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ORIGINAL PAPER

Good news and bad news are still news: experimental evidence on belief updating

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Abstract Bayesian updating remains the benchmark for dynamic modeling under uncertainty within economics. Recent theory and evidence suggest individuals may process information asymmetrically when it relates to personal characteristics or future life outcomes, with good news receiving more weight than bad news. I examine information processing across a broad set of contexts: (1) ego relevant, (2) financially relevant, and (3) non value relevant. In the first two cases, information about outcomes is valenced, containing either good or bad news. In the third case, information is value neutral. In contrast to a number of previous studies I do not find differences in belief updating across valenced and value neutral settings. Updating across all contexts is asymmetric and conservative: the former is influenced by sequences of signals received, a new variation of confirmation bias, while the latter is driven by non-updates. Despite this, posteriors are well approximated by those calculated using Bayes' rule. Most importantly these patterns are present across all contexts, cautioning against the interpretation of asymmetric updating or other deviations from Bayes' rule as being motivated by psychological biases.

Keywords Beliefs · Bayes' rule · Asymmetric belief updating · Conservatism · Overconfidence

JEL Classification C91 · D83 · D84

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1 Introduction

The ability to process new information in forming and updating beliefs is critical for a wide range of important life decisions. Students receiving grades adjust beliefs about their ability to succeed in different majors before declaring, entrepreneurs may be awarded or denied funding for their projects and must update beliefs about the viability of these projects, smokers who are informed of new health statistics on the dangers of smoking must update about these risks in deciding whether to quit.

In modeling such situations, it is typically assumed that individuals use Bayes' rule to update their beliefs. Individuals who receive partially informative signals about states of the world are assumed to incorporate this information in an unbiased, calculated way. While Bayesian updating is the current paradigm theoretically, it is also accepted that it has a strong normative basis.

Given the importance of updating beliefs for decision making in economic contexts, experimental evidence on updating has been studied for some time (e.g., Kahneman and Tversky 1973; Grether 1980, 1992; Camerer 1987, 1995; Holt and Smith 2009). These studies greatly contributed to our understanding of how individuals update their beliefs, and highlighted the existence of cognitive biases, as updating deviated from Bayes' rule in systematic ways. Even so, the nature of the updating tasks in these studies differed considerably from the real updating decisions that motivated them. Unlike updating decisions that are economically relevant to individuals, updating in lab experiments typically involved events such as drawing balls from urns, where subjects hold no personal or financial stake in the outcome, beyond an incentive payment for accuracy. Henceforth, I refer to such events as value neutral; information about them is just news, neither good nor bad.

In contrast, value relevant or valenced events are those in which an individual strictly prefers one outcome to another, and news about the outcome can be categorized as good or bad. This distinction may be critically important, as there is now a small but growing body of theory and empirical evidence suggesting that there exist further psychological biases in how information is processed in value relevant contexts, depending on whether it is perceived as good or bad news (e.g., Eil and Rao 2011; Sharot et al. 2011; Ertac 2011; Mobius et al. 2014; Kuhnen 2014). Drawing in part on this evidence, Sharot et al. (2012) claim: "Humans form beliefs asymmetrically; we tend to discount bad news but embrace good news."

In this paper I examine whether updating differs across value relevant and neutral contexts. My primary focus is on understanding whether there exist additional psychological biases which lead to asymmetric updating when news is good or bad, beyond the cognitive biases which have been previously found for value neutral contexts. I examine binary events that are either (1) ego relevant, (2) financially relevant, or (3) value neutral. These consist of two uncertain events that are objective in nature, involving the rolling of virtual dice; one subjective, involving estimation of historical temperatures; and one that pertains to ego, involving relative performance on a math and verbal skills quiz. Financial relevance is introduced randomly at the subject-event level, with the endowment of additional financial prizes of $80 in the outcomes of interest. As this experiment utilizes a financially incentivized belief elicitation procedure, this introduces a different type of financial stake. To minimize confusion, I refer to this type of financial stake as an accuracy payment.

Information comes in the form of partially informative binary signals regarding the outcomes of the events. I elicit beliefs utilizing the incentive compatible elicitation procedure of Grether (1992), Holt and Smith (2009), and Karni (2009). The primary analysis focuses on between subject variation in updating patterns and follows Mobius et al. (2014) in estimating an empirical model of belief updating that nests Bayesian updating as a special case, but allows for differential response to affirmative versus negative signals. The elicitation procedure improves on previous work that utilizes other elicitation procedures, such as the quadratic scoring rule (QSR), that are not invariant to subjects' risk preferences.[1]

The results show that, common to previous studies, updating behavior deviates from the strict mechanics of Bayesian updating. Updating is conservative, with many non-updates, and asymmetric, with negative signals receiving more weight than affirmative signals. I find evidence that observed asymmetry is affected by the sequence of signals received, with more negative sequences showing more negative asymmetry, a new type of confirmation bias. Yet critically, these deviations do not differ across value relevant and value neutral contexts, i.e. regardless of whether signals contain good or bad news, or are simply conveying neutral information. While I am able to reject the Bayesian benchmark with statistical precision, posteriors are well approximated by those calculated using Bayes' rule. These results are consistent with Holt and Smith (2009) who found important deviations from Bayes' rule, yet also that average posteriors appear to approximate their Bayesian counterparts well, particularly for intermediate priors.

Overall the analysis indicates the importance of observing a broad set of counterfactual belief updates, as results of this paper demonstrate how narrowly comparing two events can lead to conclusions that don't hold up to broader comparisons with other events. Specifically, updating patterns appear more asymmetric when updating about one's own performance on the ego relevant quiz rather than another's performance, yet similar asymmetry is present when subjects update about objective dice events. These results thus caution against attributing biased updating patterns to contexts where such bias is psychologically plausible, as updating patterns are similar across settings where such bias is clearly implausible. The remainder of the paper is as follows. The following section discusses recent theoretical and empirical work investigating belief updating. Next, I outline the experimental design, followed by a description of the results, and concluding with a brief discussion.

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[1] Antoniou et al. (2015) discuss issues that may arise with inference of updating behaviors when elicitation procedures are not robust to risk preferences.

2 Related literature

This paper is related to a sizeable literature on studying how individuals process information and whether this is well approximated by Bayes' rule. The majority of these studies investigate updating about value neutral events, where subjects have no personal or financial stake in the outcome, excepting a payment for accurate belief reports. These studies noted a number of cognitive biases corresponding to deviations from Bayes' rule.

Kahneman and Tversky (1972), Kahneman and Tversky (1973), and Grether (1980) found evidence in support of a "representativeness" heuristic, whereby individuals neglect prior or base rate information when facing samples that mimic proportions or qualities of their parent population.[2] More broadly, base rate bias/neglect is often used in reference to a general tendency to over respond to information, relative to a Bayesian. Earlier, Edwards (1968) had observed a seemingly opposing bias, conservatism, the tendency for individuals to under respond to information, ending up with posteriors closer to their priors than if they had followed Bayes' rule.

This evidence demonstrated that individuals do not appear to follow the exact mechanics of Bayes' rule. Yet across contexts, Bayesian approximation does relatively well, and fewer deviations are observed for more experienced subjects, see Camerer (1987) and Camerer (1995). More recently, Holt and Smith (2009) find that belief updating is consistent with Bayes' rule at the aggregate level, however they find systematic deviations which are more pronounced for extreme values of the prior, using a similar analysis to this paper.

Beyond these cognitive biases, which are invariant to the valence of news or signals, neuroscientists, psychologists, and economists have posited the existence of additional psychological biases, i.e. updating biases that are present only when information is valenced. There are a number of psychologically plausible motivations for why updating may differ when the context is financially or personally relevant. The proposed theories share a common consequence: an asymmetry that did not feature in the earlier discussion of cognitive biases, specifically, an over-weighting of good news relative to bad news.

The first such motivation is that asymmetric updating may enable individuals to nurture biased beliefs about their abilities or about future outcomes. For example, Landier (2000), Yariv (2005), Mayraz (2014), and Mobius et al. (2014) present models where individuals gain utility from holding positive beliefs, and process information in a biased manner (over-weighting good news relative to bad news) in order to nurture such positive beliefs. Second, biased information processing is similarly rational if optimistic beliefs improve health outcomes, e.g. Scheier and Carver (1987). Finally, biased beliefs could also be nurtured for strategic purposes, as in Benabou and Tirole (2002) regarding self-confidence.

