Ambiguous Information and Dilation: An Experiment*

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Abstract

With common models of updating under ambiguity, new information may *increase* the relevant ambiguity: the set of priors may 'dilate.' We test experimentally one sharp case: agents bet on a risky urn and get information that is truthful or not based on the draw from an Ellsberg urn. Under typical models, the set of priors should dilate; ambiguity averse agents should lower their value of bets; ambiguity seeking should increase it. Instead, we find that ambiguity averse agents do not change it; ambiguity seeking ones increase it substantially. We also test bets on ambiguous urns and find sizable reactions.

Key words: Updating, Ambiguous Information, Ambiguity Aversion, Ellsberg Paradox, Maxmin Expected Utility

JEL: C91, D81, D90.

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1 Introduction

We study experimentally reactions to information of ambiguous reliability. Agents receive one of two messages that are truthful or misleading depending on the draw from an Ellsberg bag. We study this for three reasons.

First, this tests a key implication of common updating models under ambiguity: that information may increase the amount of relevant ambiguity—the so-called 'dilation' of sets of priors. It is known that with the two widespread updating rules for MaxMin Expected Utility—Full-Bayesian and Maximum Likelihood—the set of relevant priors may become larger (dilate) after information. This makes ambiguity averse agents strictly *worse off* after some information; they should be willing to pay to avoid it. Whether this is empirically true, and to the extent predicted by theory, received little attention. Our experiment tests a crisp case: in our experiment dilation should occur after *any* message—a case termed 'all news is bad news' by Gul and Pesendorfer (2018).

Second, the information we study is related to applications of ambiguity to strategic settings, where many results depend on the dilation property. Bose and Renou (2014) study a mechanism design problem where an unambiguous allocation stage is preceded by an ambiguous mediated communication stage; Beauchêne, Li, and Li (2019) study Bayesian persuasion with ambiguity averse receiver and a sender who can commit to ambiguous signals. In the motivating examples of both papers, the ambiguity lies in having messages that are either the truthful or not—like in our experiment. Both papers assume Full Bayesian updating, and results rely crucially on its dilation property. We test it.

Third, more in general our experiment studies ambiguous information, focusing on the case in which the ambiguity is on the reliability. While ambiguity in informativeness may be common in real life, only a very small recent literature discussed below has studied it.

Experiment. Subjects first evaluate bets on the color drawn from an urn, which may be risky or ambiguous. Then, they receive a message about the color drawn; but this message is truthful or misleading depending on the draw from a standard 2-color Ellsberg bag of chips. We ask subjects to acknowledge the message and measure how the value of bets change after it. We also measure the value (positive or negative) of this information. In one set of questions, the payoff-relevant draw is made from a risky, 50/50 urn. In another, it is from an ambiguous urn. We also measure subjects' ambiguity aversion.

Relation to Theories. Common models of updating under ambiguity make clear predictions. Consider the MaxMin Expected Utility model (MMEU) of Gilboa and Schmeidler (1989) with set of priors Π. Two updating rules are widespread: Full-Bayesian (FB), where the set of priors after information is the Bayesian Update of all priors in Π (Wasserman and Kadane, 1990); and Maximum-Likelihood (ML), where the updated set includes only priors in Π that satisfy a maximum-likelihood criterion (Gilboa and Schmeidler, 1993). When the payoff-relevant state is risky, before information the relevant set of priors is a singleton. But after ambiguous information like in our experiment, with Full-Bayesian (FB) or Maximum-Likelihood (ML) the relevant set of priors *dilates* and is no longer a singleton: because of the ambiguity in information, bets on the risky urn *become ambiguous*. Ambiguity averse agents should then decrease the value of bets after information; and pay to avoid information. The opposite is true for ambiguity seeking. Note that these predictions hold for any message. Appealing or not, this is a feature of both updating rules.

Results. When the payoff-relevant state is risky, we find that ambiguity averse or neutral subjects (the majority) typically do *not* change their value of bets after information. The median change is zero, and the majority has exactly zero change. For ambiguity averse subjects there is also no robust relation between how averse they are and either the size of the change or the probability it is non-zero. These subjects also typically give zero value to information.

Ambiguity seeking subjects instead typically *increase* substantially their valuation after information. The change in value is strongly related to their degree of ambiguity affinity. Yet, many still value the information close to zero.

When the payoff-relevant state is ambiguous, ambiguity averse subjects slightly *increase* their valuation, ambiguity seeking subjects *decrease* it.

Implications. We conclude the paper discussing implications of our results. The finding that ambiguity averse subjects do not react to information when the payoff-relevant state is risky contradicts the dilation property of both FB or ML updating, crucial in applications.

There are two natural implications. First, subjects may be following other updating rules. Proxy updating (Gul and Pesendorfer, 2018) was designed precisely to rule out the cases of 'all news is bad news.' While the exact functional form cannot be applied to our setup—it is defined for totally monotone capacities which is not the case here—our results are strongly supportive of this approach. Subjects could also be following the Dynamically Consistent updating of Hanany and Klibanoff (2007, 2009), where agents form an ex-ante optimal plan contingent on information and implement it after. This rule is compatible with our findings and satisfies dynamic consistency; however, it violates consequentialism, in the sense that agents will take into account what acts return in unrealized events.

Alternatively, subjects may use FB or ML but complement it by *strategically* choosing if and when to process the information. While with Subjective Expected Utility information is always weakly valuable—ignoring it gives no benefit—under ambiguity we have seen it is no longer the case. Incorporating the possibility of strategically choosing not to process information in updating would substantially change predictions and implications of these models; to our knowledge, this has not been studied.

Literature. The theoretical literature discusses different updating rules (Gilboa and Marinacci, 2013, Sec. 5). An experimental literature tested some implications like dynamic consistency and consequentialism (Cohen, Gilboa, Jaffray, and Schmeidler, 2000; Dominiak, Duersch, and Lefort, 2012; Bleichrodt, Eichberger, Grant, Kelsey, and Li, 2018; Esponda and Vespa, 2019), how sampling from ambiguous sources affects ambiguity preferences (Ert and Trautmann, 2014), learning from sequences of observations (Moreno and Rosokha, 2016), in groups (De Filippis, Guarino, Jehiel, and Kitagawa, 2016), or from stock prices (Baillon, Bleichrodt, Keskin, l'Haridon, and Li, 2017).

Three very recent papers study ambiguous information: Epstein and Halevy (2019); Liang (2019); Kellner, Le Quement, and Riener (2019).[1] A common different with our work is that they do not study the dilation property, which is instead our primary focus. Building on Epstein and Schneider (2007, 2008), Epstein and Halevy (2019) define attitude to signal ambiguity, the ambiguity on the informativeness of a signal. After a careful theoretical analysis, the paper tests it experimentally. Focusing on a setup with ambiguity, they find that signal ambiguity significantly increase deviations from Bayesian updating. While related to our work in the interest on ambiguous signals, in Epstein and Halevy (2019) the payoff-relevant state is ambiguous and signals are always informative, but the agent does not know how much; instead, in our experiment the payoff-relevant state can be risky and the ambiguity is on *whether* the signal is informative or misleading. The papers are thus complementary: our focus is less extensive on ambiguous information, but allows us to test the dilation of the set of priors and the form of ambiguous information used in the theoretical literature.

A contemporaneous paper by Liang (2019) studies updating with both risky and ambiguous state under both simple and uncertain (compound and ambiguous) signals. It compares updating under different types of signals that correspond to the same average simple signal and finds that subjects under-react to uncertain information, which is more pronounced for good news rather than bad news. Also contemporaneous, Kellner et al. (2019) studies messages with ambiguous reliability, but asymmetric and with three messages, one of which is informative. They find a relation between reactions and ambiguity attitude; and a similar reaction to ambiguous and compound-risk signals. Their design does not allow tests of dilation.

Lastly, as noted above, the ambiguous information we study is used in applications of models of ambiguity to strategic environments (Bose and Renou, 2014; Beauchêne et al.,

[1] We learned about Epstein and Halevy (2019) before finalizing our design. We thank Yoram Halevy for very useful discussions.

2019). Assuming FB, a key driving force of their results is the dilation property. We test it and find little support.

2 Theories of Updating and Ambiguous Information

For a state space S and set of prizes X preferences are represented by the MMEU: agents have linear utility $u : X \to \mathbb{R}$, a closed, convex set of priors $\Pi \subseteq \Delta(S)$, and evaluate act $f : S \to X$ by $\min\limits_{\pi\in\Pi} E_\pi[u \circ f]$ if ambiguity averse; or by $\max\limits_{\pi\in\Pi} E_\pi[u \circ f]$ if ambiguity seeking. In line with our experiment, we posit $S = \Omega \times M$ where[2]

- $\Omega = \{R, B\}$: the payoff-relevant state, the color of the ball that determines payment;
- $M = \{r, b\}$: the message received.

