

The “Fake News” Effect: An Experiment on Motivated Reasoning and Trust in News*

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Abstract

On many factual questions, people hold beliefs that are biased and polarized in systematic ways. One potential explanation is that when people receive new information, they engage in *motivated reasoning* by distorting their inference in the direction of beliefs that they are more motivated to hold. This paper develops a model of motivated reasoning and tests its predictions using a large online experiment in the United States. Identifying motivated reasoning from Bayesian updating has posed a challenge in environments where people have preconceived beliefs. I create a new design that overcomes this challenge by analyzing how subjects assess the veracity of information sources that tell them that the median of their belief distribution is too high or too low. In this environment, a Bayesian would infer nothing about the source veracity, but motivated reasoning predicts directional distortions. I reject Bayesian updating in favor of politically-driven motivated reasoning on eight of nine hypothesized topics: immigration, income mobility, racial discrimination, crime, gender-based math ability, climate change, gun laws, and the performance of other subjects. Subjects also engage in motivated reasoning about their own performance. Motivated reasoning from these messages leads people’s beliefs to become more polarized and less accurate.

JEL classification: C91; D83; D84; D91; L82

Keywords: motivated reasoning; biased beliefs; polarization; fake news

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1 Introduction

“So far as I can see, all political thinking for years past has been vitiated in the same way. People can foresee the future only when it coincides with their own wishes, and the most grossly obvious facts can be ignored when they are unwelcome.”

—George Orwell (Partisan Review, 1945)

On many topics, people extensively disagree about the answers to factual questions, and their beliefs are often inaccurate in predictable directions. People have differing beliefs about questions related to income mobility, crime rates, and racial discrimination in labor markets; tend to be biased in the direction that is more representative of their political party’s stances; and often overestimate their own political knowledge (e.g. Alesina, Stantcheva, and Teso 2018; Flynn, Nyhan, and Reifler 2017; Ortoleva and Snowberg 2015). As shown by Meeuwis et al. (2019) and Gerber and Huber (2009), these beliefs can affect consumer, financial, and political behavior. Given the importance of these issues, why does such bias and belief polarization persist? This paper helps answer this question by analyzing how beliefs change when people receive new information.

After receiving a piece of news, people form their posterior beliefs by incorporating their prior beliefs and their perceived informativeness of the information. If we only observe beliefs at a snapshot in time, two people’s disagreement can be consistent with several explanations: for instance, they may have had different priors, they may differently perceive the informativeness of the news, or they may have different inference processes. The first two channels are often relevant in politicized settings. First, Democrats and Republicans often have different preconceived notions, leading to differences in posteriors; this can be consistent with Bayes’ rule and with prior-confirming behavioral biases. Second, Democrats and Republicans often consume different news sources, and may find arguments akin to those from MSNBC and from Fox News differentially informative.¹

This paper studies the third channel: people form different posteriors, even if they have the same priors and receive the same information, because they distort their updating process. When people receive information, they are often reminded of what beliefs they currently hold, and of particular beliefs they find more attractive to hold. In the model of *motivated reasoning* developed in this paper, people distort their updating process in the direction of these particular beliefs (*motives*). The model defines motives to be a function that maps beliefs to the real numbers. Agents make inferences using a modified Bayes’ rule, weight-

¹There is ample evidence consistent with these channels (e.g. Taber and Lodge 2006; Kahan, Hoffman, et al. 2012; Nyhan and Reifler 2010; Nyhan and Reifler 2013; Nyhan, Reifler, and Ubel 2013).

ing priors and likelihoods as a Bayesian would, but act as if they receive an extra signal that puts more weight on higher-motive states. Motives are often heterogeneous, such as on politicized issues. In such a setting, the model shows how motivated reasoning can lead agents to over-trust news that reinforces their biases, can cause belief polarization, and can lead to miscalibrated and overconfident beliefs.

While there is an intuition in the literature that motivated reasoning plays a role in inference, particularly in political domains, designing an experiment that identifies the bias has been a challenge in domains where people enter the experiment with different beliefs (as discussed in Kahan 2016a and Sunstein et al. 2017). This paper’s main experimental contribution is to construct a new design to disentangle motivated reasoning from Bayesian inference in such settings. In the experiment, subjects make inferences about the veracity of messages that are equally likely to tell them that their current median beliefs are biased upward or biased downward. Because subjects report their median beliefs, they believe that both a source that sends a truthful message and a source that sends a false message are equally likely to send a “greater than” or a “less than” message. Therefore, there is nothing for a Bayesian to infer. However, motivated reasoners will trust messages more if the messages better align with their motivated beliefs.²

The context of this experiment concerns Americans’ assessments of the veracity of news about economic, political, and social issues. The news veracity setting is useful for identifying motivated reasoning, and is particularly salient in the United States today. According to Gallup (2018a) and the Knight Foundation (2018), fewer than one in four Americans has confidence in the news media, a sizable majority believe that “fake news is a threat to democracy,” and less than half can even “think of a news source that reports the news objectively.”³

I run a within-subject experiment on Amazon Mechanical Turk with approximately 1,000 Americans. Subjects are given factual questions about nine *politicized* topics (on economic, political, and social issues), three neutral topics, and one question about on own performance in the experiment. The list of topics and pre-hypothesized motives is in Table 1.

