numbers under paired t-tests are two-sided p-values.

evaluation of uncertain bets in problems without belief updating, I use the ε-α-maxmin model to represent the subjective probability of winning:

$$Pr(p_h \text{ or } p_l) = W(p_h, p_l; \varepsilon, \alpha).$$

To model evaluations of simple bets conditional on uncertain information, I apply the ε-α-maxmin formula used in Full Bayesian updating to obtain the subjective information accuracy: $W(\psi_h, \psi_l; \varepsilon, \alpha)$ for good reports and $W(\psi_l, \psi_h; \varepsilon, \alpha)$ for bad reports. Then I apply this subjective information accuracy to the generalized Bayes' rule: $Pr^{GB}(G|p, g, W(\psi_h, \psi_l; \varepsilon, \alpha))$ for good reports and $Pr^{GB}(G|p, b, W(\psi_l, \psi_h; \varepsilon, \alpha))$ for bad reports.[41]

To model evaluations of uncertain bets conditional on simple information, I apply the ε-α-maxmin formula used in both Full Bayesian updating and Dynamically consistent updating to obtain the subjective prior belief and then apply this subjective prior to the generalized Bayes' rule: $Pr^{GB}(G|W(p_h, p_l; \varepsilon, \alpha), m, \psi)$ for both good and bad reports.

Note that because the generalized Bayes' rule shares the same monotonicity properties of Bayes' rule, all of the comparative statics results in Sections 3, 5.1 and 5.2 remain valid. Table B.2 summarizes the empirical model for CEs of bets in each part of the experiment.

[41]Although the empirical model is based on Full Bayesian updating, it can accommodate the qualitative prediction of Dynamically consistent updating, which is under-/over-reaction.

Part	Prior	Information	Empirical model for CEs
1	Simple	No information	$CE(p) = M^{Prelec}(p)$
2	Simple	Simple	$CE(p, m, \psi) = M^{Prelec}\left(Pr^{GB}(G \mid p, m, \psi)\right)$
3	Simple	Uncertain	$CE(p, g, \psi_h \text{ or } \psi_l) = M^{Prelec}\left(Pr^{GB}(G \mid p, g, W(\psi_h, \psi_l; \varepsilon, \alpha))\right)$ $CE(p, b, \psi_h \text{ or } \psi_l) = M^{Prelec}\left(Pr^{GB}(G \mid p, b, W(\psi_l, \psi_h; \varepsilon, \alpha))\right)$
4	Uncertain	No information	$CE(p_h \text{ or } p_l) = M^{Prelec}\left(W(p_h, p_l; \varepsilon, \alpha)\right)$
5	Uncertain	Simple	$CE(p_h \text{ or } p_l, m, \psi) = M^{Prelec}\left(Pr^{GB}(G \mid W(p_h, p_l; \varepsilon, \alpha), m, \psi)\right)$

Table B.2: Summary of the empirical model

Importantly, I allow a subject to have different attitudes toward uncertain information and uncertain priors. I also allow attitudes toward compound uncertainty to be different from attitudes toward ambiguity. In other words, I will separately estimate $2 \times 2 = 4$ potentially different ε's and also four α's.

The empirical model is identified using the experimental data. Specifically, the risk preference is identified by CEs of simple bets without new information. The parameters in the generalized Bayes' rule are identified by the differences between CEs of simple bets conditional on simple information and CEs of simple bets without new information. The four sets of ε's and α's are identified by the differences between CEs in tasks where the odds of bets or information accuracy is uncertain and those in the corresponding simple tasks.

B.4 Estimation method

I estimate the empirical model using non-linear least squares at the aggregate level assuming homogeneous parameters across subjects.[42] In the estimation, I do not impose constraints on the values of estimates.

B.5 Estimates of the incidental parameters

Table B.3 shows the estimates of the incidental parameters (the estimates of uncertainty attitudes can be found in Table 5.2). The degree of risk aversion (b) is small and insignificant, but subjects exhibit strong and significant insensitivity (a) in their risk preference. Regarding inherent belief-updating biases unrelated to compound or ambiguous uncertainty, subjects under-weight priors by half. They also under-weight bad reports by 27% while weighting good reports in a Bayesian manner.

[42]Specifically, this procedure finds the parameters that minimize the sum of squared differences between the CE of a bet in the data and that generated by the empirical model. The sum is taken over tasks and subjects.

Parameter	Estimate (s.e.)
a	0.77 (0.04)
b	1.03 (0.03)
β	0.51 (0.04)
r_g	0.97 (0.07)
r_b	0.73 (0.06)

Table B.3: Aggregate estimates of incidental parameters

Notes: All parameters are assumed to be homogeneous among subjects. Standard errors are computed by a bootstrap clustered at the subject level. The model is estimated using non-linear least squares.

C Additional results on the experiment

C.1 An alternative classification for behaviors in uncertain information rounds

In this section, I consider two alternative subject categories based on behaviors in uncertain information rounds: absolute confirmation bias and absolute contradiction bias. In an uncertain information round where the odds of the bets are not 50%, if a subject's uncertainty premium for the bet with higher-than-50% odds is weakly negative, her uncertainty premium for the other bet is weakly positive, and at least one of the two is not zero, then I classify this subject into the category of absolute confirmation bias. If, on the contrary, the bet with high odds has a weakly positive uncertainty premium, the other one has a weakly negative premium, and at least one is not zero, then this subject is absolute contradiction-biased. In rounds where the odds are 50-50, I do not classify subjects into these two categories.

Table C.1 shows the number of subjects in these two categories. Except in one round, there are more subjects in the category of absolute contradiction bias in every uncertain information round. This suggests that uncertainty in information accuracy does not lead to prevalent confirmation bias.

C.2 Order effects and anchor effects in the experimental data

In this section, I show that the experimental results are robust to order effects and anchor effects. Recall that in the experiment there are three different orders among parts, and two orders between compound and ambiguous uncertainty within parts (Table C.2). To check for order effects, I estimate the structural model separately for subjects who face each of the five orders and compare the resulting estimates for the key parameters. Table C.3 shows the result. Across different cuts of data, the α's

Prior (Red, $Blue$)	Midpoint Information accuracy	Type of information	Absolute confirmation bias	Absolute contradiction bias	N
(60%, 40%)	60%	Ambiguous	21	23	71
(70%, 30%)	70%	Ambiguous	23	33	94
(70%, 30%)	50%	Ambiguous	30	56	137
(60%, 40%)	60%	Compound	36	29	106
(70%, 30%)	70%	Compound	36	45	123
(70%, 30%)	50%	Compound	28	62	137

Table C.1: Absolute confirmation bias and absolute contradiction bias

Notes: This table shows the numbers of subjects that are classified into absolute confirmation bias and absolute contradiction bias. Only subjects who face comparable belief-updating problems in the uncertain information round and its corresponding simple information round are counted.

are consistently larger than 0.5 and the ε's are consistently larger than 0. This suggests that our key results are robust to order effects.

In all three different orders among parts, Part 2 (simple prior with simple information) comes before Part 3 (simple prior with uncertain information) and Part 5 (uncertain prior with simple information). This raises the question whether subjects anchor their answers in Parts 3 and 5 to those in Part 2.

To address this concern, I first conduct a within-subject analysis by running a paired t-test between the conditional CEs in each uncertain information (prior) problem and their counterparts in the corresponding simple problem. The subjects who are included in the paired t-tests are those who receive comparable reports in the two corresponding rounds,[43] so their conditional CEs in the uncertain information (prior) round could potentially be anchored to their answers in the corresponding simple round. The other subjects who do not receive comparable reports are not subject to the anchor effect, and I compare the mean of their conditional CEs in the uncertain information (prior) problem to the mean conditional CE in the corresponding simple problem in an unpaired t-test, which is a between-subject analysis.

Table C.4 reports results for uncertain information problems. For subjects who receive comparable reports in the uncertain information problem and the corresponding simple problem ("within-subject"), it is apparent that uncertain information leads to under-reaction to news. There is also

[43]Receiving comparable reports in two corresponding rounds means that the uncertainty premiums of the red bet and the blue bet in the uncertain information (prior) round can be calculated from data. See Section 4 and Appendix A.2 for the definition of uncertainty premiums.