Π^Ω denotes the marginal sets over Ω. In line with our experimental design, we assume that, for all priors, the likelihood that a message is truthful or not is independent of the payoff-relevant state, i.e., with a common abuse of notation, $\pi(r|R) = \pi(b|B)$ and $\pi(b|R) = \pi(r|B)$. Moreover, if $\bar{\pi}$ is the prior for which messages are not informative—$\bar{\pi}(r|R) = \bar{\pi}(b|R) = 0.5$—we assume $\bar{\pi} \in \Pi$ and, if $|\Pi| \neq 1$, that it is in the relative interior.

Updating Rules. For event $B \subseteq S$, Π_B denotes the set of beliefs after message B. We consider the following updating rules.[3]

Full Bayesian (FB) updating, also known as prior-by-prior updating, was studied by Wasserman and Kadane (1990) and Jaffray (1992) and axiomatized by Pires (2002) and Ghirardato, Maccheroni, and Marinacci (2008). The most common updating rule in applications, it is defined by

$$^{\mathsf{FB}}\Pi_B := \{\pi(\cdot|B) | \pi \in \Pi\}.$$

The *Maximum Likelihood* (ML) rule, introduced by Dempster (1967) and Shafer (1976), and axiomatized by Gilboa and Schmeidler (1993), coincides with the Dempster-Shafer updating rule when Π is the core of a convex capacity. It is defined by

$$^{\mathsf{ML}}\Pi_B := \{\pi(\cdot|B) | \pi \in \operatorname*{argmax}_{\pi' \in \Pi} \pi'(B)\}.$$

Variables of Interest. Consider certainty equivalents of \$$x$ bets placed on the chosen color being drawn from the urn (i.e., in Ω) before and after a message. Abusing notation,

[2] Following standard practice, we use the most parsimonious description of the state space.

[3] Epstein and Schneider (2007) and Kovach (2015) discuss combinations of the rules below. When the payoff-relevant state is risky, our main case of interest, predictions coincide with the rules below.

$m \in \{r, b, \emptyset\}$ denotes either message $m \in M$ or no information. Then:

$$c_m := \begin{cases} \max_{\omega \in \{R,B\}} \min_{\pi \in \Pi_m^\Omega} \pi(\omega) u(x), & \text{if amb. averse,} \\ \max_{\omega \in \{R,B\}} \max_{\pi \in \Pi_m^\Omega} \pi(\omega) u(x), & \text{if amb. seeking.} \end{cases}$$

The *Information Premium* is the difference between certainty equivalents with and without information,

$$P_m := c_m - c_\emptyset.$$

The *Value of Information* is the MaxMin (or MaxMax) expected difference between these certainty equivalents:

$$V := \begin{cases} \min_{\pi \in \Pi} \int P_m \, \mathrm{d}\pi, & \text{if amb. averse,} \\ \max_{\pi \in \Pi} \int P_m \, \mathrm{d}\pi, & \text{if amb. seeking.} \end{cases}$$

Risky Payoff State. Suppose that the payoff-relevant state is risky.

Proposition 1. *Consider an agent whose preferences follow the MMEU with set of priors* Π *such that* $\forall \pi \in \Pi$, $\pi(R) = \pi(B) = 0.5$. *Then:*

1. *If* $|\Pi| > 1$ *and the agent is* ambiguity averse, *with FB and ML:* $\forall m,\ P_m < 0,\ V < 0$;

2. *If* $|\Pi| > 1$ *and the agent is* ambiguity seeking, *with FB and ML:* $\forall m,\ P_m > 0,\ V > 0$;

3. *If the agent is* ambiguity neutral, *i.e.,* $|\Pi| = 1$, *with FB, ML:* $\forall m,\ P_m = V = 0$.

For intuition, suppose $\Pi = \mathrm{co}(\{\pi_1, \pi_2, \pi_3\})$ where π_1 is such that messages point to the right direction: $\pi_1(r|R) = 0.8$; $\pi_2 = \pi^I$ is such that messages are uninformative: $\pi_2(r|R) = 0.5$; π_3 is such that messages point to the wrong direction: $\pi_3(r|R) = 0.2$.

Then, ${}^{\mathsf{FB}}\Pi_r^\Omega = {}^{\mathsf{FB}}\Pi_b^\Omega = [0.2, 0.8] \supset \Pi^\Omega = \{\pi\}$. Before information, the set of marginals over Ω was a singleton—we have a risky state. But it becomes full-dimensional after information. This is because the information is ambiguous and the multiplicity of priors about the truthfulness of the message generates multiple priors about payoff-relevant states. This set not only includes the original prior, but do so in the interior. Seidenfeld and Wasserman (1993) call this property of FB *dilation*. Proposition 1 shows that this holds whenever $|\Pi| > 1$. In fact, it is a particularly stark example: the dilation occurs for any message.

The implications about FB follow: because the set of priors dilates, ambiguity averse agents have strictly lower certainty equivalents; because this holds for any message, the value of information is negative. The opposite holds for ambiguity seeking.

With ML, agents focus only on priors that maximize the likelihood of the message. When $\pi(R) = 0.5$ for all $\pi \in \Pi$, the likelihood of both messages is 0.5: thus, all priors in Π are considered and ML coincides with FB.

Ambiguous Payoff State. When the payoff-relevant state is ambiguous predictions depend on the shape of Π.

Proposition 2. *Consider an agent with a set of priors* Π*. Then:*

1. *If* $\Pi > 1$*, with* FB *and* ML*: both* P *and* V *can be zero, negative, or positive for both ambiguity averse and seeking agents;*

2. *If* $|\Pi| = 1$*, with* FB *and* ML*:* $\forall m, P_m = V = 0$*.*

When the payoff-relevant state is ambiguous, updating rules make no general predictions. Intuitively, this depends on the set of priors across Ω and informativeness. Below is an example in which the set of priors shrinks to a singleton. The proof of Proposition 2 shows the other cases.

Example 1 (Contraction)**.** Fix any $a \in (0, 0.5)$, and let $\Pi = \mathrm{co}(\pi_1, \pi_1)$, where

$$\begin{aligned} \pi_1^{\Omega}(R) &= a, & \pi_1(r|R) = \pi_1(b|B) &= 1 - a, \\ \pi_2^{\Omega}(R) &= 1 - a, & \pi_2(r|R) = \pi_2(b|B) &= a. \end{aligned}$$

Here the shape of Π induces a 'negative correlation:' for each $\pi \in \Pi$, the Bayesian posterior about R after message r is 0.5. There is no more ambiguity. Under both FB or ML ${}^{\mathsf{FB}}\Pi_r^{\Omega} = {}^{\mathsf{ML}}\Pi_r^{\Omega} = \{\hat{\pi}\} \subset [a, 1 - a] = \Pi_{\Omega}$, where $\hat{\pi}(R) = 0.5$. Under either FB or ML ambiguity averse agents have $d_r > 0$; $d_r < 0$ for ambiguity seeking.

3 Experiment

3.1 Design

After an instruction phase and a comprehension questionnaire, the experiment includes two parts for a total of 6 questions. In each, subjects were asked to compare fixed amounts of money with a bet on their chosen color drawn from an urn. With two exceptions mentioned below, all bets paid \$20 if the ball was of the chosen color, zero otherwise; subjects were asked to compare each bet with a list of amounts of money increasing from \$0 to \$20, in a Multiple Price List (MPL; Holt and Laury, 2002). To simplify the task, subjects had to click only once in each list, indicating the point where to switch from the bet to the amount of money.[4]

[4]By monotonicity, subjects should prefer the bet against low amounts (e.g., \$0), and 'switch' as the amount grows (e.g., close to \$20). The software (oTree; Chen, Schonger, and Wickens, 2016) asked to indicate the point where to switch. Subjects were also allowed to indicate no switch, i.e., only the bet or the amounts of money. This procedure simplified the choice, but forced a monotonicity. Subjects received extensive instruction and training.

Different questions involved urns of two types. Risky urns had a known composition: 100 balls, 50 of each color. Ambiguous urns had 100 balls of two colors with an unknown composition.

Questions were of three kinds. For each kind, the subject answered one question where the payoff-relevant urn was risky, and one in which it was ambiguous.

1. **Basic Questions.** Q1 and Q4 asked subjects to pick a color to bet on and then the certainty equivalent of a $20 bet using the MPL procedure. In Q1, the urn was risky. In Q4, it was ambiguous. Comparing the answers, we obtain a measure of ambiguity aversion.

2. **Information Questions.** Q2 and Q5 again measured the certainty equivalent of a bet, but after information. At the beginning of the question, the computer drew a ball from the payoff-relevant urn—determining the color that pays the bet—and a chip from a bag with 100 chips of 2 colors and unknown composition. The computer then displayed a message for the subject indicating the color of the ball drawn from the urn. Whether this message was truthful or misleading, however, depended on the chip drawn: if the chip was of one color, the computer told the truth; otherwise, it reported the opposite. In these questions, subjects are first shown the urn, then shown how is the message determined, then given the information. They then had to acknowledge the information, clicking on the corresponding color. With the message remaining on the screen, they had to pick a color to bet on, and evaluate the bet using an MPL. In Q2, the payoff-relevant urn was risky; in Q5, it was ambiguous.