A number of studies have begun to investigate these biases. In an unincentivized study, Sharot et al. (2011) examined how individuals updated their beliefs about future life events such as being diagnosed with Alzheimer's disease or being robbed.

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[2] Representativeness bias was also found and studied by Grether (1992) and Holt and Smith (2009).

They found that individuals updated more in response to good news relative to bad news.[3] Another unincentivized study by Wiswall and Zafar (2015) finds some evidence that college students revise beliefs more when they receive information that average future earnings are greater than expected, relative to receiving information that earnings are less than expected.

As it is typically not possible to financially incentivize the elicitation of future life events, economists have turned to study belief updating about value relevant events in the laboratory. Crucially, these studies have differed from early work, not only in context, but also in analysis. As there is little theoretical motivation for observing asymmetric updating in value neutral contexts, previous work did not examine the relative weight placed on affirmative versus negative signals. With value relevant contexts, this changed. This has important implications for the comparability of results, as the wealth of analysis from earlier work cannot be brought to bear on more recent studies. This feature of the existing literature presents a clear rationale for the examination of robust counterfactual settings, an advantage of the current paper.

Recent and ongoing work on belief updating in value relevant contexts often focuses on a particular context of interest, along with one counterfactual. Most relevant is Mobius et al. (2014), who pair an experiment with a theoretical model of optimally biased Bayesian updating in the context of ego relevant events. In the experiment they examine how individuals update beliefs about scoring in the top 50% on an intelligence test, using the same elicitation procedure as this paper. They find evidence that individuals update asymmetrically, over-weighting good signals relative to bad, and conservatively, updating too little in response to either type of signal. To provide evidence that these biases are not present outside of ego relevant contexts they compare the results to a follow-up where a subset of the same subjects complete the updating task for a robot, with the result that both conservatism and asymmetry are reduced.

Regarding financial relevant events, Barron (2016) investigates updating beliefs when individuals have a financial stake in the outcome of drawing balls from two urns. His experiment complements this paper, focusing on one type of event while exogenously varying different values priors, as opposed to the across event variation that is the focus here. Barron (2016) does not find evidence of asymmetric over-weighting of good news. In contrast to the current paper financial stakes are smaller (10 GBP rather than $80), and the focus precludes examining different types of events, e.g. ego relevant.

Other related papers on ego relevant tasks are Buser et al. (2018), Eil and Rao (2011), Ertac (2011). Buser et al. (2018) is most similar, however their focus is on heterogeneity in deviations from Bayes' rule, as such they do not have an ego irrelevant control. Eil and Rao (2011) and Ertac (2011) differ in their information structure; the former finds evidence of positive asymmetric updating for relative intelligence and beauty, while the latter finds the opposite asymmetry, that bad news

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[3] Of note is that there is recent work which critiques some of the evidence for asymmetric updating in these types of studies within psychology and neuroscience, see Shah et al. (2016).

is weighted more than good news. While results of Ertac (2011) are similar to those of this paper, the conclusions differ starkly.[4]

A common challenge inherent to this literature involves the construction of an appropriate counterfactual updating task. Clearly, evidence of biased updating in value relevant contexts could relate to cognitive biases identified by earlier work, rather than psychological biases. Individuals may update differently for different base rates or priors, or for different distributions of received signals. Even the objective versus subjective nature of the event may affect updating behavior.[5] To overcome this challenge, the current paper contains a more comprehensive set of updating decisions which form a natural set of counterfactuals that can be used to evaluate behavior. Observing this broader set of decisions may alter the interpretations of deviations from Bayes' rule in important ways, as the results of this paper will show.

3 Experimental design

The experiment was conducted at New York University, at the Center for Experimental and Social Science (CESS). Recruitment was done via the CESS online system, where undergraduate students are notified by email when an experiment is scheduled, and have the opportunity to sign up. A total of 326 subjects participated, in 32 different sessions for an average of 10 subjects per session.[6] The average subject payment was $24.96 for approximately 75 min including a $10 showup fee. The experimental data is also studied in Coutts (2015), there with the aim of distinguishing models of belief bias. That paper focuses exclusively on prior formation, and does not examine updating behavior.

Individuals in the experiment faced four different binary events and a sequence of four incentive compatible belief elicitations for each event. First, their prior beliefs about the probability of the event were elicited. Next they received a binary signal, regarding whether the event had occurred. This signal was true with two-thirds probability, and false with one-third probability. After receiving this signal their beliefs were again elicited, and the same process was repeated two more times.

One concern was that the elicitation procedure or the sequence of signals might be confusing to some subjects. These features of the experiment were presented making use of intuitive explanations that aid subject understanding, following Grether (1980) who recognized their importance for experimental credibility. A large component of the experiment consisted of intuitive explanations and

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[4] Grossman and Owens (2012) examine absolute performance, but do not observe the same biases in information processing found in studies on relative performance. Clark and Friesen (2009) find little evidence of overconfidence in a related study on task experience rather than feedback.

[5] Some evidence that the objective versus subjective nature may affect updating is presented in this paper. Among the studies cited above, the majority have one counterfactual updating task, however only Barron (2016) (financially relevant) and Ertac (2011) (ego relevant) examine a counterfactual updating task that is robust to the above concerns, and in the case of Ertac (2011) only for a small subsample.

[6] Instructions are available in Online Appendix H. Because of a technical failure, one session resulted in data for only one event. 318 subjects participated in all four events.

examples, as well as practice with all of the experiment's components before the actual experiment began. A questionnaire was administered to every participant after completing the experiment. This, as well as verbal feedback, suggested that subjects had a good understanding of the various components of the experiment.

3.1 Belief elicitation

To elicit beliefs I use the method of Karni (2009), utilized also by Grether (1992), Holt and Smith (2009), and Mobius et al. (2014), which I henceforth call the lottery method.[7] Incentive compatibility follows from a dominance argument, that individuals strictly prefer a higher probability of earning the same monetary prize. In order to make comparisons of lotteries, the method additionally requires that individuals exhibit probabilistic sophistication, see Machina and Schmeidler (1992). It does not require that individuals maximize expected utility, nor does it require assumptions on risk preferences.[8] The method involves the possibility of earning a lump sum payment a, and works as follows.

Subjects are asked to report a probability $\tilde{\pi}$ that makes them indifferent between participating in a lottery that pays a with probability $\tilde{\pi}$ and 0 otherwise, or participating in a lottery that pays a whenever the event of interest occurs. After indicating $\tilde{\pi}$, the computer draws a random number r distributed uniformly from 0 to 100. If $r \geq \tilde{\pi}$, a subject participates in the lottery that pays a with probability r. If $r < \tilde{\pi}$ the subject faces the lottery that pays a when the event in fact occurs ("event lottery"). When r takes on discrete values, this mechanism is equivalent to a 101 item choice list that requires a choice between the "event lottery" and an objective lottery which pays a with percentages in the set of integers from 0 to 100, with one choice selected at random. In the experiment a is either low ($3), medium ($10), or high ($20), randomized at the session level.

In order to facilitate subjects understanding the lottery method, the experiment made use of an intuitive graphical interface.[9] Subjects were introduced to a gumball machine, that had 100 black or green gumballs. This represented a lottery with the probability of success equal to the number of green gumballs out of 100. One gumball would be drawn from the machine, at random. Subjects were told that the computer had a list of 101 gumball machines, each with a different proportion of green gumballs, and that one of these would be randomly selected, i.e. the discrete uniform distribution.

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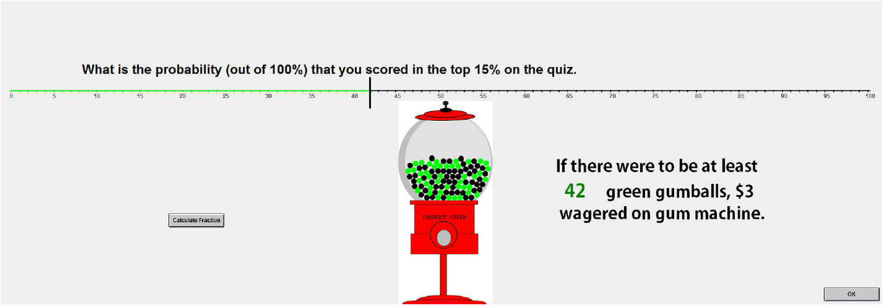
[7] See Karni (2009) for a more detailed description of the lottery method, though the method has been described in a number of earlier papers, see Schlag et al. (2015). The mechanism has also been referred to as the "crossover method", "matching probabilities", and "reservation probabilities".