As previewed above, the experimental design has two main steps. First, subjects are given a variety of factual questions with numerical answers. On each question, the medians of subjects’ belief distributions are elicited, so that subjects think the true answer is equally

²Because there is nothing to infer, the result cannot be due to general over- or under-weighting of priors or likelihoods. As discussed later, this design also shows that motivated reasoning is hard to reconcile with utility-maximizing beliefs like those in Brunnermeier and Parker (2005); Benabou and Tirole (2011); or Mobius et al. (2014).

³Among those who *can* name an objective news source, there is not a single outlet that both 5 percent of Democrats and 5 percent of Republicans think of as objective.

| Topic | Pro-Democrat Motives | Pro-Republican Motives |
|-----------------------|-----------------------------|-------------------------------|
| US crime | Got better under Obama | Got worse under Obama |
| Upward mobility | Low in US after tax cuts | High in US after tax cuts |
| Racial discrimination | Severe in labor market | Not severe in labor market |
| Gender | Girls better at math | Boys better at math |
| Refugees | Decreased violent crime | Increased violent crime |
| Climate change | Scientific consensus | No scientific consensus |
| Gun reform | Decreased homicides | Didn't decrease homicides |
| Media bias | Media not dominated by Dems | Media is dominated by Dems |
| Party performance | Higher for Dems over Reps | Higher for Reps over Dems |
| Own performance | Higher for self over others | Higher for self over others |
| Random number | Neutral | Neutral |
| Latitude of US | Neutral | Neutral |
| Longitude of US | Neutral | Neutral |

Table 1: The list of topics and pre-hypothesized motives in the experiment. The first nine topics are called politicized topics. On the computer, each topic is a hyperlink that links to the exact question wording in Appendix C.

likely to be above or below their medians. Second, subjects are given one binary message that is chosen randomly from either a True News source or a Fake News source; the message tells them whether the answer was above or below their median. If the message is from True News, it is always accurate. If the message is from Fake News, it is always inaccurate. Subjects are not told which source the message came from; instead, they make inferences about the source’s veracity from the message.

Since messages relate the true answer to subjects’ subjective median, Bayesian subjects would believe that it is equally likely for either source to report either message. That is, the subjective likelihood that a True News source would report that the answer is greater than the median is $1/2$, and the subjective likelihood that a Fake News source would report that the answer is greater than the median is also equal to $1/2$. Therefore, a “greater than” message is uninformative about the veracity of the news source to a Bayesian. Likewise, a “less than” message is also uninformative to a Bayesian.

On the other hand, a subject who engages in motivated reasoning will trust the news more if it sends a message that supports what he is more motivated to believe. The main hypothesis in this paper is that the direction of motivated beliefs is driven by political preferences on these topics. In other words, it predicts that people will assess messages that align with beliefs of their political party (*Pro-Party news*) to be more truthful, while assessing messages that misalign (*Anti-Party news*) to be less truthful.

The main result of the experiment is that Bayesian updating is rejected in favor of politically-motivated reasoning on these topics. While a Bayesian would believe that Pro-Party and Anti-Party news are equally likely to be True News on the politicized topics, subjects in the experiment believe that Pro-Party messages are 9 percentage points (standard error (s.e.) 0.7 percentage points) more likely than Anti-Party messages to come from the True News source. This gap increases in the partisanship of the subject, and assessments on neutral topics lie in between Pro-Party news and Anti-Party news veracity assessments. This design allows for enough statistical power to test motivated reasoning for each topic individually; for eight of the nine politicized topics, the main effect is significant at the $p = 0.001$ level. On each of these topics, this experiment provides novel evidence for motivated reasoning; unlike in prior studies, these results are not confounded by alternative explanations involving Bayesian updating or prior-confirming biases.⁴ In addition, there is evidence for