3. **Information-Value Questions.** Q3 and Q6 were similar to the questions above, but measured also the value of information. First, subjects faced a MPL in which they chose between no information and information plus an increase or decrease of their potential winning for the question (from a base of $20), ranging from -$5 to $5. After their choice, the computer randomly picked a line from this MPL and implemented their selection: if in that line the subject chose no information, they proceeded with the evaluation of the bet without it; if they chose the information and a change of payoffs, they received both before evaluating the bet. In Q3, the underlying urn was risky; in Q6, it was ambiguous.

All questions used different urns and different colors, reducing the possibility of hedging across questions. This was clearly explained. Similarly, the bags that determined the information were all different and involved different colors. For symmetry, all colors for urns and bags were randomly selected in each instance from a unique set.[5]

[5] Colors were selected randomly for each subject and each question. The set of colors was identical for urns and bags, except that for each subject we avoided repetitions and the pairing of too similar colors.

Table 1: Questions

		Payoff Urn	*Info*
Part I	Q1	Risky	No
	Q2	Risky	Yes
	Q3	Risky	Evaluate
Part II	Q4	Ambiguous	No
	Q5	Ambiguous	Yes
	Q6	Ambiguous	Evaluate

Order and Incentives. The 6 questions were grouped into two parts. Part I included the 3 questions involving bets on risky urns, in the following order: Q1, the evaluation of a bet of a risky urn; Q2, the evaluation of a bet on a risky urn after information; Q3, the evaluation of a bet on a risky urn after deciding whether to receive or not the information. Part II was identical, but with ambiguous urns. Questions are summarized in Table 1. Subjects received the parts in two possible orders: in Order A, Part I then Part II; the opposite in Order B.

Subjects received a participation fee of \$10 and a completion fee of \$15. In addition, one of the 6 questions were randomly selected for payment with equal probability; then, one of the lines of the MPL with the comparison between bets and sure amounts of money were randomly selected, again with equal probability.[6]

3.2 Predictions and Construction of Variables

We now map the theoretical predictions derived in Section 2 to our experiment. From the answers in the MPLs comparing bets and amounts of money, we can approximate the value of the certainty equivalent of each bet. From the MPLs comparing information vs. no information (in Q3 and Q6), we can approximate the value of information.

Because in our experiment choices involve different urns, we have to make two assumptions. First, that Π before information is the same in questions of the same type. This is justified by the fact they used identical urns with colors randomly drawn. Second, we assume that subjects' ambiguity attitude is the same across questions and with respect to information- and payoff-relevant states, as we have implicitly done in the theoretical

[6] Paying randomly selected questions is incentive compatible under Expected Utility but in general; no general incentive compatible mechanism exists (Karni and Safra, 1987; Azrieli, Chambers, and Healy, 2018). A few studies indicate that this may not be a concern (Beattie and Loomes, 1997; Cubitt, Starmer, and Sugden, 1998; Hey and Lee, 2005; Kurata, Izawa, and Okamura, 2009), but recent contributions suggest caution (Freeman, Halevy, and Kneeland, 2019).

Table 2: Predictions for Information Premium P and Value of Information V

	Risky payoff state			*Ambiguous payoff state*		
amb. att.	averse	neutral	seeking	averse	neutral	seeking
FB	–	0	+	+/0/–	0	+/0/–
ML	–	0	+	+/0/–	0	+/0/–

discussion in Section 2. In particular, we assume that if Π^{Ω} is not a singleton when the payoff-state is ambiguous, then the set of beliefs about messages is also not a singleton.

We identify ambiguity attitude comparing the answer to Q1 (risky urn, no info) and Q4 (ambiguous urn, no info): a higher/equal/lower certainty equivalent in Q1 than in Q4 indicates ambiguity aversion/neutrality/seeking. The *Ambiguity Premium* is the difference between the value in Q1 and the value in Q4.

The *Information Premium P* is defined as: for risky urns, the value in Q2 minus the value in Q1; for ambiguous urns, the value in Q5 minus the value in Q6. The *Value of Information V* is elicited directly: in the first part of Q3 for risky urns, in the first part of Q6 for ambiguous ones.

Table 2 summarizes the theoretical predictions. Because predictions coincide for the Information Premium and the Value of Information, they are shown together.

How variables are constructed. Because MPLs have a finite grid, our elicitation of certainty equivalents and of the value of information is bound to be approximate. Following standard practice, we use as value the middle-point between the two elements of the grid where the switch occurred.[7] But the true certainty equivalent may lay anywhere in that range. This approximation may matter in computing if their difference is equal, smaller, or bigger than zero. We take the following conservative approach. Recall that the Information Premium is the difference between two certainty equivalents, each obtained via a MPL. When computing whether it is above, at, or below zero, we report it in two ways: first, using the procedure above, and denote results by $> 0, < 0, = 0$. Second, we report the percentage of answers that are are compatible with zero value, and denote them by ≈ 0.[8]

For Value of information, the grid is \$0.1 around 0, and 0 is an option on the grid. This

[7] For example, if the agent chose the bet again \$10 but the next item on the grid, say \$10.2, against the bet, then we set the certainty equivalent at \$10.1.

[8] For example, suppose in Q1 the agent chooses the bet against \$10, and the next item in the grid, say, \$10.2, against the bet; in Q2, the agent switches one step below, and picks the bet against \$10.2 but the the next item, say \$10.5, against it. With our procedure, the values are 10.1 for Q1 and 10.35 for Q2, indicating a positive difference. But this behavior is also compatible with an agent who has zero difference: if the true certainty equivalent is \$10.2 in both question, the behavior above may be due to breaking the indifference in different ways. This behavior is marked > 0 but also ≈ 0.

means that no subject can, by construction, have a value of 0: they must have either 0.05 and -0.05. Both are compatible with the agent having a certainty equivalent of exactly zero.[9] In calculations we use these numbers; but in reporting >0, =0, or <0, we put 0.05 and -0.05 in =0 category. Thus, zero values may be overestimated.

Finally, to compute ambiguity attitude, we take a conservative approach: we classify as ambiguity averse or seeking only subjects whose behavior is not compatible with ambiguity neutrality: thus, subjects who switch in two adjacent lines in Q1 and Q4 are classified as ambiguity neutral.[10] We may thus overestimate ambiguity neutral agents. (Given the results below, our main conclusions would not change with a different classification.)

3.3 Results

A total of 91 subjects participated in 4 sessions run in the PeXL laboratory in Princeton University in February 2019, recruited from volunteer undergraduate students at that institution. Sessions lasted approximately 30 minutes; average earnings were $35.2.

We begin with broad features of the data. First, while MPLs forced a single switch, they allowed extreme answers. We eliminated from our analysis 2 subjects who reported dominated answers (e.g., chose a bet with payment of $20 against $20) in multiple questions. Including them changes almost nothing (Appendix C.2 shows results including them).

Second, the distribution of ambiguity averse, neutral, seeking is 35 (39.3%), 37 (41.6%), and 17 (19.1%).[11] Median ambiguity premia are relatively high for both averse ($2.5) and seeking subjects (-$2). (Table 5 in Appendix C.1 contains all details.)

Third, order effects. We used two different orders: risky states first (Order A) and ambiguous states first (Order B). This had some effect: for example, the fraction of ambiguity averse subjects was higher in Order A. However, our patterns hold throughout. Tables and Figures in the main body use both orders, but in the text we discuss also the order in which specific question types appeared first, with less contamination (Order A for risky state, B for the ambiguous one). Table 6 in Appendix C.1 contains all data by order.

Risky Payoff State. We begin with the case in which payments depend on the draw from a risky urn. The results are reported on the left part of Table 3 and represented graphically on Figure 1: the top panel depicts, on the left, a scatter plot of the Information Premium

[9] If the value of information is zero, agents should be indifferent between No information and Information with $0 changes. If No Information is chosen, the switch occurs between $0 and $0.1 and the value is coded 0.05; if Information is chosen, the switch occurs between $-0.1 and $0 and the value is coded -0.05.

[10] Like above, agents may have the same certainty equivalent but break the indifference in opposite ways and give answers that are different but adjacent.

[11] The fraction of ambiguity averse is a bit lower than general population results (Camerer, Chapaman, Ortoleva, and Snowberg, 2018) but not dissimilar from other highly selective universities. Recall also that our procedure may overestimate ambiguity neutral agents.

Table 3: Results

amb. att.	Risky payoff state All	averse	neutral	seeking	Ambiguous payoff state All	averse	neutral	seeking
	Information Premium P							
median	0	0	0	1	0	0	0	-1
mean	0.46	-0.56	0.6	2.2	0.13	0.57	0.08	-0.68
≈ 0	65%	69%	78%	29%	58%	54%	76%	29%
$= 0$	56%	57%	68%	29%	52%	49%	70%	18%
> 0	28%	11%	30%	59%	24%	34%	14%	24%
< 0	16%	31%	3%	12%	25%	17%	16%	59%
	Value of Information V							
median	-0.05	-0.05	-0.05	0.05	-0.05	-0.05	-0.05	-0.05
mean	-0.41	-0.23	-0.73	-0.09	-0.43	-0.11	-0.64	-0.61
$= 0$	54%	51%	51%	65%	57%	57%	60%	53%
> 0	10%	11%	5%	18%	10%	14%	5%	12%
< 0	36%	37%	43%	18%	33%	29%	35%	35%
# of obs.	89	35	37	17	89	35	37	17

and the Ambiguity Premium. Colors represent ambiguity attitude: red for averse, blue for neutral, green for seeking. On the right is a stacked bar plot depicting the proportions of values that are $>, <$ and $= 0$. The bottom panel repeats this for the Value of Information.