[8] While this method is a variant of the Becker–Degroot–Marschak (BDM) mechanism, note that it is not subject to the critique of Karni et al. (1987), as the method identifies parallel probabilities that lead to indifference between two lotteries; see Healy (2016).

[9] Subject understanding of methods of belief elicitation has been a concern for many experimental economists. Schlag et al. (2015) provides a nice overview of the literature discussing the effects of complexity of elicitation procedures on responses. Schotter and Trevino (2014) is a good overview more generally on eliciting beliefs in laboratory settings.



What is the probability (out of 100%) that you scored in the top 15% on the quiz.

If there were to be at least 42 green gumballs, $3 wagered on gum machine.

Fig. 1 Screenshot from the experiment: slider. The gumball machine was used to provide an intuitive representation of the lottery method. Subjects would indicate on the slider the minimum threshold, i.e. the number of green gumballs there had to be in the machine before they would prefer to wager the accuracy payment (here $3) on the gumball machine rather than the event, "you scored in the top 15% on the quiz". The proportion of green gumballs in the picture adjusted as the slider was moved

They were then asked to indicate on a graphical slider, exactly what point they would prefer to base their potential earnings on the "gumball lottery" instead of the "event lottery", which paid off if the event of interest occurred. Figure 1 provides screenshots of the gumball machine, as well as the slider subjects had to move. Subjects were given significant practice with the slider, with non-paid practice events, before the primary experiment began.

3.2 Events

The four events, presented in random order, are a key source of variation in the experiment.[10] Of these four events, two involve rolling dice, and their probabilities can be objectively calculated.[11] The outcome of these events was determined by chance, and individuals could not affect these outcomes.

The other two events are subjective, based upon tasks that individuals had completed prior to the beginning of the experiment. Most relevant to previous studies of asymmetric updating is an event where individuals had to estimate the probability they scored in the top 15% on a 5 minute, ego relevant quiz. Percentiles in the quiz were generated by comparing scores to 40 individuals who took the quiz in previous piloting, which was known to students. The quiz involved multiple choice questions on math and English skills, similar to standardized college entry

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[10] One of the events (easy dice) was fixed as the final event. The other three events were randomly ordered at the session level. Updating behavior does not differ by order.

[11] It is difficult to find a rigorous definition of what makes a probabilistic process "objective". I follow the definition of Gilboa and Schmeidler (2001).

[12] This quiz was taken before individuals made any choices, and before they had any knowledge of the four events. Subjects were told truthfully that performing better on the test would lead to higher expected payments.

[13] Individuals were correct if the true temperature was within plus or minus 5 degrees Fahrenheit of their estimate. In fact, there is no correlation between beliefs about getting this question correct and actually getting the question correct.

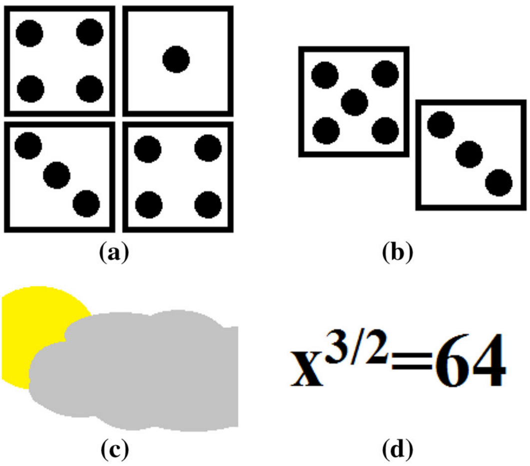

Fig. 2 Description of events. **a** Hard dice: the computer rolls four dice. Event occurs when exactly two out of those four dice was a specified number (e.g. 4). The probability of this is $\binom{4}{2}\left(\frac{1}{6}\right)^2\left(\frac{5}{6}\right)^2=\frac{150}{1296}$ or approximately 11.57%. **b** Easy dice: the computer rolls two dice. Event occurs when two different specified numbers were the only numbers to come up (e.g. 5-3, 3-5, 3-3, 5-5). The probability of this is $\frac{4}{36}$ or approximately 11.11%. **c** Weather: event occurs if the individual correctly estimated the average temperature on a specified random day in NYC in the previous year (2013), +/- 5 ° F. In the sample, 25.77% of subjects were in the correct range. **d** Quiz: event occurs if the individual scored in the top 15% on an ego relevant multiple choice quiz (self). For a subset of participants the event pertained to a random partner's performance instead of their own (other). Percentiles were generated in comparison to 40 pilot quiz-takers

tests in the USA.[12] In order to generate a sensible control group, every individual in the experiment had a 30% chance of being selected to estimate the performance of a randomly selected anonymous partner in the room, rather than their own performance. 95 out of 318 subjects were randomly selected for this control, independent of any other treatments in the experiment.

The fourth event was whether the individual correctly answered a question about what the weather (mean temperature) was on a randomly selected day in New York City in the previous calendar year. This question is not objective in the sense of the dice questions, but it also does not appear to involve skill or ability.[13] Figure 2 summarizes the four events that all individuals faced.

One important feature of these events are the relatively low probabilities, due to budget constraints. Empirically the events occurred on average 15% of the time, with the implication that there will be significantly more negative than affirmative signals. In the data, 63% of the signals are indeed negative, which, as the results sections will discuss, may affect updating behavior. Importantly, while the probability of events were low, priors were significantly higher.[14] The average prior is 36%, and over one-third of priors are greater than or equal to 50%, which facilitates comparisons with other studies.

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[14] See Coutts (2015) for a discussion of this phenomenon.

3.3 Stakes

Another key source of variation in the experiment involved varying the financial stakes. Within each event, individuals had a 50% chance of receiving an additional \$80 if that event occurred. This financial stake was made salient as subjects physically drew a token from a bag, that was labelled either \$80 or \$0. If they drew a \$0 token, they knew that they would have no financial stake in the event, they could only potentially earn an accuracy payment for their belief report. If they drew an \$80 token, they knew that they could potentially earn \$80, if the event in fact occurred, and they were selected for payment for that specific outcome.

In this latter case, at the end of the experiment *only* one of the financial stake *or* the accuracy payment is paid, chosen at random. This design feature ensured independence between the financial stake and accuracy payment, to maintain incentive compatibility by eliminating hedging opportunities in a manner similar to Blanco et al. (2010). Incentive compatibility is preserved assuming a state-wise monotonicity assumption, which is required whenever one pays for one randomly selected decision, see Azrieli et al. (2018). Further details of this procedure and conditions for incentive compatibility can be found in Online Appendix A.

3.4 Signals (news)

News comes in the form of noisy, binary signals, after the first elicitation (prior). Signals were explained with the aid of pictures of “gremlins”, in a procedure related to that of Mobius et al. (2014). In this experiment, individuals were told that there were three gremlins that all knew whether the event had occurred. Two of the three gremlins always told the truth, while one gremlin always lied. The subjects were then told one gremlin had been randomly selected, and that gremlin either provided them an affirmative signal (the event had occurred), or a negative signal (the event had not occurred).

In this way signals were true with probability $\frac{2}{3}$, which differs slightly from the signal strength of $\frac{3}{4}$ in Mobius et al. (2014). After receiving the signal, posterior beliefs were elicited again using the lottery method. Subjects were given three independent signals (knowing the structure in advance) and were informed that the gremlins were drawn with replacement in order to maintain a constant probability of $\frac{2}{3}$ that the signal was true.

In total subjects had their beliefs elicited four times for each of the four events: one prior elicitation, and three posterior, for a total of 16 elicitations. One of the elicitation rounds was randomly selected at the end for payment in accordance with the procedure discussed in Online Appendix A.

Figure 3 depicts screenshots from the experiment that showcase the use of gremlins as graphical aids.[15] In addition, individuals also had practice with receiving signals and updating beliefs with non-paid practice events, before the paid experiment began.