Session	Order between parts	Ambiguous block first?	Number of subjects
1	1-4-2-3-5	No	16
2	1-4-2-3-5	No	16
3	1-4-2-3-5	No	13
4	1-4-2-3-5	Yes	16
5	1-4-2-5-3	No	15
6	1-2-3-4-5	No	16
7	1-2-3-4-5	Yes	16
8	1-4-2-5-3	Yes	15
9	1-4-2-5-3	Yes	15
10	1-2-3-4-5	No	11
11	1-2-3-4-5	Yes	16

Table C.2: Description of sessions

			Ambiguous block first?		Order between parts		
			No	Yes	1-2-3-4-5	1-4-2-3-5	1-4-2-5-3
α	Comp	Accuracy	0.55 (0.03)	0.52 (0.02)	0.50 (0.02)	0.55 (0.02)	0.55 (0.03)
		Priors	0.57 (0.02)	0.56 (0.03)	0.59 (0.02)	0.53 (0.03)	0.56 (0.02)
	Amb	Accuracy	0.57 (0.02)	0.60 (0.03)	0.53 (0.03)	0.61 (0.02)	0.61 (0.03)
		Priors	0.64 (0.03)	0.56 (0.02)	0.59 (0.03)	0.60 (0.03)	0.60 (0.02)
ε	Comp	Accuracy	0.23 (0.05)	0.00 (0.07)	0.03 (0.07)	0.06 (0.06)	0.24 (0.05)
		Priors	0.09 (0.06)	0.14 (0.08)	0.09 (0.09)	0.25 (0.06)	-0.07 (0.07)
	Amb	Accuracy	0.19 (0.06)	0.17 (0.08)	0.22 (0.08)	0.04 (0.08)	0.29 (0.04)
		Priors	0.17 (0.07)	0.04 (0.10)	0.07 (0.09)	0.18 (0.07)	-0.01 (0.07)

Table C.3: Order effects in estimates of uncertainty attitudes

Notes: This table shows the estimates of α's and ε's by the order between compound and ambiguous blocks and the order among parts. Numbers in parentheses are standard errors computed by a bootstrap clustered at the subject level.

evidence of pessimism caused by uncertain information accuracy. First, the effect sizes are more likely to be significant for good news than for bad news. Second, in half of the comparisons with neutral information, CEs conditional on uncertain information are significantly lower. (In the other comparisons with neutral information, the uncertain CEs are higher but the differences are not significant.) The results of the between-subject analysis are more noisy, but the overall patterns of under-reaction and pessimism remain present.

Table A.5 reports results for uncertain prior problems. Despite the noise in the results, in the majority of the comparisons in both within- and between-subject analysis, the conditional CEs of uncertain bets are lower than their simple counterparts, suggesting that uncertain priors in belief-updating problems lead to pessimism.

Taken together, the key effects of uncertain information and uncertain priors are robust to order effects and anchor effects.

Prior and info	Type of information	within-subject $\overline{CE}(simp) - \overline{CE}(unc)$	N	between-subject $\overline{CE}(simp) - \overline{CE}(unc)$	N(simp)	N(unc)
odds=30%, accu=70%	compound	1.25 (0.11)	28	0.11 (0.93)	54	16
good news	ambiguous	2.4 (0.06)	15	-0.81 (0.45)	54	32
odds=40%, accu=60%	compound	0.8 (0.23)	59	1.19 (0.27)	91	26
good news	ambiguous	1.14 (0.12)	29	0.09 (0.93)	91	31
odds=50%, accu=70%	compound	0.52 (0.14)	163			
good news	ambiguous	1.66 (0)	164			
odds=60%, accu=60%	compound	0.55 (0.25)	47	-0.24 (0.75)	73	33
good news	ambiguous	1.9 (0)	42	3.25 (0)	73	63
odds=70%, accu=70%	compound	0.86 (0.02)	95	2.08 (0.02)	111	26
good news	ambiguous	0.54 (0.1)	79	1.74 (0.03)	111	39
odds=30%, accu=70%	compound	0.16 (0.57)	95	-0.1 (0.91)	111	26
bad news	ambiguous	-0.32 (0.4)	79	0.32 (0.67)	111	39
odds=40%, accu=60%	compound	-0.28 (0.47)	47	-1.56 (0.05)	73	33
bad news	ambiguous	-0.12 (0.83)	42	1.54 (0.02)	73	63
odds=50%, accu=70%	compound	-0.59 (0.07)	163			
bad news	ambiguous	-0.47 (0.14)	165			
odds=60%, accu=60%	compound	-0.64 (0.15)	59	-1.42 (0.15)	91	26
bad news	ambiguous	-1.1 (0.16)	29	-1.67 (0.07)	91	31
odds=70%, accu=70%	compound	-1.14 (0.22)	28	-4.05 (0)	54	16
bad news	ambiguous	-0.73 (0.56)	15	-2.7 (0.01)	54	32
odds=30%, accu=50%	compound	-0.33 (0.33)	163			
neutral news	ambiguous	-0.17 (0.66)	162			
odds=70%, accu=50%	compound	0.6 (0.05)	163			
neutral news	ambiguous	0.65 (0.03)	162			

Table C.4: Within- and between-subject comparison between CEs of simple bets conditional on uncertain and simple information

Notes: This table shows the differences in mean conditional CEs between uncertain information problems and simple information problems. Numbers in parentheses are p-values in t-tests, and N is the number of subjects included. For example, the top row of the table states that there are 28 subjects who receive good reports both in the compound information problem and in the simple information problem where the prior is 30% and (midpoint) information accuracy 70%. Among these subjects, the difference in mean conditional CEs between these two problems is \$1.25 and the p-value of the paired t-test is 0.11. Sixteen subjects receive a good report in the compound information problem but not in the simple problem, and there are 54 subjects who receive a good report in the simple problem in total. The difference between the mean simple conditional CE of the latter group and the mean compound conditional CE of the former is 0.11, and the p-value of the unpaired t-test is 0.93.

D Additional results on the ε-α-maxmin preferences

D.1 Representing ε-α-maxmin preferences using Choquet integrals

Under Choquet expected utility (CEU) (Schmeidler, 1989), each event $E \subseteq S$ is assigned a value called *capacity* by a set function $v : 2^S \to [0, 1]$. A capacity satisfies the following two conditions:

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

Capacities generalize probability measures by allowing measures of sets to be non-additive. Given a capacity and a vNM utility function for simple lotteries, a CEU agent evaluates an act by taking the Choquet integral of utility. Formally, denote by $u(s)$ the vNM utility of the lottery assigned to state $s \in S$, then the CEU evaluation of the act is

$$\int_{\mathbb{R}} v\left(\{s \in S | u(s) \geq t\}\right) dt.$$

Now I show the CEU representation of the ε-α-maxmin preferences. I construct the capacity of each event so that it equals the ε-α-maxmin evaluation of a bet that pays out 1 util if this event happens and 0 otherwise. Recall that $W(x, y; \varepsilon, \alpha) = (1 - \varepsilon)[(1 - \alpha)x + \alpha y] + \varepsilon \cdot 0.5$. In a problem with uncertain prior (p_h or p_l), $p_h > p_l$, and no information, let the state space be $\{G, B\}$. Then the capacity of each event is

- $v(\{G\}) = W(p_h, p_l; \varepsilon, \alpha)$,
- $v(\{B\}) = W(1 - p_l, 1 - p_h; \varepsilon, \alpha)$.

In a problem with simple prior p and uncertain information accuracy (ψ_h or ψ_l), $\psi_h > \psi_l$, let the state space be $\{Gg, Gb, Bg, Bb\}$, where the capital letter represents the true outcome of the bet and the lower-case letter the realized report.[44] The capacity of each event is

- $v(\{Gg\}) = p \cdot W(\psi_h, \psi_l; \varepsilon, \alpha)$,
- $v(\{Gb\}) = p \cdot W(1 - \psi_l, 1 - \psi_h; \varepsilon, \alpha)$,
- $v(\{Bg\}) = (1 - p) \cdot W(1 - \psi_l, 1 - \psi_h; \varepsilon, \alpha)$,

[44]The definition of state space is natural because it is the coarsest common refinement of the partition generated by the events with uncertain probabilities $\{\{Gg, Bb\}, \{Gb, Bg\}\}$ and the partition generated by the payoffs $\{\{Gg, Gb\}, \{Bg, Bb\}\}$.