Considering all subjects, the mean Information Premium is positive, but the median is zero: 56% of subjects have exactly zero; and 65% have behavior compatible with it. The mean value of information is slightly negative, while the median is compatible with zero. To test the theoretical predictions, however, we have to separate our analysis by the ambiguity attitude.

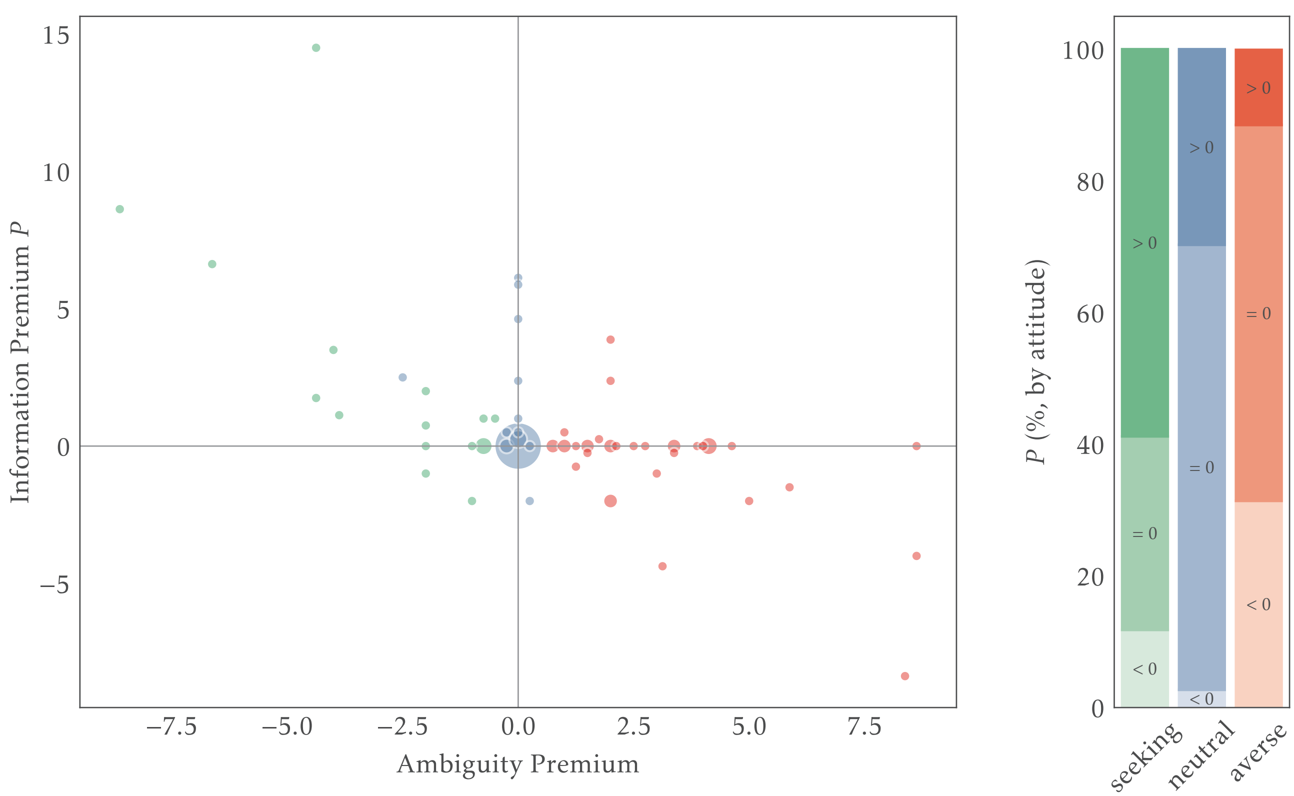
For ambiguity averse subjects, we find that the median Information Premium is zero: in fact, a majority of 57% (52% focusing on Order A) have a value of exactly zero; an even larger one 69% (61% in Order A) has values compatible with zero, denoted ≈ 0. Of the remaining subjects, negative values are more common, but only for 31% of subjects (39% in Order A).

A coherent picture emerges if we look at the Value of Information: it is zero for most ambiguity averse subjects. (Recall that -0.05 is compatible with indifference with zero). Of the minority with non-zero values, the larger group (37%) has negative values.

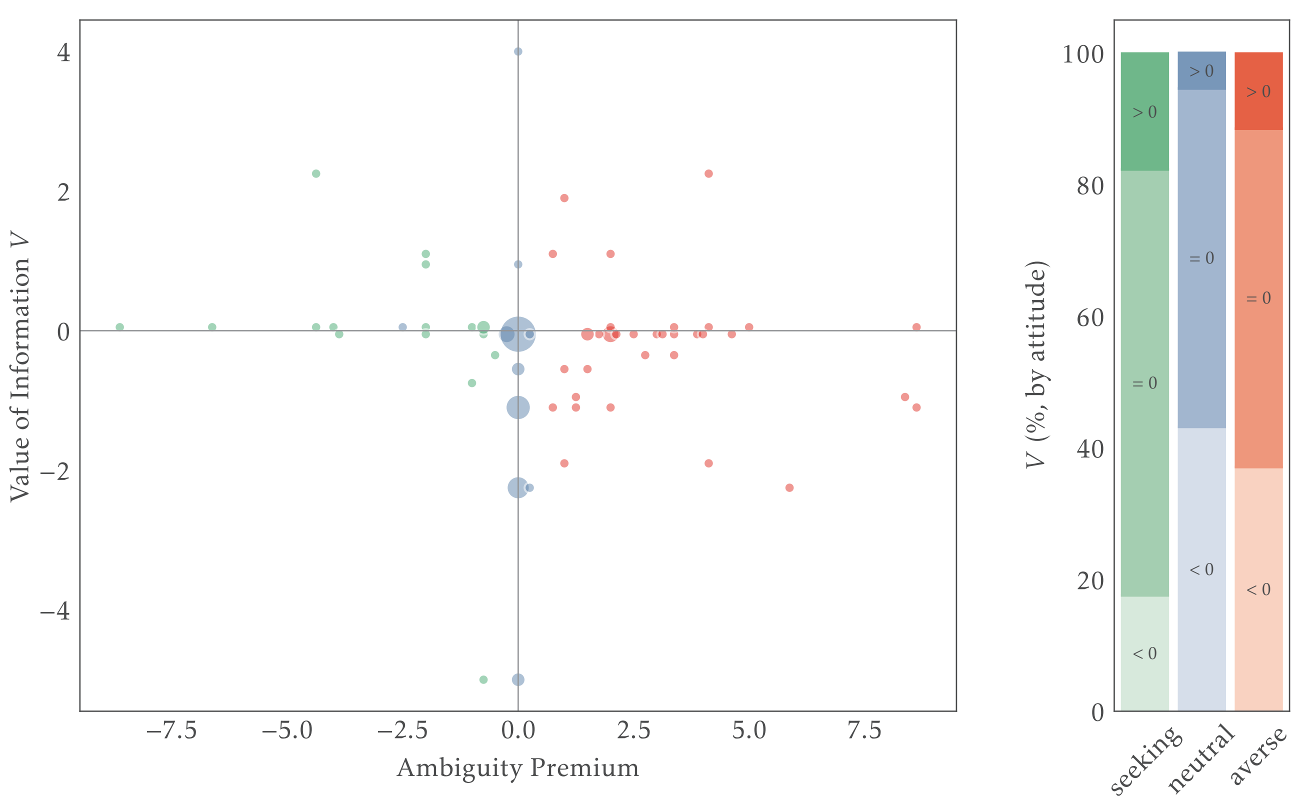
We can also test the relation between the degree of ambiguity aversion and the chances of having non-zero, or stronger reaction to information. Note that such relation is pre-

Figure 1: Results, Risky Payoff-Relevant State, Graphically

(a) **Information Premium** P



(b) **Value of Information** V



dicted by FB or ML if we assume that the size of the sets of priors about information- and payoff-relevant states are correlated.

The plots in Figure 1 already suggest that, aside from the outliers in the bottom right, we do not have this relation for ambiguity averse subjects. This is confirmed by statistical analysis.

First, for ambiguity averse subjects, the likelihood of having a non-zero Information Premium is not related to the Ambiguity Premium (Probit, $z = 0.69, p = 0.491$).

Second, we can test if Information Premium and Ambiguity Premium are negatively related for ambiguity averse subjects. Note that, all else equal, our design is biased to generate this (negative) correlation spuriously: because both variables are constructed using the answer to Q1—the certainty equivalent of the bet on a risky urn without information—noise in this measure would generate a negative spurious relation. (See 3.4 for more discussion.)