⁴Papers that find asymmetric responses to information on these topics include: Taber and Lodge (2006) [gun laws]; Alesina, Stantcheva, and Teso (2018) [upward mobility]; Cappelen, Haaland, and Tungodden (2018) [responses to taxation]; Haaland and Roth (2019) [racial labor market discrimination]; Sarsons (2017), Kunda and Sinclair (1999), and Iyengar and Westwood (2015) [gender and performance]; Alesina, Miano, and Stantcheva (2018), Haaland and Roth (2018), and Druckman, Peterson, and Slothuus (2013) [impact of immigrants]; Nyhan and Reifler (2013) and Nyhan, Reifler, and Ubel (2013) [perceptions of elected officials]; and Sunstein et al. (2017) [climate change]. Many results from these papers can be explained by motivated

performance-driven motivated reasoning on a question asking subjects to rate their performance on the experiment relative to others. These main results are robust to a host of alternative explanations.⁵

Secondly, results support the hypothesis that the error in subjects' current beliefs is due in part to motivated reasoning. The theory predicts that, since people who motivatedly reason about an issue will form directionally-biased beliefs on average, we can partly infer what people's motivated beliefs are by looking at their current beliefs. That is, under this hypothesis, *error* predicts *motive*. In the experiment, this hypothesis means that people will give higher veracity assessments to news that (falsely) reinforces their error compared to news that (truthfully) brings them closer to the correct answer. Indeed, in the experiment, people trust the error-reinforcing Fake News more than the error-correcting True News, and only on topics where motivated reasoning is expected to play a role. This gap persists when controlling for whether the news is Pro-Party or Anti-Party.

Thirdly, the theory explains how motivated reasoning can lead to other behavioral biases. Motivated reasoning may provide a link between overprecision and partisanship, a relationship documented in Ortoleva and Snowberg (2015). In an environment with normally-distributed priors and likelihoods, people's belief distributions are more likely to be miscalibrated when they have stronger motives, and their 50-percent confidence intervals will contain the true answer less than 50 percent of the time. This result is borne out in the experiment: subjects' intervals are significantly overprecise on politicized and performance questions, while they are not overprecise on neutral topics. The model also discusses how motivated reasoning can lead to both underperformance and overconfidence, since the bias leads to erroneously extreme beliefs that news sources are either very likely to be True News or are very likely to be Fake News. Indeed, in the experiment subjects perform significantly worse than if they had always said there was a 50 percent chance of the source being True News or Fake News.

Motivated reasoning not only affects how people trust or distrust news, but also impacts how people change their beliefs about the politicized topics themselves, and leads to belief polarization. Subjects are significantly more likely to revise their beliefs away from the population mean than towards it. This form of polarization is entirely accounted for by the news reasoning.

⁵The main predictions are identical if subjects mistakenly believe Fake News sends random messages instead of always-false messages, and results are not driven by subjects who have skewed distributions and may misreport their median. Importantly, there is also evidence for asymmetric updating regarding their beliefs about the initial question. Subjects are significantly more likely to change their beliefs in the direction of the message if the news is Pro-Party than if the news is Anti-Party, and this asymmetry is entirely captured by the differences in news veracity assessments of those sources. This suggests that the results cannot be explained by expressive preferences or mistakenly treating Fake News as Anti-Party news.

veracity assessments, suggesting that subjects are polarizing because of their misinference of the veracity of Pro-Party and Anti-Party news; it also shows that informational content is *not* a necessary condition for polarization.⁶ Politically-motivated reasoning helps reconcile the notions that the ideological polarization of beliefs may be high, even if the ideological polarization of information acquisition is modest (the latter shown by Gentzkow and Shapiro 2011).⁷

There is no other sizable demographic heterogeneity in motivated reasoning on the politicized topics, neither in direction or magnitude, once party preference is controlled for.⁸ Differences in treatment effects across subjects of different demographic groups are statistically indistinguishable from zero, and estimates are precise enough to rule out even modest effect sizes. This result suggests that motivated reasoning is homogeneous across demographic groups — and that even on many issues that are explicitly about particular groups, such as gender and math ability, racial discrimination, and income mobility — motivated beliefs are principally driven by politics.

However, when subjects are asked about their own performance, there is substantial heterogeneity in motivated reasoning by gender. Men motivatedly reason to believe they outperformed others, and women do not motivatedly reason in either direction on average.⁹ Motivated reasoning can help explain the gender gap in overconfidence, and more broadly suggests that politically-motivated reasoning may be a more universal phenomenon than performance-motivated reasoning in this context.