- $\nu(\{Bb\}) = (1-p) \cdot W(\psi_h, \psi_l; \varepsilon, \alpha)$,
- $\nu(\{Gg, Gb\}) = p$,
- $\nu(\{Bg, Bb\}) = 1 - p$,
- $\nu(\{Gg, Bb\}) = W(\psi_h, \psi_l; \varepsilon, \alpha)$,
- $\nu(\{Gb, Bg\}) = W(1-\psi_l, 1-\psi_h; \varepsilon, \alpha)$,
- $\nu(\{Gg, Bg\}) = \begin{cases} p \cdot W(\psi_h, \psi_l; \varepsilon, \alpha) + (1-p) \cdot W(1-\psi_h, 1-\psi_l; \varepsilon, \alpha), & \text{if } p \geq 0.5 \\ p \cdot W(\psi_l, \psi_h; \varepsilon, \alpha) + (1-p) \cdot W(1-\psi_l, 1-\psi_h; \varepsilon, \alpha), & \text{if } p < 0.5 \end{cases}$,
- $\nu(\{Gb, Bb\}) = \begin{cases} p \cdot W(1-\psi_l, 1-\psi_h; \varepsilon, \alpha) + (1-p) \cdot W(\psi_l, \psi_h; \varepsilon, \alpha), & \text{if } p \geq 0.5 \\ p \cdot W(1-\psi_h, 1-\psi_l; \varepsilon, \alpha) + (1-p) \cdot W(\psi_h, \psi_l; \varepsilon, \alpha), & \text{if } p < 0.5 \end{cases}$,
- $\nu(\{Gg, Gb, Bg\}) = p + (1-p) \cdot W(1-\psi_l, 1-\psi_h; \varepsilon, \alpha)$,
- $\nu(\{Gg, Gb, Bb\}) = p + (1-p) \cdot W(\psi_h, \psi_l; \varepsilon, \alpha)$,
- $\nu(\{Gg, Bg, Bb\}) = p \cdot W(\psi_h, \psi_l; \varepsilon, \alpha) + 1 - p$,
- $\nu(\{Gb, Bg, Bb\}) = p \cdot W(1-\psi_l, 1-\psi_h; \varepsilon, \alpha) + 1 - p$.

In a problem with uncertain prior (p_h or p_l), $p_h > p_l$, and simple information accuracy ψ, let the state space be $\{Gg, Gb, Bg, Bb\}$, where the capital letter represents the true outcome of the bet and the lower-case letter the realized report. The capacity of each event is

- $\nu(\{Gg\}) = W(p_h, p_l; \varepsilon, \alpha) \cdot \psi$,
- $\nu(\{Gb\}) = W(p_h, p_l; \varepsilon, \alpha) \cdot (1-\psi)$,
- $\nu(\{Bg\}) = W(1-p_l, 1-p_h; \varepsilon, \alpha) \cdot (1-\psi)$,
- $\nu(\{Bb\}) = W(1-p_l, 1-p_h; \varepsilon, \alpha) \cdot \psi$,
- $\nu(\{Gg, Gb\}) = W(p_h, p_l; \varepsilon, \alpha)$,
- $\nu(\{Bg, Bb\}) = W(1-p_l, 1-p_h; \varepsilon, \alpha)$,
- $\nu(\{Gg, Bb\}) = \psi$,
- $\nu(\{Gb, Bg\}) = 1 - \psi$,

- $\nu(\{Gg, Bg\}) = \begin{cases} W(p_h, p_l; \varepsilon, \alpha) \cdot \psi + W(1-p_h, 1-p_l; \varepsilon, \alpha) \cdot (1-\psi), & \text{if } p_h + p_l \geq 1 \\ W(p_l, p_h; \varepsilon, \alpha) \cdot \psi + W(1-p_l, 1-p_h; \varepsilon, \alpha) \cdot (1-\psi), & \text{if } p_h + p_l < 1 \end{cases},$
- $\nu(\{Gb, Bb\}) = \begin{cases} W(p_l, p_h; \varepsilon, \alpha) \cdot (1-\psi) + W(1-p_l, 1-p_h; \varepsilon, \alpha) \cdot \psi, & \text{if } p_h + p_l \geq 1 \\ W(p_h, p_l; \varepsilon, \alpha) \cdot (1-\psi) + W(1-p_h, 1-p_l; \varepsilon, \alpha) \cdot \psi, & \text{if } p_h + p_l < 1 \end{cases},$
- $\nu(\{Gg, Gb, Bg\}) = W(p_h, p_l; \varepsilon, \alpha) \cdot \psi + 1 - \psi,$
- $\nu(\{Gg, Gb, Bb\}) = W(p_h, p_l; \varepsilon, \alpha) \cdot (1-\psi) + \psi,$
- $\nu(\{Gg, Bg, Bb\}) = W(1-p_l, 1-p_h; \varepsilon, \alpha) \cdot (1-\psi) + \psi,$
- $\nu(\{Gb, Bg, Bb\}) = W(1-p_l, 1-p_h; \varepsilon, \alpha) \cdot \psi + 1 - \psi.$

D.2 Proofs of results on ε-α-maxmin preferences

Proof of Propositions 1 and 4. Eichberger et al. (2007) defines Full Bayesian updating for capacities as follows. The capacity of event A conditional on realized report E is

$$\nu(A|E) = \frac{\nu(A \cap E)}{\nu(A \cap E) + 1 - \nu(A \cup E^c)}.$$

We can obtain the Full Bayesian conditional evaluations of bets by directly applying the definition above to the CEU representation of ε-α-maxmin preferences. For example, in an uncertain information problem, the capacity of G conditional on report g is

$$\begin{aligned} \nu(\{Gg\}|\{Gg, Bg\}) &= \frac{\nu(\{Gg\})}{\nu(\{Gg\}) + 1 - \nu(\{Gg, Gb, Bb\})} \\ &= \frac{p \cdot W(\psi_h, \psi_l; \varepsilon, \alpha)}{p \cdot W(\psi_h, \psi_l; \varepsilon, \alpha) + (1-p) \cdot (1 - W(\psi_h, \psi_l; \varepsilon, \alpha))} \\ &= Pr^{Bayes}(G|p, g, W(\psi_h, \psi_l; \varepsilon, \alpha)). \end{aligned}$$

Hence, the evaluation of the bet conditional on report g is

$$u(g) = (1-\nu(\{Gg\}|\{Gg, Bg\}))\cdot 0 + \nu(\{Gg\}|\{Gg, Bg\})\cdot 1 = \nu(\{Gg\}|\{Gg, Bg\}) = Pr^{Bayes}(G|p, g, W(\psi_h, \psi_l; \varepsilon, \alpha)).$$

The conditional evaluation given report b and those in uncertain prior problems can be similarly derived.

The comparative statics of the conditional evaluations with respect to α and ε are straightforward.

Proof of Propositions 2 and 5. Under Dynamically consistent updating (Hanany and Klibanoff, 2007), the agent forms a contingent plan of actions before the report realizes and executes the plan resolutely after observing the report. In our example where the agent chooses between a bet and a certain amount of utils, the contingent plan denoted by $a = (a(g), a(b))$ specifies an action $a(m) \in \{Bet, Sure\}$ conditional on the good report and the bad report. Let $U(a(m), E)$ denote the utility of action $a(m)$ under payoff-relevant event E. The optimal plan maximizes utility from the ex-ante perspective. In an uncertain information problem, the ex-ante utility of an agent with an ε-α-maxmin preference is

$$W(\psi_h, \psi_l; \varepsilon, \alpha) \cdot [p \cdot U(a(g), G) + (1-p) \cdot U(a(b), B)] + (1 - W(\psi_h, \psi_l; \varepsilon, \alpha)) \cdot [p \cdot U(a(b), G) + (1-p) \cdot U(a(g), B)]$$

if her plan of action is (Bet, Bet), $(Bet, Sure)$ or $(Sure, Sure)$ and

$$W(\psi_l, \psi_h; \varepsilon, \alpha) \cdot [p \cdot U(a(g), G) + (1-p) \cdot U(a(b), B)] + (1 - W(\psi_l, \psi_h; \varepsilon, \alpha)) \cdot [p \cdot U(a(b), G) + (1-p) \cdot U(a(g), B)]$$

if her plan is $(Sure, Bet)$.

It is straightforward that the payoff of (Bet, Bet) equals p and that of $(Sure, Sure)$ equals the certain amount u. Note that both payoffs are independent from the information accuracy. The intuition is that if the agent's action is unaffected by the realization of information, then the ex-ante utility is not exposed to the uncertainty in the information. This is in contrast with the ex-post utility conditional on the realized report. The only choice that makes the ex-post conditional evaluation independent from the uncertainty in the information is choosing the certain amount of utils.

Since $W(\psi_h, \psi_l; \varepsilon, \alpha) \geq 1 - W(\psi_l, \psi_h; \varepsilon, \alpha)$, it can be shown by simple algebra that $(Sure, Bet)$ always leads to lower ex-ante utility than $(Bet, Sure)$. Hence, I only need to consider (Bet, Bet), $(Sure, Sure)$ and $(Bet, Sure)$ as the candidate optimal plans.