Even despite this, in our data Information Premium and Ambiguity Premium are not robustly related. While an OLS regression does give a relation (t=3.65, p=0.001), this is driven by the two outliers in the bottom right.[12] Eliminating the outliers eliminates the relation ($t = 0.99, p = 0.331$). A Quantile regression with all subjects finds no relation ($t = 0.00, p = 1$).

There is also no relation between the Value of Information and the Ambiguity Premium ($t = 0.91, p = 0.369$).

Patterns are very different for ambiguity seeking subjects: 59% (86% in Order A), have *positive* Information Premium. Both median and mean are also remarkably high ($1 or $3.5; $2.2 or $5.2 in Order A). The Value of Information, however, remains zero for the majority. (Recall, however, that this may be an overestimation.)

For ambiguity seeking subjects the plots in Figure 1 suggest a positive relation between Ambiguity Premium and Information Premium. This is confirmed by statistical analysis: regressing the two we find a significant, positive relationship ($t = 3.91, p = 0.001$). Note, however, that this relation could be spuriously strengthened by our design, as discussed above. There is no relation with the Value of Information ($t = 1.09, p = 0.292$).

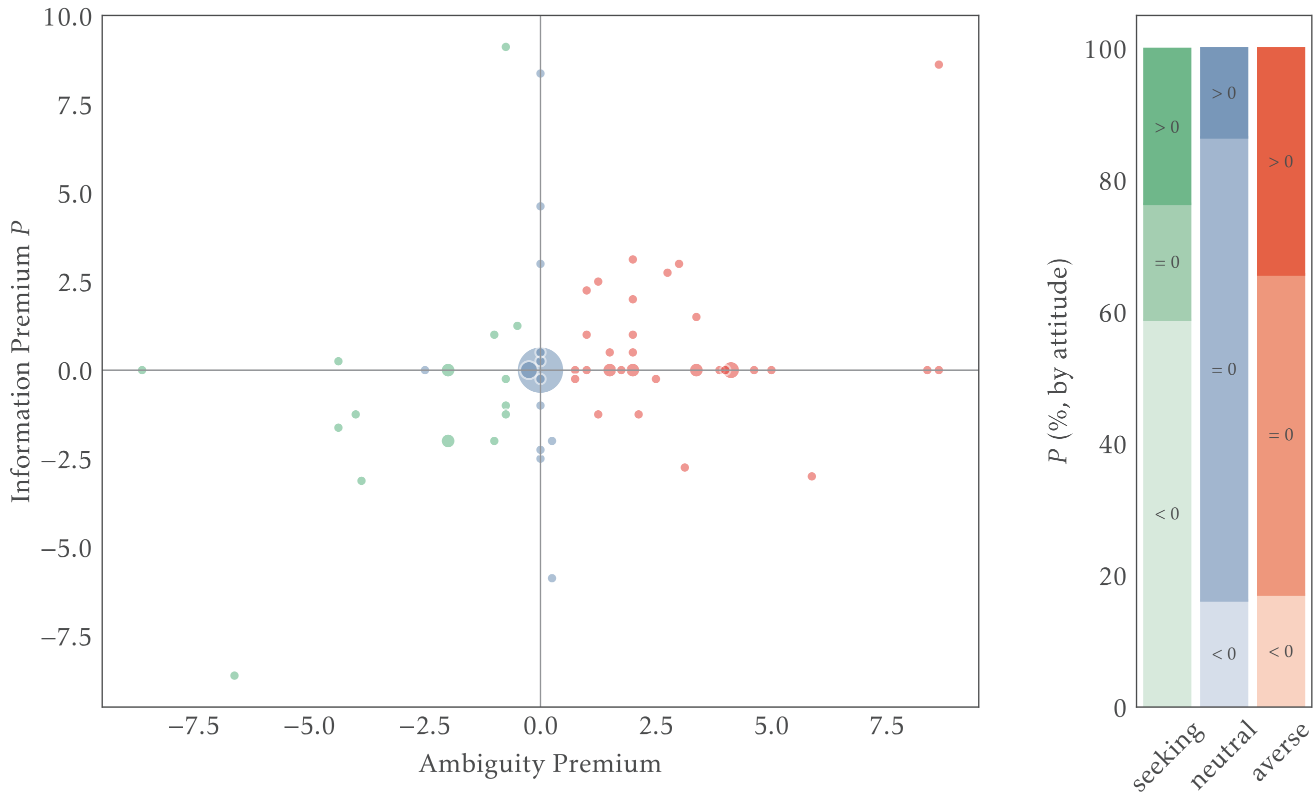
Ambiguity neutral subjects also exhibit a large majority of zero values; non-zero ones tend to be more often positive (albeit small). About half of them also have zero Value of Information; of the others, almost all give a negative value.

Ambiguous Payoff State. Results appear on the right part of Table 3 and in Figure 2. Clear, but different patterns emerge.

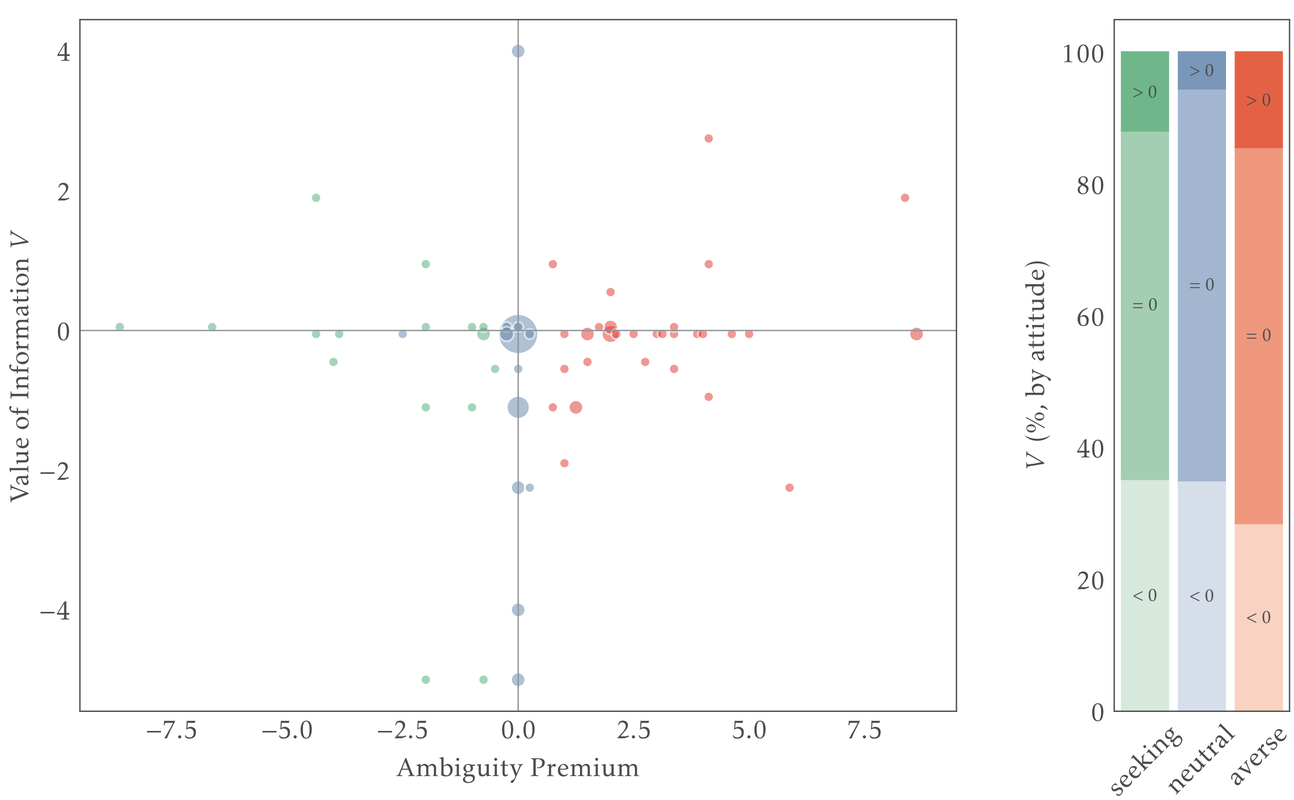
[12]In turns, this is due to their very unusual response in Q1, where both give 18.5 as the certainty equivalent of a 50/50 bet $20/$0. This gives huge values for both measures and generates the strong relation.

Figure 2: Results, Ambiguous Payoff-Relevant State, Graphically

(a) **Information Premium** P



(b) **Value of Information** V



Considering all subjects, the median Information Premium is again zero, but the mean is slightly positive. The majority still reports zero. Similar results hold for the Value of Information, albeit with a small, negative mean.

Ambiguity averse subjects have again a median Information Premium close to zero; a sizable fraction has Value of Information either zero or compatible with it. But these are smaller fractions than above: many (34%, and up to 50% in Order B) has strictly *positive* Information Premium.

The opposite pattern holds for ambiguity seeking subjects: now a large majority (59%, and 70% in Order B) has *negative* Information Premium. The Value of Information, however, remain predominantly zero in both cases.

Ambiguity neutral subjects, unsurprisingly, exhibit patterns similar to those found with risky urns.