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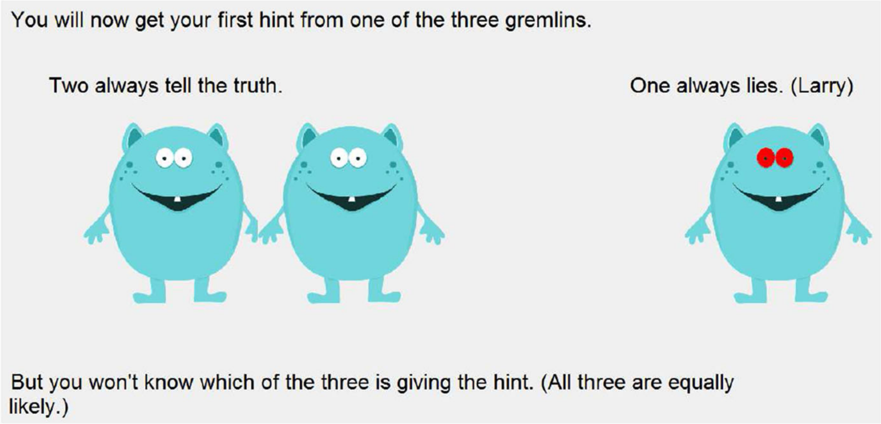
[15] Images are from www.mycutegraphics.com, by author Laura Strickland.



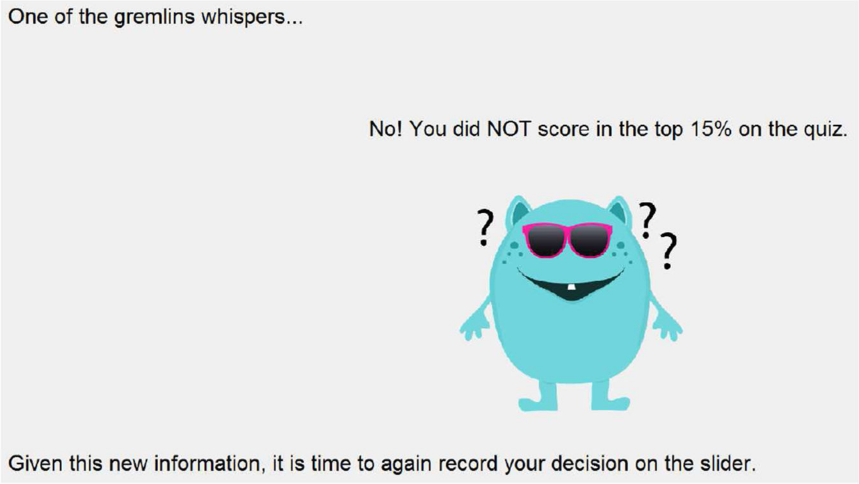
You will now get your first hint from one of the three gremlins.

Two always tell the truth.

One always lies. (Larry)

But you won't know which of the three is giving the hint. (All three are equally likely.)

(a)



One of the gremlins whispers...

No! You did NOT score in the top 15% on the quiz.

Given this new information, it is time to again record your decision on the slider.

(b)

Fig. 3 Screenshots from the experiment: signals. **a** Screenshot introducing signals. **b** Screenshot of a received (negative) signal

3.5 Classifying good/bad news (value relevant) from just news (value neutral)

To summarize the treatments, accuracy payments of $a \in \{3, 10, 20\}$ were randomized at the session level, while financial stakes of \$0 or \$80 were randomized at the subject-event level. Additionally, for the quiz event, 30% of subjects were randomly allocated to a control treatment where they were asked to update about another randomly selected individual's performance.

Thus, for an event that a given subject was allocated an \$80 financial stake, information about whether the event occurred will contain good or bad news.

Information which indicates such an event is more likely, corresponds to an increase in the expected probability of earning the $80, and vice-versa.

For those events that a given subject was allocated a $0 stake, whether information/news is good or bad depends on the event itself. To the extent that individuals gain utility from believing they have high ability, the quiz event (estimating own performance) involves a personal, non-pecuniary stake. Thus for this quiz event, binary signals about performance will contain either good news (they are in the top 15%), or bad news (they are not in the top 15%).

These contexts are in contrast with value neutral events where there are no personal stakes: the two dice events and the weather event, *and* those in which subjects held a $0 (rather than $80) financial stake in the outcome. Here signals contain information about outcomes, but these outcomes are irrelevant to individual well being. In other words, news is simply news.[16]

Of 1280 events, 634 involved a financial stake of $80, which means signals regarding these events are categorized as value relevant. The remaining 646 events had no financial stake.[17] However, of these 646 events, 115 were the quiz (self) event which is a personal stake. Thus altogether, I classify 749 events as potentially relating to good/bad news (value relevant), and 531 events as just news (value neutral).

4 Results

4.1 Overview of pooled results

As a first pass at examining updating behavior I plot reported subject beliefs and compare these to posterior beliefs that would have resulted if subjects updated using Bayes' rule. Following the discussion in the previous section, I split the sample into events where subjects have a financial or personal stake in the outcome, and events where subjects have no such stake.

The former include all events where subjects stand to earn $80 if the event occurs, as well as the event that involved whether they scored in the top 15% on the quiz. For these events, information in the form of noisy signals is valenced. The latter events do not involve individual ability and subjects have no additional financial stake in the outcome of the event. Thus, signals provide new information about these outcomes, information which is neither good nor bad. Belief reports are financially incentivized using the lottery method.

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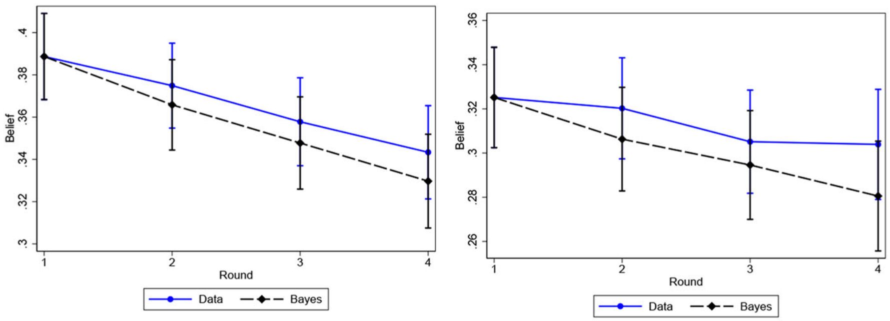
[16] As noted before, accuracy payments are a form of financial stake. However, *ex-ante*, an individual has no reason to care whether an event occurs or not, as long as their belief report is accurate. It may be argued that the weather event involves a personal stake, if individuals derive utility from correctly estimating historical temperatures. I do not find this likely, but regardless, none of the results in this paper hinge on the inclusion of the weather event.

[17] The reason they are not equal is that some sessions had odd numbers of subjects, and the physical drawing of $0 or $80 always involved an equal proportion of both stakes.



(a) **(b)**

Fig. 4 Evolution of beliefs **a** financial/personal stake: good/bad news, **b** No stake: just news. The path of beliefs starting from the prior (round 0) and after each sequential signal (rounds 1 through 3). **a** Quiz (self) event and all instances where subjects could earn \$80 if the event occurred. **b** All other instances. Average individual responses are the blue solid line, the Bayesian benchmark is marked as the black dashed line. Bayesian benchmark takes prior beliefs, and uses Bayes' rule to calculate how beliefs would evolve given the signals that subjects actually received. Error bands represent 95% CI. **a** $N = 749$ **b** $N = 531$ observations per round. (Color figure online)

Figure 4 plots the average reported belief for the prior, as well as the belief after receiving each signal. Included in the same figure is the path that beliefs would take if individuals were perfect Bayesians, given the subject's first reported belief.

From Fig. 4 one can see that there are slight deviations from Bayes' rule for both subsamples, as individual's update slightly more conservatively. However the difference between reported posteriors and Bayesian posteriors is not significant at any conventional level. There are slight differences in prior belief formation across the two groups, part of which is accounted for by the presence of the quiz (self) event. In fact, priors are biased upwards for all events, as detailed in Coutts (2015).