We know that $(Sure, Sure)$ yields a higher utility than (Bet, Bet) if and only if $u > p$. Hence, to pin down the optimal plan for each u, we only need to find the u such that $(Bet, Sure)$ is optimal. The plan $(Bet, Sure)$ yields a higher utility than $(Sure, Sure)$ if and only if

$$W(\psi_h, \psi_l; \varepsilon, \alpha) \cdot p \cdot (1 - u) - (1 - W(\psi_h, \psi_l; \varepsilon, \alpha))(1 - p) \cdot u > 0$$

$$\iff u < Pr^{Bayes}(G|p, g, W(\psi_h, \psi_l; \varepsilon, \alpha)).$$

Similarly, $(Bet, Sure)$ yields a higher utility than (Bet, Bet) if and only if

$$u > Pr^{Bayes}(G|p, b, W(\psi_h, \psi_l; \varepsilon, \alpha)).$$

The two inequalities can be simultaneously satisfied if and only if $(1-\alpha)\psi_h + \alpha\psi_l > 0.5$. When this condition holds, it is easy to check that $(Bet, Sure)$ is indeed optimal in the interval between the two right-hand side expressions. If we interpret the upper and lower boundaries of the interval in which $(Bet, Sure)$ is optimal as the "conditional evaluations" given good and bad reports, respectively, then these "conditional evaluations" coincide exactly with the Bayesian conditional evaluations with the information accuracy being $W(\psi_h, \psi_l; \varepsilon, \alpha)$.

If $(1-\alpha)\psi_h + \alpha\psi_l < 0.5$, then there is no u such that $(Bet, Sure)$ is optimal. Hence, the agent's optimal plan is to not respond to the information at all: she always chooses the certain amount of utils if $u > p$ and always takes the bet if $u < p$, *regardless of the realized report*.

In an uncertain prior problem, the ex-ante utility of an agent with an ε-α-maxmin preference is

$$W(p_h, p_l; \varepsilon, \alpha) \cdot [\psi \cdot U(a(g), G) + (1-\psi) \cdot U(a(b), G)] + (1 - W(p_h, p_l; \varepsilon, \alpha)) \cdot [(1-\psi) \cdot U(a(g), B) + (1-\psi) \cdot U(a(b), B)].$$

The ex-ante expected utility of $(Sure, Sure)$ is still u but that of (Bet, Bet) is now $W(p_h, p_l; \varepsilon, \alpha)$. The ex-ante expected utility of $(Bet, Sure)$ is again always higher than that of $(Sure, Bet)$.

We know that (Bet, Bet) yields a higher ex-ante payoff than $(Sure, Sure)$ if $u > W(p_h, p_l; \varepsilon, \alpha)$. Simple algebra shows that $(Bet, Sure)$ yields a higher payoff than $(Sure, Sure)$ if and only if

$$u < Pr^{Bayes}(G | W(p_h, p_l; \varepsilon, \alpha), g, \psi)$$

and $(Bet, Sure)$ yields a higher payoff than (Bet, Bet) if and only if

$$u > Pr^{Bayes}(G | W(p_l, p_h; \varepsilon, \alpha), b, \psi).$$

The two inequalities above can always be compatible. Note that the two expressions on the right-hand side are exactly the same as the conditional evaluations in the same uncertain prior problem under Full Bayesian updating. This suggests that for uncertain prior problems, Full Bayesian updating and Dynamically consistent updating make the same predictions under ε-α-maxmin preferences.

The comparative statics of conditional evaluations with respect to ε and α are straightforward.

Proof of Propositions 3 and 6. In an uncertain information problem, the likelihood of report g is $p \cdot \psi + (1-p) \cdot (1-\psi)$. If $p > 0.5$, then the likelihood is increasing in ψ and thus ψ_h is selected. If $p < 0.5$, then ψ_l is selected upon the realization of g. Similarly, the likelihood of report b is $p \cdot (1-\psi) + (1-p) \cdot \psi$. If $p > 0.5$, then ψ_l is selected and if $p < 0.5$, ψ_h is selected. If $p = 0.5$, then both ψ_h and ψ_l are retained regardless of the realized report. Uncertain prior problems are analogous.

E Additional results on the correlation between different kinds of uncertainty attitudes

In this section, I derive tests of correlations between uncertainty attitudes for priors and information accuracy. The correlation tests I construct are based on the signs of uncertainty premiums. For a bet whose prior is either p_h or p_l, define the sign of its uncertainty premium in a problem without belief updating as

$$SP(p_h \text{ or } p_l) = sign\left(CE(\frac{p_h + p_l}{2}) - CE(p_h \text{ or } p_l)\right) := \begin{cases} 1, & \text{if } CE(p_h \text{ or } p_l) < CE(\frac{p_h+p_l}{2}) \\ 0, & \text{if } CE(p_h \text{ or } p_l) = CE(\frac{p_h+p_l}{2}) \\ -1, & \text{if } CE(p_h \text{ or } p_l) > CE(\frac{p_h+p_l}{2}) \end{cases}.$$

For a simple bet with uncertain information, define the sign of uncertainty premium as

$$SP(p, m, \psi_h \text{ or } \psi_l) = sign\left(Pm(p, m, \psi_h \text{ or } \psi_l)\right),$$

where $Pm(\cdot, \cdot, \cdot \text{ or } \cdot)$ is defined in Section 4. Similarly, define the sign of uncertainty premium of an uncertain bet in a problem with belief updating as

$$SP(p_h \text{ or } p_l, m, \psi) = sign\left(Pm(p_h \text{ or } p_l, m, \psi)\right),$$

where $Pm(\cdot \text{ or } \cdot, \cdot, \cdot)$ is defined in Appendix A.2.

The following proposition lays out the basis for the tests of correlations between different kinds of uncertainty attitudes.

Proposition 7 *Suppose that an ε-α-maxmin agent uses either Full Bayesian updating, Dynamically consistent updating, or Maximum likelihood updating and adapts it to the generalized Bayes' rule. Then*

1. *if the agent's attitudes toward uncertain information and uncertain priors (in problems without updating) are described by the same ε-α-maxmin preference, then*

$$SP(50\%, g, 90\% \text{ or } 50\%) = SP(90\% \text{ or } 50\%);$$

2. *if the agent's attitudes toward uncertain information and uncertain priors (in problems with*

updating) are described by the same ε-α-maxmin preference, then

$$SP(50\%, g, 90\% \text{ or } 50\%) = SP(90\% \text{ or } 50\%, -, 50\%);$$

3. *if the agent's attitudes toward uncertain priors in problems with and without updating are described by the same ε-α-maxmin preference, then*

$$SP(90\% \text{ or } 50\%, -, 50\%) = SP(90\% \text{ or } 50\%) \text{ and } SP(10\% \text{ or } 50\%, -, 50\%) = SP(10\% \text{ or } 50\%).$$

To see why item 1 in the proposition is true, note that for an ε-α-maxmin agent who uses Full Bayesian updating adapted to the generalized Bayes' rule, the comparison between $CE(50\%, g, 90\% \text{ or } 50\%)$ and $CE(50\%, g, 70\%)$ boils down to the comparison between $W(90\%, 50\%; \varepsilon, \alpha)$ and 70%. If the same ε and α apply to both uncertainty in information accuracy and uncertainty in priors (in problems without updating), then the same comparison between $W(90\%, 50\%; \varepsilon, \alpha)$ and 70% also determines the comparison between $CE(90\% \text{ or } 50\%)$ and $CE(70\%)$. Moreover, this statement is also true if the agent uses the other two belief-updating rules. This is because the conditional CEs under Dynamically consistent updating coincide with Full Bayesian updating for good news, and those under Maximum likelihood updating are the same as Full Bayesian updating if $p = 50\%$. Similar arguments also apply to items 2 and 3. The formal proof of Proposition 7 is in Appendix E.2. In the 2020 version of this paper, I show that the proposition also holds under several extensions of the smooth model and Segal's two-stage model.

I compute the correlation between the two sides of each equation in Proposition 7 to test for correlation between attitudes toward two different kinds of uncertainty. Table E.1 shows the results. While the correlations that involves attitudes toward uncertain information are all very close to zero, the correlations between attitudes toward uncertain priors with and without belief updating have larger magnitudes and, in most cases, high significance. The results remain qualitatively unchanged if I restrict the tests to a subsample of subjects who adhere well to some basic rationality properties (see Appendix E.1.) Taken together, these results imply that with or without the updating, subjects have rather consistent uncertainty attitudes toward priors. By contrast, their attitudes toward uncertainty in information accuracy are distinct from how they treat uncertain priors.