Overall, we have a positive relationship between the Information Premium and the Ambiguity Premium ($t = 2.73, p = 0.008$), but this does not hold separately for ambiguity averse ($t = 0.95, p = 0.349$) or seeking ($t = 1.80, p = 0.091$) subjects. There is also no relation with the Value of Information ($t = 0.97$ overall; $t = 1.44$ for averse; $t = -1.15$ for seeking).

Comparison with Theory. We have seen that common theoretical models predict that with risky state, ambiguity averse agents should have *negative* Information Premium and Value of Information. Instead, we find that the majority has zero for both. Only a minority (31%) has negative Information Premium. For ambiguity seeking subjects, a large majority has a positive Information Premium, as predicted by the models. However, this is not reflected in the Value of Information: while these theories predict it should be strictly positive, it is too often zero.

3.4 Concerns

We now discuss possible concerns. (A separate one, that agents may ignore messages, is discussed in the next section.)

Noise in Q1. As mentioned above, the answer to Q1 is used to compute both the Ambiguity Premium and the Information Premium. If measured with noise, this may have two effects.

First, it may induce a spurious correlation. We have seen that for ambiguity averse subjects, we do not have such correlation, and thus do not have this concern. For ambiguity seeking, we do—and this concerns suggest caution in interpreting it.

Second, it may lead to a misclassification of subjects' ambiguity attitude. Suppose $c_{\varnothing}^{\text{observed}} = c_{\varnothing}^{\text{true}} + \varepsilon$. If $\varepsilon < 0$, this biases P *upwards* and increases ambiguity *seeking*. This suggests that we may be misclassifying some agents as ambiguity seeking and also overestimate their P. Again, this suggests caution in interpreting positive values of P for ambiguity seeking subjects.

If $\varepsilon > 0$, this biases downwards the Information Premium and increases Ambiguity Aversion: this leads to overestimate ambiguity *aversion* and have values of P that are too low. But this is not our concern—compared to the theory, we find values of P that are too high for ambiguity averse agents.

In general, even if our subjects are incorrectly classified, theoretical predictions is that we should observe negative Information premia P for a sizable fraction of the population; we do not. Thus, our results that find *no* negative reactions to information predicted by theory are not subject to these concerns.

Other forms of noise. Noise in the answers to other questions, if independent across question and with zero mean, would wash away and not bias our results. In fact, compared to theory, we find values with and without information to be too often identical—pointing to consistency rather than noise.

Complexity. Questions with information are more complex, which may be adding a confound, especially since reactions to complexity are known to relate to ambiguity attitude (Halevy, 2007; Dean and Ortoleva, 2019). But following this literature, complexity should lower the Information Premium for ambiguity averse agents. Our key finding, instead, is that it is too high, and thus does not seem to be caused by the confound.

3.5 Discussion and Implications

We study ambiguity of information of one particular form: whether the message is truthful or misleading. While only a very special case of ambiguous information, it allows us to test the dilation property of updating models, a property crucial to many applications to strategic settings. Common models predict that ambiguity averse agents should lower their value of bets after information, for any message—'all news is bad news.' We test this and reject it. The large majority of ambiguity averse agents do *not* react to this information.

Two possibilities appear natural. Either subjects follow a different updating rule; or, they follow FB or ML but complement them by *strategically* choosing not to process some information.

Other Updating rules? Proxy and DC Updating. Subjects may be following other updating rules. Proxy (P) updating was introduced in Gul and Pesendorfer (2018) precisely with the goal of avoiding the case of dilation after every message; indeed, the motivation includes examples reminiscent of our experiment. Unfortunately, their exact functional form cannot be applied to our exact case, as it is defined for totally monotone capacities, which cannot be the case for our experiment with risky states (see Appendix A for more). However, our results are very strongly supportive of the approach they suggest.

A second possibility is that subjects follow the Dynamically Consistent (DC) updating rule introduce in Hanany and Klibanoff (2007, 2009). According to it, before information agents consider available acts and messages and make a choice contingent on each message that maximizes the *ex-ante* overall utility; after information, these choices are implemented. In the context of our experiment, DC updating implies that an ambiguity averse agent would not react to information, while an ambiguity seeking one would increase the certainty equivalent—as these are their ex-ante optimal choices, because the former wants to reduce exposure to ambiguity while the latter wants to increase it. This is in line with our findings. However, as opposed to FB, ML, and P, this updating rule is dynamically consistent but violates consequentialism: agents' choices after information will take into account what acts return also in *unrealized* events.[13]

Choosing *if* to process information. The main empirical patterns we document—that with risky payoff-relevant states ambiguity averse agents do not react to information while ambiguity seeking agents do—could also be explained by another, simple approach, that is however outside current models.

Messages do not seem to be generally ignored in our data. First, during the experiment subjects are forced to acknowledge them by clicking on the corresponding color. Second, many subjects do react to the information: most ambiguity seeking agents with risky payoff-relevant urns, and many ambiguity averse agents with ambiguous payoff-relevant urn. Overall, the pattern seems to be that messages are ignored when harmful—by ambiguity averse agents with risky payoff-relevant states—and not ignored when possibly beneficial.

We may thus consider the possibility that agents choose *strategically* when and if to process the information: before applying any updating rule, subjects may first evaluate the information structure at hand and choose whether they will or not react to the messages it generates. If they choose not to react, they simply ignore it; if they do react, they may apply FB or ML. Note that disregarding information is never useful under Expected-Utility—there, information has weakly positive value and there is no reason to ignore it. But we

[13] Instead, FB, ML, and P satisfy consequentialism but violate dynamic consistency. In general, the two properties are incompatible under ambiguity (see the discussion in Siniscalchi, 2009). Dominiak et al. (2012) and Bleichrodt et al. (2018) test dynamic consistency and consequentialism, and find more support for the latter.

have seen that this is no longer the case under ambiguity. It may thus be reasonable for subjects to disregard information when harmful—when 'all news is bad news.'

While potentially a sensible strategy, the approach above is crucially *outside* the FB or ML models: accounting for it would change model predictions substantially, including controversial implications that have major impacts on applications like the ones mentioned above. If subjects are strategically disregarding information, widespread models are missing a crucial aspect of behavior. To our knowledge, this has not yet been studied.

Appendices

A On Proxy Updating

Gul and Pesendorfer (2018) introduce the Proxy updating rule with the goal of addressing the possibility of 'all news is bad news.' However, this is currently defined only for totally monotone capacities; unfortunately, we cannot express our preferences this way, at least when the state space is risky. To see why, consider the framework introduction in Section 2 for the case in which the payoff-relevant state is risky. Our assumptions for this case are that we have a set of priors $\Pi \subseteq \Delta(\Omega \times M)$ such that for each $\pi \in \Pi$:

$$\pi(R) = \pi(B) = 0.5$$

$$\pi(r|R) = \pi(b|B)$$

$$\pi(b|R) = \pi(r|B).$$

Any set of priors with these characteristics does not induce a totally monotone capacity. Note that the conditions above imply $\pi(R,r) = \pi(B,b)$ and $\pi(B,r) = \pi(R,b)$. Note also that $\pi(R) = \pi(R,r) + \pi(R,b) = \pi(R,r) + \pi(B,r) = \pi(r) = 0.5$. Similarly we obtain $\pi(b) = 0.5$. Let ρ denote the capacity induced by Π. We know

$$\rho(R) + \rho(B) = \rho(r) + \rho(b) = 1.$$

Suppose that ρ is totally monotone. Then its mobius transformation μ must satisfy

$$\mu(\{(R,r)\}) + \mu(\{(R,b)\}) + \mu(\{(B,r)\}) + \mu(\{(B,b)\}) + \mu(\{R\}) + \mu(\{B\}) = 1 \tag{1}$$

$$\mu(\{(R,r)\}) + \mu(\{(R,b)\}) + \mu(\{(B,r)\}) + \mu(\{(B,b)\}) + \mu(\{r\}) + \mu(\{b\}) = 1. \tag{2}$$

However, (1) implies that $\mu(\{r\}) + \mu(\{b\}) = 0$. Combining with (2), it implies

$$\mu(\{(R,r)\}) + \mu(\{(R,b)\}) + \mu(\{(B,r)\}) + \mu(\{(B,b)\}) = 1,$$

i.e., there is no ambiguity, and this only happens when $|\Pi| = 1$, contradiction.

B Examples and Proofs

B.1 Examples of Dilation and Contraction with Ambiguous States

In the main body of the paper we have seen an example in which the set of priors can contracts with ambiguous information when the payoff-relevant state is ambiguous. We now give examples of how it can dilate or remain unchanged.