Beyond this, no substantive differences are apparent in patterns of updating across the two subsamples. Thus from an initial look at the data, updating does not appear to differ when news is good or bad, compared to when news is simply news.[18] The correlation between empirical posterior beliefs and posterior beliefs calculated using Bayes' rule is 0.89, higher than that found in Mobius et al. (2014). Pooling across the three updating rounds, the average posterior is 33.8%, while the average Bayesian posterior, calculated using subject priors, is 32.5%. These are remarkably similar, though it is noteworthy that the difference is significantly different from zero at the 1% level using a Wilcoxon rank-sum test. Interestingly, despite the high correlation between actual posteriors and Bayesian posteriors, the aggregate data includes a large number of non-updates. 41% of reported posteriors are identical to reported priors and only 9% of subjects update in every round.

To summarize thus far, updating appears to be well approximated by Bayes' rule, despite a large number of non-updates. However, looking only at aggregated

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[18] In Online Appendix G I present these figures for all events, all financial stake, and all accuracy payment conditions separately. From those figures, one can see that there are some slight differences in updating behavior across events, but financial stakes or accuracy payments do not appear to alter updating behavior.

posterior beliefs may potentially obscure how individuals react to signals, and may be affected by the fact that negative signals are more prevalent. I next use a flexible empirical framework to examine how individuals respond to both affirmative or negative signals, which, depending on the event and stake conditions, may be interpreted as good or bad news. This permits a more rigorous investigation into whether individuals update asymmetrically, when the outcomes of events are either ego relevant or financially relevant, as has been found in previous literature.

4.2 Information processing: framework

I now provide a more detailed analysis, following Mobius et al. (2014) by using a flexible model of updating that retains the structure of Bayes' rule, but allows for the possibility that individuals place different weight on the prior, affirmative signals, or negative signals. The model is a variant of that used originally by Grether (1980), and more recently by Holt and Smith (2009). Bayes' rule can be written in the following form, considering binary signals, $s_t = k \in \{0, 1\}$, and letting $\hat{\mu}_t$ be the belief at time t:

$$\frac{\hat{\mu}_t}{1-\hat{\mu}_t} = \frac{\hat{\mu}_{t-1}}{1-\hat{\mu}_{t-1}} \cdot LR_k \tag{1}$$

where LR_k is the likelihood ratio of observing signal $s_t = k \in \{0, 1\}$. In this experiment, $LR_1 = 2$ and $LR_0 = \frac{1}{2}$, given the signal strength of $\frac{2}{3}$. Taking natural logarithms of both sides and using an indicator function, $I\{s_t = k\}$, for the type of signal observed,

$$logit(\hat{\mu}_t) = logit(\hat{\mu}_{t-1}) + I\{s_t = 1\}\ln(LR_1) + I\{s_t = 0\}\ln(LR_0). \tag{2}$$

The empirical model nests this Bayesian benchmark as follows,

$$logit(\hat{\mu}_{it}) = \delta logit(\hat{\mu}_{i,t-1}) + \beta_1 I(s_{it} = 1)\ln(LR_1) + \beta_0 I(s_{it} = 0)\ln(LR_0) + \epsilon_{it}. \tag{3}$$

δ captures the weight placed on the log prior odds ratio. β_0 and β_1 capture responsiveness to either negative or affirmative signals respectively. In the context of the experiment, $s_{it} = 1$ corresponds to a signal that YES the event had occurred, while $s_{it} = 0$ corresponds to a signal that NO the event had not occurred. Since $I(s_{it} = 0) + I(s_{it} = 1) = 1$ there is no constant term. ϵ_{it} captures non-systematic errors.

This framework allows for the testing of the primary hypotheses of this paper. Bayes' rule is a special case of this model when $\delta = \beta_0 = \beta_1 = 1$. Additionally, as described in Mobius et al. (2014), Bayes' rule satisfies three additional properties: invariance, sufficiency, and stability. When $\delta = 1$, the updating process is said to satisfy invariance, i.e. the change in logit beliefs depends only on past signals. Sufficiency requires that after controlling for prior beliefs, lagged information does not significantly predict posterior beliefs. Finally, stability requires that the structure of updating is stable across rounds.

Given past evidence, it seems unlikely subjects will satisfy the strict requirements of Bayesian updating. As a secondary hypothesis, I significantly weaken the requirement of Bayesian updating to a flexible model that may involve a number of different cognitive biases. The only restriction I impose, is that these cognitive biases do not differ on average across value relevant and value neutral contexts. Thus subjects may be conservative, or suffer from representativeness bias, but if these biases do not lead to differential updating patterns across valenced and non valenced contexts, then they have not entered into the domain of psychological bias.

The key tests of whether there are psychological biases in updating involve whether updating differs across valenced and neutral contexts. Using superscripts V and N respectively on the framework parameters for these contexts, the key hypotheses are presented in Fig. 5. The central hypothesis of interest in this paper, is whether there are differences in asymmetric updating, presented on the final line of Fig. 5. While this asymmetric updating hypothesis was posited before the experiment was conducted, it was not pre-registered.

Importantly, the relevant benchmark for evidence of psychological bias is not Bayes' rule, but actual observed updating behavior in value neutral contexts. This significantly raises the bar for detecting deviations, as prima facie evidence suggests that individuals already suffer from cognitive biases in information processing.

As a first line of investigation, in Online Appendix C I examine the three properties of invariance, sufficiency, and stability for Bayes' rule. Overall, the pooled data do *not* support these properties, though the magnitude of deviations is relatively small.[19] I now turn to the main empirical framework of Eq. 3.

Table 1 presents the aggregate data, as well as the two subsamples introduced earlier, pooling across all updating rounds. Note that significance is indicated as different from the Bayesian benchmark prediction of one, *not* zero. Standard errors are clustered at the individual level. In the primary sample I do not include posterior beliefs that were updated in the opposite direction that Bayes' rule predicts, which amounts to dropping 4.8% of observations. I include all other subjects, including those who never update their beliefs.[20]

Table 1 provides the finer details of updating behavior that Fig. 4 is unable to capture. What is first apparent is that updating behavior deviates from the strict Bayesian prediction that all coefficients are equal to 1. There is substantial conservatism in response to both affirmative and negative signals, as indicated by coefficients less than one for β_1 and β_0. Of note is that the degree of conservatism is less than that found in studies by Mobius et al. (2014) and Buser et al. (2018).

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[19] One valid concern regarding the OLS analysis is in using priors as a dependent variable. Since priors are lagged posteriors, this creates a potential issue if there is substantial heterogeneity in response to signals, which could lead to upwardly biased estimates of δ, see Mobius et al. (2014). Instrumenting with higher order lagged beliefs or lagged Bayesian beliefs is possible, however such techniques do not alter the results reported. Recovering unbiased estimates of δ is also not central to the results of this paper.

[20] 4.8% is less than the approximately 10% in Mobius et al. (2014) and Buser et al. (2018). As Bayesian posteriors will never be at the boundary for intermediate priors, the framework is agnostic for beliefs of 0 or 1. Following Mobius et al. (2014) and Buser et al. (2018), these observations are dropped, amounting to 6% of the sample. In Online Appendix Table F1 I examine implications of these sampling restrictions, following Grether (1992) and Holt and Smith (2009) by replacing boundary observations by 0.01 or 0.99 respectively.