E.1 Analysis with a "more rational" subsample

Another concern is that the no-correlation results may be driven by "confused" subjects who do not even adhere to basic rationality properties. To show that this is not the case, I first consider

Test	Correlation coefficient	
	Ambiguity	Compound
SP(50%, g, 90% or 50%)=SP(90% or 50%)	0 (0.99)	0.08 (0.28)
SP(50%, g, 90% or 50%)=SP(90% or 50%,-,50%)	0.03 (0.71)	0 (0.97)
SP(90% or 50%,-,50%)=SP(90% or 50%)	0.26 (0)	0.15 (0.05)
SP(10% or 50%,-,50%)=SP(10% or 50%)	0.22 (0)	0.1 (0.19)

Table E.1: Results of correlation tests

Notes: This table lists the correlation coefficients of the tests that are valid under Full Bayesian updating, Dynamically consistent updating and Maximum likelihood updating adapted to generalized Bayes' rule. Numbers in parentheses are p-values with the null hypothesis being that the correlation is zero.

several such rationality properties and show that subjects' adherence to them are reasonably good. Subsequently, I repeat the correlation tests within the sample of more "rational" sample and show that the results are virtually unchanged.

I consider the following four monotonicity properties in problems with simple priors and no updating: $CE(30\%) \leq CE(40\%)$, $CE(40\%) \leq CE(50\%)$, $CE(50\%) \leq CE(60\%)$, and $CE(60\%) \leq CE(70\%)$. Among all 165 subjects, 109 satisfy all of these properties, 38 satisfy three of them, 14 satisfy two, and 4 people one. I also consider two monotonicity properties in problems with simple priors and simple information: $CE(50\%, g, 70\%) \geq CE(50\%)$ and $CE(50\%, b, 70\%) \leq CE(50\%)$.[45] 117 subjects satisfy both inequalities and 43 subjects satisfy one of them.

To address the concern that the no-correlation results may be driven by "confused" subjects, I repeat the tests with the 131 subjects who violate at most one of the six monotonicity properties listed in the previous paragraph. Table E.2 shows that the results are qualitatively the same.

E.2 Proof of Proposition 7

Suppose an agent's attitudes toward uncertain priors (in problems without updating) is described by an ε-α-maxmin preference, then her CE of an uncertain bet is given by

$$CE(p_h \text{ or } p_l) = M\left(W(p_h, p_l; \varepsilon, \alpha)\right),$$

[45]I choose these two specific properties because theoretically, any agent who has monotonic risk preference and uses the generalized Bayes' rule to update beliefs should satisfy them. In addition, all subjects report $CE(50\%, g, 70\%)$ and $CE(50\%, b, 70\%)$ in the experiment. Other similar inequalities have their shortcomings. For instance, the inequality $CE(60\%, g, 60\%) \geq CE(50\%)$ also has the aforementioned theoretical appeal, but not all subjects have their $CE(60\%, g, 60\%)$ recorded in the dataset due to random signal realization.

Test	Correlation coefficient	
	Ambiguity	Compound
SP(50%, g, 90% or 50%)=SP(90% or 50%)	-0.03 (0.77)	0.12 (0.17)
SP(50%, g, 90% or 50%)=SP(90% or 50%,-,50%)	0.07 (0.42)	0 (0.96)
SP(90% or 50%,-,50%)=SP(90% or 50%)	0.33 (0)	0.22 (0.01)
SP(10% or 50%,-,50%)=SP(10% or 50%)	0.21 (0.02)	0.08 (0.38)

Table E.2: Results of correlation tests (“rational" subsample)

Notes: This table lists the correlation coefficients of the tests that are valid under Full Bayesian updating, Dynamically consistent updating and Maximum likelihood updating adapted to generalized Bayes' rule. The sample comprises 131 subjects who violate at most one of six monotonicity properties. Numbers in parentheses are p-values with the null hypothesis being that the correlation is zero.

where $M : [0,1] \to \mathbb{R}_+$ is an increasing function that maps the (subjective) winning odds of a bet to its CE. Suppose that the same ε-α-maxmin preference also describes her attitudes toward uncertainty in information accuracy and that she follows the Full Bayesian updating rule adapted to the generalized Bayes' rule. Then the agent's CE for a simple bet is

$$CE(p, g, \psi_h \text{ or } \psi_l) = M\left(Pr^{GB}(G|p, g, W(\psi_h, \psi_l; \varepsilon, \alpha))\right)$$

conditional on an uncertain good report and

$$CE(p, b, \psi_h \text{ or } \psi_l) = M\left(Pr^{GB}(G|p, b, W(\psi_l, \psi_h; \varepsilon, \alpha))\right)$$

conditional on an uncertain bad report. Note that $M(\cdot)$ is increasing and the generalized Bayesian posterior is increasing in information accuracy conditional on a good report and decreasing conditional on a bad report. This implies that if $0 \leq y < x \leq 1$ and $x + y \geq 1$, then for any p,

$$\begin{aligned} SP(p, g, x \text{ or } y) &= sign\left(M\left(Pr^{GB}(G|p, g, \frac{x+y}{2})\right) - M\left(Pr^{GB}(G|p, g, W(x, y; \varepsilon, \alpha))\right)\right) \\ &= sign\left(M\left(\frac{x+y}{2}\right) - M\left(W(x, y; \varepsilon, \alpha)\right)\right) \\ &= SP(x \text{ or } y) \end{aligned} \tag{2}$$

and

$$\begin{aligned} SP(p, g, x \text{ or } y) &= sign\left(M\left(Pr^{GB}(G|p, b, \frac{x+y}{2})\right) - M\left(Pr^{GB}(G|p, b, W(y, x; \varepsilon, \alpha))\right)\right) \\ &= sign\left(M\left(Pr^{GB}(G|p, g, 1 - \frac{x+y}{2})\right) - M\left(Pr^{GB}(G|p, g, 1 - W(y, x; \varepsilon, \alpha))\right)\right) \end{aligned}$$

$$= sign\left(M\left(\frac{1-y+1-x}{2}\right) - M\left(W(1-y, 1-x; \varepsilon, \alpha)\right)\right)$$
$$= SP(1-y \text{ or } 1-x). \tag{3}$$

Suppose instead that the agent uses Dynamically consistent updating adapted to the generalized Bayes' rule. Then, the hypothesis that the same ε-α-maxmin preference applies to both uncertain priors (in problems without updating) and uncertain information implies that the CE of a simple bet conditional on uncertain information is

$$CE(p, m, \psi_h \text{ or } \psi_l) = M\left(Pr^{GB}(G|p, m, \max\{W(\psi_h, \psi_l; \varepsilon, \alpha), 0.5\})\right),$$

which in turn implies that if $0 < p < 1$, $0 \leq y < x \leq 1$ and $x + y > 1$, then

$$\begin{aligned} SP(p, g, x \text{ or } y) &= sign\left(M\left(Pr^{GB}(G|p, g, \frac{x+y}{2})\right) - M\left(Pr^{GB}(G|p, g, \max\{W(\psi_h, \psi_l; \varepsilon, \alpha), 0.5\})\right)\right) \\ &= sign\left(M\left(Pr^{GB}(G|p, g, \frac{x+y}{2})\right) - M\left(Pr^{GB}(G|p, g, W(x, y; \varepsilon, \alpha))\right)\right) \\ &= sign\left(M\left(\frac{x+y}{2}\right) - M\left(W(x, y; \varepsilon, \alpha)\right)\right) \\ &= SP(x \text{ or } y) \end{aligned} \tag{4}$$

and

$$\begin{aligned} SP(p, g, x \text{ or } y) &= sign\left(M\left(Pr^{GB}(G|p, b, \frac{x+y}{2})\right) - M\left(Pr^{GB}(G|p, b, \max\{W(\psi_h, \psi_l; \varepsilon, \alpha), 0.5\})\right)\right) \\ &= -sign\left(M\left(Pr^{GB}(G|p, g, \frac{x+y}{2})\right) - M\left(Pr^{GB}(G|p, g, \max\{W(\psi_h, \psi_l; \varepsilon, \alpha), 0.5\})\right)\right) \\ &= -SP(x \text{ or } y). \end{aligned} \tag{5}$$

Finally, if the agent uses Maximum likelihood updating adapted to the generalized Bayes' rule,[46] then uncertainty attitudes only have a bite on the conditional CEs if the prior is 50%, in which case the prediction coincides with Full Bayesian updating. Therefore, in this scenario Equations (2) and (3) restricted to $p = 50\%$ are the implications of an agent having the same ε-α-maxmin preference toward uncertain priors (in problems without updating) and uncertain information.

Note that the validity of Equations (2) to (5) is independent of the agent's risk preference M and the parameters in the generalized Bayes' rule. The two sides of each equation are also constructed using non-overlapping parts of data. Hence, the correlation between the two sides of each equation

[46] The Maximum likelihood updating adapted to the generalized Bayes' rule has the same selection rule as Maximum likelihood updating under Bayes' rule. The difference is that given the selected prior(s)/information accuracy level(s), beliefs are updated using the adapted Full Bayesian updating.

constitutes a test of whether subjects' attitudes toward uncertainty in priors (without information) and uncertainty in information accuracy are correlated, *given the theories under which the equation is valid*.