Example 2 (Dilation)**.** Fix any $\varepsilon \in (0, 0.5)$, let $\Pi = \text{co}(\pi_{00}, \pi_{01}, \pi_{10}, \pi_{11})$, where

$$\begin{aligned}
\pi_{00}^{\Omega}(R) &= \varepsilon, & \pi_{00}(r|R) &= \pi_{00}(b|B) = \varepsilon,\\
\pi_{01}^{\Omega}(R) &= \varepsilon, & \pi_{01}(r|R) &= \pi_{01}(b|B) = 1-\varepsilon,\\
\pi_{10}^{\Omega}(R) &= 1-\varepsilon, & \pi_{10}(r|R) &= \pi_{10}(b|B) = \varepsilon,\\
\pi_{11}^{\Omega}(R) &= 1-\varepsilon, & \pi_{11}(r|R) &= \pi_{11}(b|B) = 1-\varepsilon.
\end{aligned}$$

Intuitively, Π includes all combinations of marginals over Ω and over whether the message is informative or misleading, as if obtained as the 'product' of the two sets. In this case, we have

$$^{\mathsf{FB}}\Pi_m^{\Omega} = {}^{\mathsf{ML}}\Pi_r^{\Omega} = \left[\frac{\varepsilon^2}{\varepsilon^2 + (1-\varepsilon)^2}, \frac{(1-\varepsilon)^2}{\varepsilon^2 + (1-\varepsilon)^2}\right] \supsetneq [\varepsilon, 1-\varepsilon] = \Pi^{\Omega}.$$

Thus, under FB and ML, $P_m < 0$ and $V < 0$ if the agent is ambiguity averse; $P_m > 0$ and $V > 0$ if ambiguity seeking.

Example 3 (Unchanged)**.** Let $\Pi = \text{co}(\pi_{00}, \pi_{01}, \pi_{10}, \pi_{11})$ where π_{ij} are defined as in the previous example, but with $\varepsilon = 0$. Then we have

$$^{\mathsf{FB}}\Pi_m^{\Omega} = {}^{\mathsf{ML}}\Pi_r^{\Omega} = [0, 1] = [0, 1] = \Pi^{\Omega}.$$

Thus, independently of the ambiguity attitude we have $P_m = 0$ and $V = 0$.

B.2 Proofs

Proof of Proposition 1. Consider first the case of ambiguity neutrality. Recall that we have assumed $\pi(r|R) = \pi(b|B)$ and $\pi(b|R) = \pi(r|B)$ and that, if $\bar{\pi}$ is the prior for which messages are not informative—$\bar{\pi}(r|R) = \bar{\pi}(b|R) = 0.5$—we have $\bar{\pi} \in \Pi$. When $\Pi = \{\pi\}$, we must then have $\pi(R, r) = \pi(R, b) = \pi(B, b) = \pi(B, r) = 0.25$. In turns, this implies that the decision maker's belief over R and B will not change after receiving message r or b. Item (3) of the Proposition thus holds.

Consider now a set of priors Π with $|\Pi| > 1$. Because $\pi(R) = 0.5$ for all $\pi \in \Pi$, then there must exist $\pi_1, \pi_2 \in \Pi$ such that $\pi_1 \neq \pi_2$ and $\pi_1(R, r) + \pi_1(B, b) \neq \pi_2(R, r) + \pi_2(B, b)$. Denote $x := \max_{\pi \in \Pi} \pi(R, r) + \pi(B, b)$ and $y := \min_{\pi \in \Pi} \pi(R, r) + \pi(B, b)$. Our assumptions on Π imply $x > 0.5 > y$.

Assume now the agent is ambiguity averse and that the updating rule is FB. After message r, the Bayesian update of $\pi \in \Pi$ is $\pi(R|r) = 2\pi(R, r) = \pi(R, r) + \pi(B, b)$. Thus, $\min\limits_{\pi \in \Pi} \pi(R|r) = y < 0.5$ and $\min\limits_{\pi \in \Pi} \pi(B|r) = 1 - x < 0.5$. No matter what color the agent chooses, she is worse off compared to before the message. Then: $P_m < 0$ for each m, and $v < 0$. The case of message b is identical; the case of ambiguity seeking follows.

Finally, Assume that the agent is updating is ML. Note that under any prior π, $\pi(r) = \pi(b) = 0.5$. Therefore, ML updating is exactly the same as the ML updating, and the result maintains. ‖

Proof of Proposition 2. The case for ambiguity neutrality is the same as Proposition 1.

If $\Pi > 1$, by Example 1 in the main body, P_m can be positive for ambiguous averse agents and negative for ambiguous seeking agents when the updating is FB and ML. By Example 2 in Section B.1, P_m and V can be negative for ambiguous averse agents and positive for ambiguous seeking agents when the updating is FB and ML. By Example 3 in Section B.1, P_m and V can be zero for ambiguous seeking and ambiguous averse agents when the updating is FB and ML. We are left to show that under both FB and ML it is possible to have $V > 0$ for ambiguous averse agents; or $V < 0$ for ambiguous seeking ones.

We show both with the following example. Consider $\Pi = \text{co}(\pi_1, \pi_2)$ such that

$$\pi_1^\Omega(R) = \epsilon, \quad \pi_1(r|R) = \pi_1(b|B) = 1 - \delta,$$

$$\pi_2^\Omega(B) = \epsilon, \quad \pi_2(b|R) = \pi_2(r|B) = 1 - \delta,$$

where $\epsilon, \delta < 0.5$. It is easy to check that in this case, ML and FB coincide. When the agent is ambiguous averse, $d_r = 0.5 - \epsilon$ and $d_b = \frac{\epsilon\delta}{\epsilon\delta + (1-\epsilon)(1-\delta)} - \epsilon$. Thus, that $V = 0.5\delta - 0.5\epsilon$. Therefore, $V > 0$ if $\epsilon < \delta$. When the agent is ambiguous seeking, $d_r = \epsilon - 0.5$ and $d_b = \epsilon - \frac{\epsilon\delta}{\epsilon\delta + (1-\epsilon)(1-\delta)}$. Thus $V < 0$ if $\epsilon < \delta$. ‖

C Additional Experimental Analysis

C.1 Additional Tables

Table 4 summarizes ambiguity attitude in the sample; Table 5 summarizes ambiguity premia in the sample; Table 6 is similar to Table 3, but with statistics grouped by order.

Table 4: Ambiguity attitude in the sample

	averse	neutral	seeking	Total
A	23	22	7	52
B	12	15	10	37
Total	35	37	17	89

Table 5: Ambiguity premia in the sample

amb. att.	averse			neutral			seeking		
order	A	B	All	A	B	All	A	B	All
median	2.8	2	2.5	0	0	0	-4	-1.5	-2
mean	3.3	2.8	3.1	-0.05	-0.02	-0.03	-3.9	-1.8	-2.7
# of obs.	23	12	35	22	15	37	7	10	17

Table 6: Results (by order)

	Risky payoff state								*Ambiguous payoff state*							
amb. att.	All		averse		neutral		seeking		All		averse		neutral		seeking	
order	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B
	Information Premium P															
median	0	0	0	0	0	0	3.5	0	0	0	0	0.25	0	0	0	-1.1
mean	0.57	0.29	-0.76	-0.17	0.5	0.75	5.2	0.16	-0.17	0.54	0.25	1.2	-0.23	0.53	-1.3	-0.21
≈ 0	62%	70%	61%	83%	77%	80%	14%	40%	67%	46%	61%	42%	86%	60%	29%	30%
$= 0$	50%	65%	52%	67%	59%	80%	14%	40%	60%	40%	52%	42%	82%	53%	14%	20%
> 0	31%	24%	9%	17%	36%	20%	86%	40%	19%	30%	26%	50%	4%	27%	43%	10%
< 0	19%	11%	39%	17%	4%	0%	0%	20%	21%	30%	22%	8%	14%	20%	43%	70%
	Value of Information V															
median	-0.05	-0.05	-0.05	-0.05	-0.05	-0.55	0.05	0	-0.05	-0.05	-0.05	-0.05	-0.05	-0.55	0.05	-0.05
mean	-0.34	-0.52	-0.44	0.17	-0.48	-1.1	0.46	-0.48	-0.28	-0.63	-0.19	0.04	-0.46	-0.9	-0.01	-1
$= 0$	58%	49%	56%	42%	59%	40%	57%	70%	60%	54%	52%	67%	73%	40%	43%	60%
> 0	8%	14%	4%	25%	4%	7%	29%	10%	12%	8%	17%	8%	4%	7%	14%	10%
< 0	35%	38%	39%	33%	36%	53%	14%	20%	29%	38%	30%	25%	23%	53%	43%	30%
# of obs.	52	37	23	12	22	15	7	10	52	37	23	12	22	15	7	10

C.2 Analysis with all subjects

The analysis in the main body of the paper does not include the behavior of two subjects who reported extreme answers in a number of questions-—in particular, they chose a bet on the urn with a payment of \$20 against any amount of money, including \$20 for sure. Below we replicate Table 4 and Table 3, but include these two subjects. As is clear, almost nothing changes: both subjects were ambiguity seeking, and both faced Order B, thus these are the only changes.