Fig. 5 Hypotheses of the empirical framework

Bayes' Rule

$$\delta = 1; \qquad \beta_0 = 1; \qquad \beta_1 = 1.$$

Cognitive Biases

$$\delta^V = \delta^N; \qquad \beta_1^V = \beta_1^N; \qquad \beta_0^V = \beta_0^N.$$

Psychological Biases

$$\delta^V \neq \delta^N; \quad \text{or} \quad \beta_1^V \neq \beta_1^N; \quad \text{or} \quad \beta_0^V \neq \beta_0^N.$$

Positive Asymmetry: $\beta_1^V - \beta_0^V > \beta_1^N - \beta_0^N$

Negative Asymmetry: $\beta_1^V - \beta_0^V < \beta_1^N - \beta_0^N$

Table 1 Updating beliefs for all events

Dependent variable: logit posterior belief

Regressor	(1) Good/bad news	(2) Just news	(3) All
δ^V	0.918***		
	(0.012)		
β_1^V	0.594***		
	(0.040)		
β_0^V	0.782***		
	(0.043)		
δ^N		0.907***	
		(0.014)	
β_1^N		0.576***	
		(0.051)	
β_0^N		0.812***	
		(0.051)	
δ			0.914***
			(0.009)
β_1			0.588***
			(0.034)
β_0			0.793***
			(0.038)
P value ($\delta = 1$)	0.0000	0.0000	0.0000
P value ($\beta_1 = 1$)	0.0000	0.0000	0.0000
P value ($\beta_0 = 1$)	0.0000	0.0003	0.0000
Diff ($\beta_1 - \beta_0$)	− 0.189	− 0.236	− 0.205
P value ($\beta_1 = \beta_0$)	0.0002	0.0003	0.0000
R^2	0.84	0.82	0.84
Observations	1950	1410	3360
P value [Chow-test] for $\delta^V = \delta^N$			0.5326
P value [Chow-test] for $\beta_1^V = \beta_1^N$			0.7700
P value [Chow-test] for $\beta_0^V = \beta_0^N$			0.5852
P value [Chow-test] for $(\beta_1^V - \beta_0^V) - (\beta_1^N - \beta_0^N)$			0.5489

Analysis uses OLS regression. Difference is *significant from 1* at * 0.1; ** 0.05; *** 0.01. Robust standard errors clustered at individual level. R^2 corrected for no-constant

The coefficient on δ is significantly lower than 1. The significance of this is that subjects are updating as if the priors they held were closer to one-half, i.e. a probability weighting of prior beliefs towards one-half.[21] There is further a strong asymmetric bias that is present across Table 1, with negative signals receiving more weight than affirmative, significant at the 1% level.

However, as with the earlier patterns, there do not appear to be any differences between beliefs about events where subjects have a personal or financial stake versus those where subjects have no stake, and Table 1 shows that I cannot reject equality of any of the three coefficients using Chow tests. Additionally, I cannot reject the hypothesis that $\beta_1^V - \beta_0^V = \beta_1^N - \beta_0^N$. Thus I do not observe any evidence of psychological bias. Whether news is a source of good/bad information or simply neutral information, does not appear to alter how beliefs are updated.

At first glance the results in Table 1 seem at odds with the previous section: posteriors are well approximated by Bayes' rule, yet the framework rejects the Bayesian benchmark and finds significant asymmetry. Similarly contradictory patterns can be seen in Online Appendix Figure D1, which plots average updating behavior by type of signal received. Asymmetry is not observed for the aggregate data, and is only slightly visible when observing moderate priors.

There are two important factors in reconciling these patterns with the earlier results. First, the response to negative signals is only slightly below the Bayesian prediction, and negative signals represent the majority of signals received. Second is that the framework does not assume unitary weighting of the log odds ratio of prior beliefs. In particular, the findings that $\delta < 1$ and $\beta_0 > \beta_1$ effectively operate in opposite directions in the aggregate data. The reason is that $\delta < 1$ implies that individuals update as if priors were closer to one-half than they actually are. Because approximately two-thirds of the data involve priors less than one-half, this has the overall effect of biasing posteriors upwards, and hence reducing the appearance of this asymmetry in the raw data. The finding that $\delta < 1$ was also found by Holt and Smith (2009), there identified as a cognitive bias in general information processing.

Finally, similar to the previous section, there are no significant differences in updating behavior across the financial stake conditions, including the varying payments for accuracy, presented in Online Appendix Table B1. Regarding the accuracy payments, this is relevant to studies of the effects of stakes on behavior in lab experiments, especially regarding belief elicitation. It suggests that paying subjects more for accurate beliefs may have little effect on belief updating.[22] In the

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[21] To see this, note that the generalization in Eq. 3 implies the following relationship:

$$\frac{\hat{\mu}_t}{1-\hat{\mu}_t} = \left(\frac{\hat{\mu}_{t-1}}{1-\hat{\mu}_{t-1}}\right)^{\delta} \cdot (LR_k)^{\beta_k}.$$

When $\delta < 1$, the effect is to bias or weight the log prior odds ratio $\left(\frac{\hat{\mu}_{t-1}}{1-\hat{\mu}_{t-1}}\right)$ towards 1, i.e. subjects update as if priors $\hat{\mu}_{t-1}$ were closer to one-half. If δ were greater than 1, this effect would lead to updating as if priors greater than one-half were closer to 1, and updating as if priors less than one-half were closer to 0.

[22] Combined with Coutts (2015), which showed that increasing accuracy payments can lead to more biased prior formation, the implications are that ideal incentive payments may be relatively low.

next section I use the same analysis to investigate wether there are deviations at the event level.

4.3 Information processing by event

This section examines whether deviations from Bayesian updating are driven by specific events. Previous evidence has found that individuals update asymmetrically when provided information on their performance on a test, over-weighting good news relative to bad as in Mobius et al. (2014) and Eil and Rao (2011), or the opposite asymmetry as in Ertac (2011). I thus focus attention on the quiz (self) event: whether an individual believes they scored in the top 15% on an ego relevant quiz.[23]

Note that in studying updating behavior in one context, it is critical to have an appropriate counterfactual comparison. Deviations in a given context do provide evidence against Bayes' rule, but their attribution to a particular bias or context is only valid if one can rule out that these deviations occur in other contexts. Use of an adequate control group is standard for extrapolating that deviations do not occur across other contexts. This requires that the control group is suitably defined, and has sufficient statistical power to rule out deviations of interest. As I will discuss further, defining a suitable control group for updating on the quiz is not necessarily straightforward, and may explain why few studies in this literature are able to satisfy this requirement.

As an initial control group for the quiz event in this experiment, 30% of subjects did not update about their own performance, but instead updated about the performance of a randomly selected anonymous individual in the lab. This is an intuitive control, yet one issue is that observed prior beliefs about one's own performance tend to be greater than those about another's performance. This is problematic, as in Online Appendix Figure E1, I present some evidence that updating differs for different values of the prior.

The existence of evidence across contexts of this experiment provide additional comparison groups. There is sufficient variation across the different events and financial treatments such that differences in updating that only appear in one context would be strong evidence that such patterns are indeed context specific. On the other hand, similar differences in updating across contexts would suggest that deviations from Bayes' rule may reflect more general cognitive biases.

Table 2 presents the results of all rounds of updating corresponding to each of the four different events, splitting the quiz event into self or other performance. Examining updating across domains, there are some differences in updating behavior, yet these differences do not appear to fit a consistent pattern.

The most suggestive result is found comparing Columns 4 and 5, which respectively examine updating for own versus other performance on the quiz. Regarding own performance, there is asymmetric under-weighting of good news

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[23] The signal structure and elicitation procedure is comparable with Mobius et al. (2014) and Buser et al. (2018), who examined beliefs of subjects about scoring in the top 50%, rather than 15%.

Table 2 Updating beliefs within events

Dependent variable: logit posterior belief

Regressor	(1) Easy dice	(2) Hard dice	(3) Weather	(4) Quiz (S)	(5) Quiz (O)
δ	0.894^{***}	0.872^{***}	0.928^{***}	0.952^{**}	0.912^{**}
	(0.028)	(0.022)	(0.024)	(0.022)	(0.035)
β_1	0.476^{***}	0.404^{***}	0.684^{***}	0.590^{***}	0.709^{**}
	(0.090)	(0.062)	(0.061)	(0.054)	(0.118)
β_0	0.821^{*}	0.886	0.818^{***}	0.834^{***}	0.732^{***}
	(0.099)	(0.080)	(0.047)	(0.060)	(0.099)
P value ($\delta = 1$)	0.0002	0.0000	0.0033	0.0259	0.0130
P value ($\beta_1 = 1$)	0.0000	0.0000	0.0000	0.0000	0.0157
P value ($\beta_0 = 1$)	0.0719	0.1538	0.0001	0.0063	0.0082
Diff ($\beta_1 - \beta_0$)	-0.345	-0.482	-0.133	-0.244	-0.023
P value ($\beta_1 = \beta_0$)	0.0398	0.0000	0.0663	0.0005	0.8942
R^2	0.73	0.77	0.75	0.84	0.79
Observations	836	841	871	565	247

Analysis uses OLS regression. Difference is *significant from 1* at *0.1; **0.05; ***0.01. Robust standard errors clustered at individual level. R^2 corrected for no-constant

relative to bad news, significant at the 1% level. Yet for the comparison group, other performance, there is no significant asymmetry in updating.