There is one equation that is valid under all three theories and can be the basis of a correlation test using data from my experiment:

$$SP(50\%, g, 90\% \text{ or } 50\%) = SP(90\% \text{ or } 50\%). \tag{6}$$

Now I turn to correlations that involve attitudes toward uncertain priors in problems with updating. For an ε-α-maxmin agent who uses the adapted Full Bayesian updating or the adapted Dynamically consistent updating, the CE for an uncertain bet conditional on simple information is

$$CE(p_h \text{ or } p_l, m, \psi) = M\left(Pr^{GB}(G|W(p_h, p_l; \varepsilon, \alpha), m, \psi)\right).$$

Since M is increasing and the generalized Bayesian posterior is increasing in the prior, if an agent uses the same ε-α-maxmin model for uncertainty in priors in problems with and without belief updating, then for any $0.5 \leq \psi < 1$ and $0 \leq y < x \leq 1$,

$$SP(x \text{ or } y, m, \psi) = SP(x \text{ or } y). \tag{7}$$

If the agent uses the adapted Maximum likelihood updating, then Equation (7) is valid if $\psi = 50\%$. Hence, if I require the correlation tests in my experiment to be valid under all three theories, then they need to be based on the equations

$$SP(90\% \text{ or } 50\%, -, 50\%) = SP(90\% \text{ or } 50\%) \tag{8}$$

and

$$SP(10\% \text{ or } 50\%, -, 50\%) = SP(10\% \text{ or } 50\%) \tag{9}$$

Now suppose that an agent uses the same ε-α-maxmin model for uncertainty in information accuracy and uncertainty in priors (in problems with updating). If she uses the adapted Full Bayesian updating, then for any $0 < p < 1$, $0.5 \leq \psi < 1$ and x and y such that $0 \leq y < x \leq 1$ and $x + y \geq 1$,

$$SP(x \text{ or } y, m, \psi) = SP(p, g, x \text{ or } y), \tag{10}$$

and

$$SP(1 - y \text{ or } 1 - x, m, \psi) = SP(p, b, x \text{ or } y). \tag{11}$$

If she uses the adapted Dynamically consistent updating, then for any $0 < p < 1$, $0.5 \leq \psi < 1$ and x and y such that $0 \leq y < x \leq 1$ and $x + y > 1$, Equation (10) holds and

$$SP(x \text{ or } y, m, \psi) = -SP(p, b, x \text{ or } y). \tag{12}$$

If the agent uses the adapted Maximum likelihood updating, then Equations (10) and (11) hold when $p = \psi = 50\%$. Therefore, the equation that is valid under all three theories and can form a basis for a correlation test using data in my experiment is

$$SP(90\% \text{ or } 50\%, -, 50\%) = SP(50\%, g, 90\% \text{ or } 50\%). \tag{13}$$

F Individual-level relation between attitudes toward compound uncertainty and ambiguity

Structural estimates in Section 5.3 show that at the aggregate level, the insensitivity and uncertain aversion induced by ambiguity tend to have larger magnitudes than those induced by compound uncertainty. In this section, I examine the individual-level relation between attitudes toward compound uncertainty and ambiguity. On the one hand, compound uncertainty and ambiguity differ on whether the full probability distribution over states is explicitly specified. On the other hand, both types of uncertainty are more complex than simple risks. Hence, investigating the association between compound and ambiguity attitudes sheds light on the relative importance of “unknown unknown" and complexity in decisions under uncertainty.

If an agent treats compound and ambiguous information identically, then

$$CE^{Comp}(p, m, \psi_h \text{ or } \psi_l) = CE^{Amb}(p, m, \psi_h \text{ or } \psi_l)$$

for any prior p, report m and information accuracy ψ_h and ψ_l. Similar equations hold for uncertain priors with or without belief updating if an agent holds the same attitudes toward compound and ambiguous uncertainty in priors.

Among all cases where a subject's CE for a simple bet and its compound and ambiguous counterparts are all available, there are 39% where the CEs of the compound and ambiguous bets are identical. The analogous percentages for uncertain information and uncertain priors (in problems with updating) are 36% and 35%.[47] To construct benchmarks for these percentages where attitudes

[47] If I do not require the simple CE to be available, the percentages are 39%, 35% and 35%, respectively.

	$\frac{Amb=Comp}{All}$	$\frac{Amb=Comp\neq Simp}{\neg(Amb=Comp=Simp)}$	$\frac{Simp=Amb}{All}$	$\frac{Simp=Comp}{All}$
Info accuracy	36% (22%)	22% (18%)	30%	30%
Priors (without updating)	39% (23%)	26% (16%)	29%	30%
Priors (with updating)	35% (21%)	23% (16%)	28%	26%

Table F.1: Relation between compound uncertainty and ambiguity

Notes: The first column of this table shows the percentages of cases where corresponding compound and ambiguous CEs are identical. Numbers in parentheses are the maximum of these percentages in 500 simulations where compound and ambiguous CEs are randomly permuted among those that share the same simple counterpart. The second column excludes cases where the corresponding simple, compound, and ambiguous CEs are all the same. The third column shows the proportions of cases where the ambiguous CE is equal to the corresponding simple CE, whereas the last column is analogous for the match between compound CEs and simple CEs.

toward compound and ambiguous uncertainty are independent, I generate independent uniform random permutations of the compound CEs and ambiguous CEs among those that share the same corresponding simple CE.[48] Using the permuted data, I calculate the same three percentages as before. Among 500 simulations, the highest numbers are 22%, 23%, and 21% for uncertain priors (without updating), uncertain information, and uncertain priors (with updating), respectively. These numbers are significantly lower than the actual percentages of cases where a subject's compound CE is equal to her corresponding ambiguous CE, which implies that the match between compound and ambiguity attitudes is not merely coincidence. Furthermore, I show in Table F.1 that the result is not simply driven by cases where the corresponding simple, compound, and ambiguous CEs are all the same, as the conclusion remains even if I exclude these cases. Moreover, there are more cases where the compound CE coincides with its corresponding ambiguous CE than where either of these two matches the simple CE. Taken together, my results show that compound uncertainty and ambiguity are often treated as the same by subjects.

[48]For example, there are 18 subjects who report $CE(60\%, g, 60\%) = 12$ and among these 18 subjects, there are 11 whose $CE^{Comp}(60\%, g, 90\% \text{ or } 30\%)$ is not missing. Hence, I randomly permute these 11 CEs which are conditional on compound information. Similarly, there are 13 subjects among the 18 whose $CE^{Amb}(60\%, g, 90\% \text{ or } 30\%)$ is not missing. I generate an independent random permutation of these 13 CEs conditional on ambiguous information.

G Additional results on stock market reactions to earnings forecasts

G.1 A model of asset pricing with uncertain information

In this section, I derive the effects of uncertain information accuracy on stock prices in a simple representative-agent model. The model has three dates, labeled 0, 1, and 2. The representative agent owns a share of a stock, which is a claim to a dividend d whose true amount is revealed at date 2. At date 1, a piece of information m about the dividend is realized. At date 0, the representative agent has a rational expectation about the amount of dividend, which is described by the pdf $F(d)$.