Table 7: Ambiguity attitude in the sample (all observations)

	averse	neutral	seeking	Total
A	24	20	8	52
B	12	15	12	39
Total	36	35	20	91

Table 8: Results (all observations)

	Risky payoff state				*Ambiguous payoff state*			
amb. att.	All	averse	neutral	seeking	All	averse	neutral	seeking
				Information Premium P				
median	0	0	0	0.88	0	0	0	-0.62
mean	0.42	-0.56	0.59	2	0.11	0.57	0.04	-0.64
≈ 0	65%	69%	79%	28%	59%	54%	76%	33%
$= 0$	56%	57%	68%	28%	52%	49%	68%	22%
> 0	28%	11%	29%	56%	23%	34%	13%	22%
< 0	16%	31%	3%	17%	25%	17%	18%	56%
				Value of Information V				
median	-0.05	-0.05	-0.05	0.05	-0.05	-0.05	-0.05	-0.05
mean	-0.41	-0.23	-0.71	-0.09	-0.42	-0.11	-0.63	-0.57
$= 0$	55%	51%	53%	67%	58%	57%	60%	56%
> 0	10%	11%	5%	17%	10%	14%	5%	11%
< 0	35%	37%	42%	17%	32%	29%	34%	33%
# of obs.	91	35	38	18	91	35	38	18

D Instructions and Screenshots

Subjects received instructions in a presentation; they also received a condensed version printed out. The slides of the presentation are available at:
http://denisshishkin.com/papers/ambiguous_information/instructions.pdf.
The print-out is available at:
http://denisshishkin.com/papers/ambiguous_information/handout.pdf.

Below are screenshots of the experiment interface of Part I of Order A. Part II and Order B are similar. For completeness, all screenshots are available at
http://denisshishkin.com/papers/ambiguous_information/screenshots.pdf.

Question 1

Jar composition:

x 50 x 50

In this question, the jar has 50 Aquamarine and 50 Red balls.

Please, choose a color of the ball to bet on:

Red Aquamarine

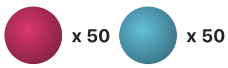
For each row below, which option would you prefer?

Receive $20 if the **BALL DRAWN** is:	Receive
Red	$0.00
Red	$3.00
Red	$5.00
Red	$6.00
Red	$6.50
Red	$7.00
Red	$7.25
Red	$7.50
Red	$7.75
Red	$8.00
Red	$8.25
Red	$8.50
Red	$8.75
Red	$9.00
Red	$9.25
Red	$9.50
Red	$9.75
Red	$10.00
Red	$10.25
Red	$10.50
Red	$10.75
Red	$11.00
Red	$11.25
Red	$11.50
Red	$11.75
Red	$12.00
Red	$12.25
Red	$12.50
Red	$12.75
Red	$13.00
Red	$13.50
Red	$14.00
Red	$15.00
Red	$17.00
Red	$20.00

Continue

Question 2

Jar composition:



In this question, the jar has 50 **Magenta** and 50 **Cyan** balls.

Information

To determine whether to tell the truth or to lie, the computer has drawn a chip from a bag with 100 chips, either **Yellow** or **Pink**. The composition of the bag is **unknown**: there may be no **Yellow** chips or no **Pink** chips, or **any other composition**.

If the chip drawn is **Yellow**: the computer tells the **truth**.
If the chip drawn is **Pink**: the computer **lies**.

Here is the information given by the computer:

The Ball Drawn is **Magenta**

Remember, that this may or may not be the truth!

Please, acknowledge the information above. That is, click on the corresponding color:

Magenta Cyan

Please, choose a color of the ball to bet on:

Cyan Magenta

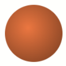
For each row below, which option would you prefer?

Receive $20 if the BALL DRAWN is:			Receive
Magenta	○	○	$0.00
Magenta	○	○	$3.00
Magenta	○	○	$5.00
Magenta	○	○	$6.00
Magenta	○	○	$6.50
Magenta	○	○	$7.00
Magenta	○	○	$7.25
Magenta	○	○	$7.50
Magenta	○	○	$7.75
Magenta	○	○	$8.00
Magenta	○	○	$8.25
Magenta	○	○	$8.50
Magenta	○	○	$8.75
Magenta	○	○	$9.00
Magenta	○	○	$9.25
Magenta	○	○	$9.50
Magenta	○	○	$9.75
Magenta	○	○	$10.00
Magenta	○	○	$10.25
Magenta	○	○	$10.50
Magenta	○	○	$10.75
Magenta	○	○	$11.00
Magenta	○	○	$11.25
Magenta	○	○	$11.50
Magenta	○	○	$11.75
Magenta	○	○	$12.00
Magenta	○	○	$12.25
Magenta	○	○	$12.50
Magenta	○	○	$12.75
Magenta	○	○	$13.00
Magenta	○	○	$13.50
Magenta	○	○	$14.00
Magenta	○	○	$15.00
Magenta	○	○	$17.00
Magenta	○	○	$20.00

Continue

Question 3

Jar composition:

 x 50  x 50

In this question, the jar has 50 **Blue** and 50 **Orange** balls.

Choosing whether to receive information

In this question, before you compare bets on the color of the ball with certain prizes, you can **choose** whether you want to receive information about the color of the ball.

To determine whether to tell the truth or to lie, the computer has drawn a chip from a bag with 100 chips, either **Indigo** or **Violet**. The composition of the bag is **unknown**: there may be no **Indigo** chips or no **Violet** chips, or **any other composition**.

 x ?  x ?

If the chip drawn is **Indigo**: the computer tells the **truth**.
If the chip drawn is **Violet**: the computer **lies**.

For each row below, which option would you prefer?

Option A	Option B
No information	Information and *reduce* your winnings by $5.0
No information	Information and *reduce* your winnings by $3.0
No information	Information and *reduce* your winnings by $2.5
No information	Information and *reduce* your winnings by $2.0
No information	Information and *reduce* your winnings by $1.8
No information	Information and *reduce* your winnings by $1.6
No information	Information and *reduce* your winnings by $1.4
No information	Information and *reduce* your winnings by $1.2
No information	Information and *reduce* your winnings by $1.0
No information	Information and *reduce* your winnings by $0.9
No information	Information and *reduce* your winnings by $0.8
No information	Information and *reduce* your winnings by $0.7
No information	Information and *reduce* your winnings by $0.6
No information	Information and *reduce* your winnings by $0.5
No information	Information and *reduce* your winnings by $0.4
No information	Information and *reduce* your winnings by $0.3
No information	Information and *reduce* your winnings by $0.2
No information	Information and *reduce* your winnings by $0.1
No information	Information and *increase* your winnings by $0.0
No information	Information and *increase* your winnings by $0.1
No information	Information and *increase* your winnings by $0.2
No information	Information and *increase* your winnings by $0.3
No information	Information and *increase* your winnings by $0.4
No information	Information and *increase* your winnings by $0.5
No information	Information and *increase* your winnings by $0.6
No information	Information and *increase* your winnings by $0.7
No information	Information and *increase* your winnings by $0.8
No information	Information and *increase* your winnings by $0.9
No information	Information and *increase* your winnings by $1.0
No information	Information and *increase* your winnings by $1.2
No information	Information and *increase* your winnings by $1.4
No information	Information and *increase* your winnings by $1.6
No information	Information and *increase* your winnings by $1.8
No information	Information and *increase* your winnings by $2.0
No information	Information and *increase* your winnings by $2.5
No information	Information and *increase* your winnings by $3.0
No information	Information and *increase* your winnings by $5.0

Continue

Question 3

Based on your choice in the randomly selected row, your payoff will be **increased by $0.5** and you will now make choices **with information.**

Jar composition:

In this question, the jar has 50 **Blue** and 50 **Orange** balls.

Information

To determine whether to tell the truth or to lie, the computer has drawn a chip from a bag with 100 chips, either **Indigo** or **Violet**. The composition of the bag is **unknown**: there may be no **Indigo** chips or no **Violet** chips, or **any other composition**.

If the chip drawn is **Indigo**: the computer tells the **truth**.
If the chip drawn is **Violet**: the computer **lies**.

Here is the information given by the computer:

The Ball Drawn is **Blue**

Remember, that this may or may not be the truth!

Please, acknowledge the information above. That is, click on the corresponding color:

Blue Orange

Please, choose a color of the ball to bet on:

Blue Orange

For each row below, which option would you prefer?

Receive $20 if the BALL DRAWN is:			Receive
Orange	○	○	$0.00
Orange	○	○	$3.00
Orange	○	○	$5.00
Orange	○	○	$6.00
Orange	○	○	$6.50
Orange	○	○	$7.00
Orange	○	○	$7.25
Orange	○	○	$7.50
Orange	○	○	$7.75
Orange	○	○	$8.00
Orange	○	○	$8.25
Orange	○	○	$8.50
Orange	○	○	$8.75
Orange	○	○	$9.00
Orange	○	○	$9.25
Orange	○	○	$9.50
Orange	○	○	$9.75
Orange	○	○	$10.00
Orange	○	○	$10.25
Orange	○	○	$10.50
Orange	○	○	$10.75
Orange	○	○	$11.00
Orange	○	○	$11.25
Orange	○	○	$11.50
Orange	○	○	$11.75
Orange	○	○	$12.00
Orange	○	○	$12.25
Orange	○	○	$12.50
Orange	○	○	$12.75
Orange	○	○	$13.00
Orange	○	○	$13.50
Orange	○	○	$14.00
Orange	○	○	$15.00
Orange	○	○	$17.00
Orange	○	○	$20.00

Continue

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