This result is the opposite asymmetry of that found in Mobius et al. (2014), but is consistent with evidence from Ertac (2011). Yet, this result is greatly undermined when comparing estimates across other events. Even larger asymmetries are found for the two dice events, while a slightly smaller asymmetry can be seen for the weather event. Since these events involve outcomes that subjects have no personal stake in (and there is no difference for financial stakes), it is apparent that the differences in updating between own and other performance may be driven by factors that affect information processing more broadly, i.e. general cognitive biases, rather than a specific psychological bias. Importantly, these conclusions do not hinge on particular values of the prior, as even moderate values of the prior are associated with the same asymmetry.[24]

Overall, I am unable to reject the hypothesis that the response to signals for the quiz (self) event is the same as all other events pooled, whether aggregated or partitioned into good/bad news versus just news subsamples. The evidence suggests that the observed deviations from Bayes' rule are not generated by differential responses to good or bad news about performance, as they are present across other events that don't involve performance nor do they involve good or bad news. This suggests caution in interpreting differences in updating patterns for a specific event

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[24] Online Appendix Table E2 presents these results for moderate values of the prior.

as evidence of ego relevant psychological bias, without examining for the presence of cognitive bias in other neutral contexts.

4.4 Investigating signal structure

The previous section found negative asymmetry across most contexts, independent of whether signals were valenced. This result fits in a literature that has found evidence of positive asymmetry regarding good news versus bad news, as in Mobius et al. (2014) and Eil and Rao (2011), no asymmetry as in Buser et al. (2018) and Barron (2016), and finally negative asymmetry found by Ertac (2011).[25] As discussed, asymmetry in the framework interacts in important ways with the weight on the prior log odds ratio, δ. Thus, the framework itself, used also in Mobius et al. (2014), Buser et al. (2018), and Barron (2016), can generate different interpretations of the data. Based on the results, I now consider *ex-post* a further explanation that may account for these mixed results: signal structure.

One difference in the present paper compared with related studies is that signals are skewed in the negative direction, due to events with average probabilities less than one-half. Table 3 examines how subjects update in the last round given the sequence of signals they faced. Subjects could receive three affirmative signals, two affirmative and one negative, one affirmative and two negative, or three negative signals. One issue is that for the Quiz (self) event, the distribution of signals faced may depend on ability as higher scoring individuals are likely to receive more affirmative signals. If anything, excluding this event results in even more pronounced patterns than presented here, as Online Appendix Table E5 shows.

Contrary to the Bayesian prediction, there are clear differences in updating given different sequences of signals. Examining Columns 1 to 4 in Table 3, there is a pattern of under-weighting signals that are received less often. This also means that when subjects receive two affirmative and one negative signal, the asymmetry is reversed, as affirmative signals receive more weight than negative signals. This is important, because given the unlikely nature of many of the events in this experiment, the distribution of signals is more heavily weighted towards negative signals.

A striking pattern is found comparing Columns 5 and 6, which compares individuals who received exactly the same sequence of signals in the first two rounds (one affirmative, and one negative), but only differed in the order these signals were received.[26] These show that there is more negative asymmetry when the first signal is negative, rather than affirmative. This is surprising in light of both Bayes' rule, as well as considering other known cognitive biases, neither of which can explain this pattern. Online Appendix Table E6 presents additional robustness checks for this finding, showing that individuals are asymmetric in the positive

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[25] Of mention is that Buser et al. (2018) find evidence of positive asymmetry when considering updating mistakes in the "wrong" direction.

[26] Online Appendix Table E4 shows that updated beliefs after two rounds, i.e. the priors in the regression analysis, do not significantly differ through mean or distribution tests.

Table 3 Updating beliefs in final round by distribution of signals received

Dependent variable: logit posterior belief						
Regressor	(1) 0 '+' Signals	(2) 1 '+' Signal	(3) 2 '+' Signals	(4) 3 '+' Signals	(5) 1st '−'; 2nd '+'	(6) 1st '+'; 2nd '−'
δ	0.898***	0.881***	0.918**	0.982	0.864***	0.886***
	(0.031)	(0.025)	(0.033)	(0.068)	(0.034)	(0.033)
β_1		0.305***	0.863*	1.214	0.788**	0.828
		(0.099)	(0.079)	(0.152)	(0.105)	(0.127)
β_0	1.126	0.967	0.557***		1.105	0.834*
	(0.104)	(0.078)	(0.106)		(0.108)	(0.095)
P value ($\delta = 1$)	0.0011	0.0000	0.0156	0.7958	0.0001	0.0006
P value ($\beta_1 = 1$)		0.0000	0.0828	0.1634	0.0453	0.1776
P value ($\beta_0 = 1$)	0.2279	0.6791	0.0000		0.3323	0.0830
Diff ($\beta_1 - \beta_0$)		− 0.662	0.306		− 0.317	− 0.006
P value ($\beta_1 = \beta_0$)		0.0000	0.0193		0.0439	0.9685
R^2	0.77	0.79	0.78	0.78	0.81	0.81
Observations	253	454	270	68	266	249

Analysis uses OLS regression. Columns (1)–(4) K '+ Signals' refers to K affirmative signals, out of a possible maximum of 3. Columns (5)–(6) Compares individuals who received exactly 1 affirmative and 1 negative signal, only differing in the order these signals were received. Difference is *significant from 1* at *0.1; **0.05; ***0.01. Robust standard errors clustered at individual level. R^2 corrected for no-constant

direction after initially receiving an affirmative signal, and in the negative direction after initially receiving a negative signal.

An implication of these findings is that the observed negative asymmetry may in part be accounted for by the bias towards negative signals. While not conclusive, as the role of differently sized priors and representativeness bias likely play a role, these patterns hint at a different type of cognitive bias, undetected by previous work which traditionally has not been focused on finding asymmetry.[27] It resembles confirmation bias, see for example Rabin and Schrag (1999), but relates to confirmation on signals rather than on priors. This has potentially interesting implications, such as history dependence, where early sequences of signals may exert undue influence on posteriors. An interesting implication is that when

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[27] Priors are correlated with the types of signals received. Similarly, representativeness bias could account for some of these findings, as when subjects are in the final round and have received either 1 affirmative, 2 negative or 2 affirmative, 1 negative, this matches the signal strength of two-thirds. Thus, one may expect an asymmetric response. Online Appendix Table E7 shows that the asymmetry in the data remains even if one considers only the first two updating rounds, where the representativeness heuristic cannot be employed. Finally, if subjects update using absolute updating heuristics, e.g. updating by a fixed number of percentage points, this could potentially generate data which look on average asymmetric given average priors less than one-half. This type of strategy can be ruled out by examining whether the asymmetry is reversed for priors greater than one-half. In Online Appendix Table E3, it can be seen that this is not the case. I thank an anonymous referee for pointing out this possible explanation.

individuals have opportunities to exit (e.g. a career or major) they may exit too quickly when facing negative signals early on, or too late when facing an earlier sequence of affirmative signals.

Moreover, this additional cognitive bias could help account for observed differences in updating in recent work, operating through differences in signal structure. While signals in Mobius et al. (2014) and Eil and Rao (2011) are balanced between affirmative and negative on average, in Ertac (2011) they were less likely to be affirmative.[28] More generally, across these papers there is also variation in the size of the prior as well as differences across events themselves, suggesting that opposing findings may not be unfounded.

4.5 Conservatism, ability, and gender

In light of the results, I first briefly discuss the substantial conservatism, and next examine the relationship of conservatism and asymmetry with ability and gender. Online Appendix Table F2 examines only actively revised beliefs, and finds that conservatism is driven entirely by the 41% of non-updates.

These non-updates are not driven by a small subset of conservative individuals: only 9% of subjects update in all 12 rounds, and the median subject updates in 7 of 12 rounds.[29] Table 4 presents some reduced form estimates of the factors that correlate with active updates. An important factor appears to be the size of the prior, as subjects are less likely to update for more extreme values of the prior. Looking across events, subjects update less for the two dice events than for the other more subjective events, though this becomes insignificant with individual fixed effects. Additionally, subjects update more frequently in later updating rounds, the probability of an update is approximately 5% greater after receiving the second signal, and 14% greater after the third. Financial payments in the experiment appear to have no effect.