If the agent knows the information structure of m, denoted by $\psi(m|d)$, then her expectation about the dividend conditional on m adheres to Bayes' rule:

$$\mathbb{E}(d|m) = \frac{\int_d d \cdot \psi(m|d) \mathrm{d}F(d)}{\int_d \psi(m|d) \mathrm{d}F(d)}.$$

I now focus on the case where the agent does not know the information structure. For example, the information m may be an earnings forecast issued by an analyst who is unfamiliar to the agent. Suppose that the information structure might be either $\psi_1(m|d)$ or $\psi_2(m|d)$, and the two possibilities are equally likely. Then the Bayesian expectation about the dividend conditional on m should be

$$\mathbb{E}^{Bayes}(d|m) = \frac{\int_d d \cdot (0.5\psi_1(m|d) + 0.5\psi_2(m|d)) \, \mathrm{d}F(d)}{\int_d (0.5\psi_1(m|d) + 0.5\psi_2(m|d)) \, \mathrm{d}F(d)}.$$

In view of the experimental results in this paper, people may not follow Bayes' rule when the information structure is uncertain. Therefore, adapting the ε-α-maxmin preference and Full Bayesian updating to the current setting, I assume that the representative agent's conditional expectation about the dividend is given by

$$\mathbb{E}(d|m) = \frac{\int_d d \cdot \Big((1-\varepsilon)[(1-\alpha)\bar{\psi}(m|d) + \alpha\underline{\psi}(m|d)] + \varepsilon \cdot \psi_0(m)\Big) \, \mathrm{d}F(d)}{\int_d \Big((1-\varepsilon)[(1-\alpha)\bar{\psi}(m|d) + \alpha\underline{\psi}(m|d)] + \varepsilon \cdot \psi_0(m)\Big) \, \mathrm{d}F(d)}.$$

I assume that the pdf $\psi_0(m)$ does not depend on the true dividend d, so it represents an uninformative information structure. Which of the two information structures, ψ_1 and ψ_2, receives the relative weight α depends on which one, when mixed with ψ_0, leads to a more pessimistic expectation:

$$\bar{\psi} = arg \max_{\psi \in \{\psi_1, \psi_2\}} \mathbb{E}(d|m) = \frac{\int_d d \cdot ((1-\varepsilon)\psi(m|d) + \varepsilon \cdot \psi_0(m)) \, \mathrm{d}F(d)}{\int_d ((1-\varepsilon)\psi(m|d) + \varepsilon \cdot \psi_0(m)) \, \mathrm{d}F(d)}$$

and

$$\underline{\psi} = arg \min_{\psi \in \{\psi_1, \psi_2\}} \mathbb{E}(d|m) = \frac{\int_d d \cdot ((1-\varepsilon)\psi(m|d) + \varepsilon \cdot \psi_0(m)) \, \mathrm{d}F(d)}{\int_d ((1-\varepsilon)\psi(m|d) + \varepsilon \cdot \psi_0(m)) \, \mathrm{d}F(d)}.$$

Simple algebra lead to a counterpart of Proposition 1 in the stock market setting.

Proposition 8 *Assume that the representative investor has an ε-α-maxmin preference and uses Full Bayesian updating.*

1. *If $\varepsilon = 0$ and $\alpha = 0.5$, then her conditional expectations about the dividend coincide with the Bayesian expectations conditional on simple information with information structure $\frac{\psi_1+\psi_2}{2}$;*
2. *As α increases, the conditional expectations decrease;*
3. *As ε increases, the conditional expectations become closer to the prior expectation $\int_d d\mathrm{d}F(d)$.*

A straightforward corollary of Proposition 8 is that if $\alpha > 0.5$ and $\varepsilon > 0$, then the expectation conditional on good news, i.e. m such that $\mathbb{E}^{Bayes}(d|m) > \int_d d\mathrm{d}F(d)$, is lower than the Bayesian benchmark. This is because both $\alpha > 0.5$ and $\varepsilon > 0$ cause the agent's expectation to deviate from the Bayesian benchmark downwards. For bad news, on the other hand, the comparison with the Bayesian benchmark is ambiguous.

To study the implications on stock prices, I assume for simplicity that the representative agent is risk neutral, does not discount the future, and only cares about the dividend at date 2. Then, the stock price at each date is equal to the expectation on that date about the dividend. Moreover, the abnormal returns at date 2 are hence $R_2 = d - \mathbb{E}(d|m)$. In view of the corollary to Proposition 8, if m is good news, then the abnormal returns are expected to be positive. [49]

G.2 Variable definitions and summary statistics

G.3 Robustness checks for results on stock market reactions to earnings forecasts

[49] Epstein and Schneider (2008) introduce a recursive model where the price at date t is the expectation of the prices at date $t+1$. Making this assumption in my setting would change the stock price at date 0 but not the other results.

	With record			No record		
	N	mean	sd	N	mean	sd
Good news						
Ret[-1,1]	366,050	0.00795	0.0574	31,554	0.00887	0.0717
Ret[-1,22]	365,998	0.0135	0.133	31,553	0.0153	0.164
Ret[-1,43]	365,675	0.0151	0.183	31,539	0.0202	0.231
Ret[-1,64]	364,133	0.0172	0.227	31,462	0.0227	0.293
Ret[-1,EA+1]	364,993	0.0157	0.212	31,403	0.0206	0.272
Bad news						
Ret[-1,1]	562,312	-0.00668	0.0634	46,822	-0.00957	0.0739
Ret[-1,22]	562,235	-0.00770	0.144	46,816	-0.00976	0.164
Ret[-1,43]	561,752	-0.00727	0.194	46,778	-0.00947	0.221
Ret[-1,64]	559,170	-0.00955	0.235	46,653	-0.0128	0.276
Ret[-1,EA+1]	560,105	-0.00994	0.221	46,595	-0.0112	0.272

Table G.1: Returns after forecast revisions

Notes: This table summarizes the size-adjusted returns in different time windows around the forecast announcement, separately for with-record and no-record forecasts and for good news and bad news. It includes only forecasts that meet all of the data selection criteria. “EA+1" is the 1st trading day after the announcement of the actual earnings. For the summary statistics of $Ret[-1, EA+1]$, I exclude observations where the actual earnings announcement happens later than 190 trading days after the forecast announcement. Variable definitions are in Table G.2.

Variable	Definition
Main variables	
$Ret[t,T]$	The stock's (buy-hold) returns between the tth and the Tth trading day after the analyst's forecast announcement minus the equal-weighted average returns of stocks in the same size decile in the same period
$NoRecord$	Indicator variable: =0 if the analyst has issued a quarterly earnings forecast on this stock before and the actual earnings of that quarter have been announced; =1 otherwise
$GoodNews$	Indicator variable: =0 if the earnings forecast is a downward revision from the last forecast issued by the same analyst on the same stock's quarterly earnings; =1 if it is an upward revision
Controls	
$ForecastError$	Absolute forecast error is the absolute difference between a forecast and the actual earnings per share, normalized by the stock price two trading days prior to the forecast announcement. Forecast error is absolute forecast error normalized by the standard deviation of absolute forecast errors among all forecasts for the same stock-quarter
$StockExp$/$IndExp$/ $TotExp$	Experience (stock-specific/industry-specific/total): number of days since the analyst's first earnings forecast on the same stock/any stock in the same industry/any stock
$Companies$	Number of stocks covered by the analyst in the same year
$Industries$	Number of industries covered by the analyst in the same year
$Turnover$	Indicator variable: =0 if the analyst has not changed brokerage house in the year; =1 otherwise
$Horizon$	Number of days between the earnings forecast and the end of the forecasted quarter
$DaysElapsed$	Number of days elapsed since the last forecast issued by any analyst on the same firm's quarterly earnings or the firm's last earnings announcement, whichever is later
$BrokerSize$	Number of analysts in the same brokerage house who cover the same stock in the same year
$Coverage$	Number of analysts covering the same firm in the same year
$log(MktCap)$	Logarithm of market capitalization at the end of last year
B/M	Book-to-Market ratio at the end of last year. Winsorized at the 1st and 99th percentiles
$PastReturns$	Size-adjusted returns from seven months before forecast announcement to one month before forecast announcement. Winsorized at the 1st and 99th percentiles
$Volatility$	Standard deviation of the stock's monthly returns in the 24 months before the end of the calendar year prior to the forecast announcement
$Volume$	Average monthly turnover of the stock in the past calendar year

Table G.2: Variable definitions

	With record			No record		
VARIABLES	N	mean	sd	N	mean	sd
GoodNews	943,984	0.394	0.489	81,839	0.403	0.491
ForecastError	937,015	-0.122	0.933	80,787	-0.101	0.941
StockExp	943,984	1,389	1,418	81,839	83.38	242.0
IndExp	943,984	2,379	2,081	81,839	943.2	1,476
TotExp	943,984	3,024	2,351	81,839	1,561	1,920
Companies	943,984	16.73	8.306	81,839	14.01	9.171
Industries	943,984	4.377	2.693	81,839	3.972	2.705
Turnover	943,984	0.0321	0.176	81,839	0.0377	0.191
Horizon	943,984	42.92	46.56	81,839	40.50	50.30
DaysElapsed	943,984	11.49	15.82	81,839	13.24	16.83
BrokerSize	943,984	1.072	0.275	81,839	1.281	0.509
log(MktCap)	943,801	7.826	1.845	81,815	7.151	1.790
B/M	943,784	0.518	0.397	81,815	0.467	0.377
PastReturns	929,349	0.00338	0.297	81,255	0.0455	0.361
Volume	914,191	2.239	1.850	71,545	2.155	1.901
Coverage	943,984	13.73	8.667	81,839	11.39	8.144

Table G.3: Summary statistics

Notes: This table summarizes the indicator variable *GoodNews* and the control variables, separately for with-record and no-record forecasts. It only includes observations that meet all of the data selection criteria, i.e. forecast revisions for quarters between January 1, 1994 and June 30, 2019 such that on the forecast announcement day, there is neither an earnings announcement from the company nor earnings forecast announcements by any other analyst on the same company. Variable definitions are provided in Table G.2.

	With record			No record		
VARIABLES	N	mean	sd	N	mean	sd
GoodNews	2,412,921	0.393	0.488	168,938	0.398	0.490
ForecastError	2,401,471	-0.161	0.908	167,523	-0.146	0.927
StockExp	2,412,921	1,435	1,447	168,938	75.70	231.7
IndExp	2,412,921	2,470	2,122	168,938	971.5	1,515
TotExp	2,412,921	3,134	2,414	168,938	1,592	1,969
Companies	2,412,921	16.63	7.459	168,938	13.86	8.477
Industries	2,412,921	4.290	2.564	168,938	3.843	2.574
Turnover	2,412,921	0.0262	0.160	168,938	0.0352	0.184
Horizon	2,412,921	49.18	40.83	168,938	46.17	48.98
DaysElapsed	2,412,921	5.349	12.09	168,907	7.603	15.74
BrokerSize	2,412,921	1.070	0.273	168,938	1.287	0.513
log(MktSize)	2,412,502	8.092	1.786	168,890	7.462	1.757
B/M	2,412,450	0.493	0.384	168,889	0.445	0.365
PastReturns	2,375,825	0.00198	0.288	167,802	0.0378	0.353
Volume	2,347,292	2.452	1.912	149,676	2.402	1.996
Coverage	2,412,921	15.92	9.143	168,938	13.61	8.842

Table G.4: Summary statistics (all forecast revisions between 1/1/1994 and 6/30/2019)

Notes: This table summarizes the indicator variable *GoodNews* and the control variables, separately for with-record and no-record forecasts. It includes all forecast revisions for quarters between January 1, 1994 and June 30, 2019. Variable definitions are in Table G.2.

	(1) Ret[2,22]	(2) Ret[2,43]	(3) Ret[2,EA+1]
Ret[-1, 1]	0.0179	0.146†	0.252**
	(0.0568)	(0.0775)	(0.0808)
NoRecord	0.000717	0.00170	0.00116
	(0.00120)	(0.00158)	(0.00156)
NoRecord × Ret[-1, 1]	-0.0335	-0.0214	-0.0520
	(0.0227)	(0.0319)	(0.0364)
GoodNews	0.00689***	0.00753***	0.00939***
	(0.000929)	(0.00137)	(0.00149)
GoodNews × Ret[-1, 1]	0.0297	0.0449*	0.0280
	(0.0190)	(0.0222)	(0.0275)
NoRecord × GoodNews	-0.000648	0.000990	0.000416
	(0.00151)	(0.00206)	(0.00210)
NoRecord × GoodNews × Ret[-1, 1]	0.0510	0.100*	0.122*
	(0.0326)	(0.0478)	(0.0496)
Controls	Y	Y	Y
Controls × Ret[-1,1]	Y	Y	Y
Year-Quarter FE	Y	Y	Y
Observations	895740	895168	892678
R^2	0.009	0.012	0.015

Table G.5: Sufficiency of stock market reactions to forecast revisions: different drift lengths

Notes: This table reports the results of Regression (1) with different dependent variables. $Ret[2, 22]$ and $Ret[2, 43]$ are the stock's 1-month and 2-month size-adjusted buy-hold returns starting from the 2nd trading day after the forecast announcement, respectively. "EA+1" is the 1st trading day after the announcement of the actual earnings. In the model $Ret[2, EA + 1]$, I exclude observations where the actual earnings announcement happens later than 190 trading days after the forecast announcement. Three-dimensional (stock, analyst, year-quarter) cluster-robust standard errors in parentheses. $\dagger p < 0.10, *p < 0.05, **p < 0.01, ***p < 0.001$

Dependent Var: Ret[2,64]	(1) High innovation	(2) Isolated	(3) After 2004	(4) MktCap>2b	(5) MktCap>10b	(6) Qtr SE&FE
Ret[-1, 1]	0.307*	0.271†	0.369**	-0.00618	-0.625†	
	(0.139)	(0.137)	(0.131)	(0.158)	(0.317)	
NoRecord	0.00213	-0.00211	-0.00210	0.00498†	0.00358	0.000536
	(0.00272)	(0.00229)	(0.00243)	(0.00267)	(0.00281)	(0.00205)
NoRecord × Ret[-1, 1]	-0.0667	-0.0960	-0.105†	-0.0449	0.00603	-0.0264
	(0.0505)	(0.0629)	(0.0570)	(0.0783)	(0.136)	(0.0458)
GoodNews	0.0120***	0.0111***	0.00737***	0.00364*	0.00396*	0.0106***
	(0.00222)	(0.00182)	(0.00185)	(0.00147)	(0.00154)	(0.00176)
GoodNews × Ret[-1 1]	0.0440	0.0715*	0.0163	0.0646*	0.0633	0.0522†
	(0.0339)	(0.0353)	(0.0344)	(0.0264)	(0.0426)	(0.0266)
NoRecord × GoodNews	0.000813	0.00146	-0.000372	-0.00459	-0.00515	0.00131
	(0.00339)	(0.00280)	(0.00287)	(0.00360)	(0.00352)	(0.00247)
NoRecord × GoodNews × Ret[-1, 1]	0.229**	0.153†	0.134†	0.163	0.0522	0.107†
	(0.0780)	(0.0869)	(0.0800)	(0.135)	(0.169)	(0.0620)
Controls	Y	Y	Y	Y	Y	Y
Controls × Ret[-1,1]	Y	Y	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y	Y	Y
Year-Quarter Slope Effects	N	N	N	N	N	Y
Observations	502879	571449	649583	499077	215867	894004
R^2	0.018	0.013	0.013	0.020	0.017	0.016

Table G.6: Sufficiency of stock market reactions to forecast revisions: robustness checks

Notes: This table reports the results of Regression 1 under different cuts of the data and specifications. “High innovation" restricts attention to forecasts that fall outside the range between the same analyst’s previous forecast and the previous consensus. “Isolated" focuses on 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. “After 2004" uses forecasts announced after Jan 1, 2004. “MktCap>2b" and "MktCap>10b" focus on stocks whose market capitalization is larger than \$2 billion and \$10 billion, respectively. “Qtr SE&FE" includes the interactions between the year-quarter dummies and $Ret[-1, 1]$, in addition to year-quarter fixed effects. Three-dimensional (stock, analyst, year-quarter) cluster-robust standard errors in parentheses. $\dagger p < 0.10, *p < 0.05, **p < 0.01, ***p < 0.001$

	(1)	(2)
	Ret[-1,1]	Ret[2,64]
Revision	1.077***	2.281*
	(0.258)	(0.972)
NoRecord	-0.00258**	0.000937
	(0.000812)	(0.00297)
NoRecord × Revision	-0.113	-0.566
	(0.179)	(0.480)
GoodNews	0.0116***	0.00641**
	(0.000581)	(0.00196)
GoodNews × Revision	0.438***	2.586***
	(0.118)	(0.727)
NoRecord × GoodNews	0.00448***	-0.00163
	(0.00110)	(0.00397)
NoRecord × GoodNews × Revision	-0.0416	2.822*
	(0.336)	(1.315)
Controls	Y	Y
Controls × Revision	Y	Y
Year-Quarter FE	Y	Y
Observations	503943	502879
R^2	0.026	0.022

Table G.7: Sufficiency of stock market reactions to forecast revisions: magnitudes of revisions

Notes: This table reports the results of the following regression.

$$\begin{aligned} Ret[t,T]_i =& \eta_0 + \eta_1 Revision_i + \eta_2 NoRecord_i + \eta_3 GoodNews_i \\ &+ \eta_4 NoRecord_i \cdot GoodNews_i + \eta_5 Revision_i \cdot GoodNews_i + \eta_6 Revision_i \cdot NoRecord_i \\ &+ \eta_7 Revision_i \cdot NoRecord_i \cdot GoodNews_i + Controls_i + Controls_i \cdot Revision_i + TimeFE_i + \varepsilon_i. \end{aligned} \tag{14}$$

$Revision$ is the difference between an analyst's revised forecast on earnings per share and her previous forecast, normalized by the stock price two trading days prior to the announcement of the revision. I winsorize $Revision$ at the 1st and 99th percentiles. I only include "high-innovation" revision, i.e. forecasts that fall outside the range between the same analyst's previous forecast and the previous consensus. Three-dimensional (stock, analyst, year-quarter) cluster-robust standard errors in parentheses. $\dagger p < 0.10, *p < 0.05, **p < 0.01, ***p < 0.001$