Examining Column 3 of Table 4, I also examine the relationship between active updating and the percentile rank on the quiz. Subjects who rank one standard deviation higher on the quiz are 5.8 percentage points more likely to update, significant at the 1% level. Interestingly, the positive association between ability and updating propensity is entirely driven by women. Men who rank poorly on the quiz update more frequently than equal ability women, but scoring higher on the quiz increases the propensity to update for women, the opposite of men.

In Table 5 I examine how gender and ability affect updating behavior more generally. I do this by allowing heterogeneous response to signals by gender and percentile rank.[30] Column 1 examines only interactions with gender, the second examines ability, while the third interacts the two. Similar to Mobius et al. (2014)

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[28] In her paper, top (bottom) was less likely than not top (bottom). Nonetheless, because a signal of top (bottom) would completely reveal the state, it is not clear that the same asymmetry should persist when updating among the remaining possible states.

[29] Conservatism is correlated across events, within individuals, as found in Buser et al. (2018). 30% of the variation in non-updates can be explained by individual fixed effects.

[30] One could also interact gender and ability with the weight on the log prior odds ratio, δ. I do not report these estimates, but interactions with δ are not significant.

Table 4 Correlates of active updating decision

Dependent variable: active update				
Regressor	(1)	(2)	(3)	(4)
Prior	1.596^{***}	1.629^{***}	1.576^{***}	1.641^{***}
	(0.136)	(0.124)	(0.154)	(0.138)
Prior^2	-1.678^{***}	-1.595^{***}	-1.695^{***}	-1.628^{***}
	(0.145)	(0.133)	(0.154)	(0.140)
Event = Hard Dice			− 0.012	− 0.016
			(0.022)	(0.023)
Event = Weather			0.068^{**}	0.011
			(0.030)	(0.028)
Event = Quiz (self)			0.053^{*}	0.033
			(0.030)	(0.028)
Event = Quiz (other)			0.100^{***}	0.010
			(0.037)	(0.034)
Round 2			0.045^{***}	0.047^{***}
			(0.016)	(0.017)
Round 3			0.137^{***}	0.138^{***}
			(0.019)	(0.019)
$a = 10$			0.024	
			(0.038)	
$a = 20$			− 0.011	
			(0.038)	
Stake = 80			− 0.006	− 0.023
			(0.019)	(0.019)
Male			0.168^{**}	
			(0.066)	
Percentile score			0.199^{***}	
			(0.070)	
Male × percentile score			-0.236^{**}	
			(0.113)	
Econ major			− 0.014	
			(0.041)	
Constant	0.347^{***}		0.153^{***}	
	(0.025)		(0.053)	
Individual fixed effects	No	Yes	No	Yes
R^2	0.06	0.37	0.10	0.38
Observations	3654	3654	3483	3654

Analysis uses OLS regression, dependent variable is binary for whether subject updated prior. Difference is significant from zero at *0.1; **0.05; ***0.01. Robust standard errors clustered at individual level. Omitted event is Easy Dice. Excludes belief revisions in the opposite direction predicted by Bayes' rule

Table 5 Updating beliefs by ability and gender

Dependent variable: logit posterior belief			
Regressor	(1) Gender	(2) Ability	(3) Gender × Ability
δ	0.910***	0.914***	0.910***
	(0.010)	(0.009)	(0.010)
β_1	0.520***	0.433***	0.394***
	(0.047)	(0.076)	(0.103)
β_0	0.740***	0.776***	0.728***
	(0.048)	(0.071)	(0.097)
$\beta_1 \times$ Male	0.141*		0.135
	(0.077)		(0.159)
$\beta_0 \times$ Male	0.160**		0.198
	(0.065)		(0.142)
$\beta_1 \times$ Percentile		0.315**	0.276
		(0.133)	(0.190)
$\beta_0 \times$ Percentile		0.037	0.028
		(0.120)	(0.169)
$\beta_1 \times$ Male × Percentile			− 0.031
			(0.270)
$\beta_0 \times$ Male × Percentile			− 0.078
			(0.250)
R^2	0.84	0.84	0.84
Observations	3199	3360	3199

Analysis uses OLS regression. Difference is *significant from 0* at *0.1; **0.05; ***0.01. Robust standard errors clustered at individual level. R^2 corrected for no-constant

and Ertac (2011) I find that women update more conservatively than men, though this is no longer significant when interacted with ability. I do not find any difference in asymmetry between men and women.[31]

There is also some weak evidence that ability is related to both conservatism and asymmetry, which appears in Column 2, but is no longer significant in Column 3. Subjects with higher ability appear to put more weight on affirmative signals, but not on negative signals. The implication is that those at the top of the ability distribution would no longer exhibit significant asymmetry, and would also be less conservative. This is in contrast to the results of Mobius et al. (2014) who found that neither conservatism nor asymmetry were significantly correlated with cognitive ability.

Importantly, the pattern of greater conservatism exhibited by women seen in Column 1 is present across both valenced and neutral contexts. Thus while previous work from Ertac (2011) and Mobius et al. (2014) theorized that female conservatism may be related to self-confidence, such conservatism is equally present in ego-irrelevant contexts.[32] Moreover, when comparing the deviations from

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[31] One interesting result is that unlike evidence from Mobius et al. (2014) and Buser et al. (2018) (see Barber and Odean (2001) for an earlier discussion), women are not less confident about their performance than men on the quiz.

Bayes' rule of final beliefs, women are only one-tenth of one percentage point further from Bayes' rule than men, a difference that is not statistically significant.

5 Concluding discussion

In this experiment I set out to examine whether differences exist in how people process information across varied contexts, focusing especially on response to valenced versus value neutral information. Recent evidence from economics and neuroscience suggests the possibility of additional psychological biases in updating when information contains good or bad news, beyond any cognitive biases that have been observed when information is value neutral.

Unlike some of the findings and claims of previous literature, I do not find evidence of asymmetric over-weighting of good versus bad news. In fact I find evidence of the opposite asymmetry, as in Ertac (2011), yet such patterns are similarly present comparing information processing across valenced or value neutral contexts. Related, while there are differences in updating by gender, as found in to previous studies, these patterns in updating are present across contexts. Thus updating appears similar, whether it involves news regarding events that directly affect subjects' wellbeing, or whether it involves only information about neutral events. This result suggests that asymmetric updating found in previous studies is not a universal property of updating in ego relevant contexts. Moreover, there is evidence that deviations from Bayes' rule may reflect more general cognitive biases, rather than psychological biases in processing good or bad news.

While these results differ from some of the previous literature, they do suggest a possible unifying feature. The distribution of signals received appears to affect how individuals update beliefs, a type of confirmation bias which previously went undocumented. Thus, differences in the direction of asymmetry, e.g. between, Mobius et al. (2014) and Eil and Rao (2011), and Ertac (2011), might be explained by differences in signal content. As interest in asymmetry is recent, differences in updating across studies is not unfounded, and the paucity of work on asymmetry in value neutral contexts has hindered our ability to make relevant comparisons.[33]

Overall, while I find that many predictions of the Bayesian model are rejected in the pooled data, these discrepancies are small in magnitude. The average posterior belief is less than one percentage point away from the posterior predicted by Bayes' rule. After three rounds of updating, subjects are less than two percentage points away from the posterior that would have resulted had they used Bayes' rule all the way through, and the final posteriors of men and women are statistically indistinguishable.

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[32] Note that if gender differences in updating persist across contexts, the same implications remain: high ability women could end up less confident. An important direction for future research is to understand the source of differences in information processing by gender.

[33] There are some differences in implementation between this experiment and that of previous work. In Mobius et al. (2014) subjects participated in the experiment online, the relevant event was being in the top 50%, and signal strength differed slightly. On this last point, Ambuehl and Li (2018) suggest that subjects do not react strongly to signal precision.

Overall, this paper presents counter evidence to recent studies suggesting that psychologically plausible biases may arise in value relevant contexts, through the asymmetric processing of good news relative to bad news. Such evidence is necessary to discipline existing and future theoretical work on updating behavior, in order to better understand how individuals process information.

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