Finally, this paper contributes methodologically to the growing experimental literature on the identification of motivated reasoning. As summarized by Daniel Benjamin (2019), the current experimental evidence for motivated reasoning has been mixed: Mobius et al. (2014); Eil and Rao (2011); and Charness and Dave (2017) find that people update more from ego-positive news than ego-negative news, while Ertac (2011); Kuhnen (2014); and Coutts (2018) find the opposite.¹⁰ The design for these papers typically involves giving subjects

⁶There is a related literature that discusses the relationship between trust in news and political partisanship (Nisbet, Cooper, and Garrett 2015; Levendusky 2013; Druckman, Levendusky, and McLain 2018).

⁷Gentzkow and Shapiro (2006) and Gentzkow, Wong, and Zhang (2018) provide alternative theoretical explanations with Bayesian agents who have different priors, but this experiment’s results are not predicted by their models.

⁸Demographics include race, gender, income, age, education, religion, and whether one’s home state voted for Trump or Clinton in the 2016 presidential election.

⁹This relates to results found in Coffman, Collis, and Kulkarni (2019), which was run contemporaneously and also finds differences in updating by gender.

¹⁰It is worth noting that there is more consistent evidence for choice-based implications of motivated beliefs. This includes information avoidance and moral wiggle room (Oster, Shoulson, and Dorsey 2013; Dana, Weber, and Kuang 2007; Gino, Norton, and Weber 2016), and both risk- and ambiguity-driven distortions (Exley 2015; Haisley and Weber 2010). Yet in the setting in this paper, I do not see evidence for information avoidance: In Appendix B.2 I show that subjects are willing to pay positive amounts for

informative signals and testing for asymmetric updating from “Good” and “Bad” news, and thus requires noise-inducing strategies to disentangle motivated biases from non-motivated biases such as under-inference from information and prior-confirming biases. My design aims to better isolate the motivated reasoning channel by constructing an environment in which misweighting priors and likelihoods plays no role, as messages are uninformative about source veracity. As such, statistical power is large, results are precise, and the design can be portably used to test motivated reasoning on a wide variety of topics.

The rest of the paper proceeds as follows: Section 2 develops the model of motivated reasoning, generating testable predictions. Section 3 introduces the experimental design and hypotheses corresponding to these predictions. Section 4 discusses further details of the experiment and data.

Section 5 analyzes experimental results. Section 5.2 provides results about news veracity assessments in support of the main motivated reasoning hypotheses. Section 5.3 shows that motivated reasoning and belief polarization occur about the original question. Section 5.4 goes through several categories of robustness checks. Section 5.5 relates motivated reasoning to beliefs and overprecision. Section 5.6 relates motivated reasoning to underperformance and overconfidence. Section 6.1 discusses treatment effect heterogeneity. Section 6.2 discusses gender, overconfidence, and performance-driven motivated reasoning.

Section 7 concludes and proposes directions for future work. There are then several appendices: Appendix A provides a proof as well as several tables and figures that are omitted from the main text. Appendix B considers a version of the motivated reasoning model in which subjects form posteriors with noise, and the strength of the motivated-reasoning signal is equal to the standard deviation of this noise term. It then discusses results from a willingness-to-pay treatment consistent with the extended model’s predictions, and structurally estimates this model. Appendix C lists the exact questions, answers, and sources that subjects see. Appendix D provides results from a pre-registered replication of all the main results and many of the secondary results. The online appendices include additional robustness checks, as well as the entire experiment flow with screenshots of each page.

2 Model and Predictions

This section introduces and develops a model of motivated reasoning in which agents distort their updating process in the direction of their motivated beliefs when they receive information. The model predicts that people will over-trust news that supports their motivated beliefs compared to a Bayesian, and that we can infer what people are motivated information, and pay similar amounts for information about both motivated and neutral states.

to believe from the directional error in their *current* beliefs. In the political context, this implies that both current beliefs and strength of party preference affect the bias in information processing. It also generates secondary predictions under additional functional form assumptions, showing how motivated reasoning can lead to belief polarization, overprecision, underperformance, and overconfidence.

2.1 A Model of Motivated Reasoning

Motivated reasoning posits that agents distort their updating process to put higher likelihood on events that they are more motivated to believe. In this paper, we will often study agents who are motivated to hold beliefs that better support their preferred political party’s stances. For example, we will posit that Republicans are politically motivated to believe that murder and manslaughter rates increased during the presidency of Barack Obama, and that Democrats are politically motivated to believe that rates decreased. I will define motivated reasoning by formalizing and extending the framework of Kahan (2016a) in which agents update from information using a modified Bayes’ rule. They act as if they put appropriate weights on their prior and the signal likelihood, but receive an additional signal that puts more weight on beliefs that they are more motivated to hold.

To formalize, suppose that agents are inferring about the probability that an event is true (T) or false ($\neg T$), and have prior $\mathbb{P}(T)$. We compare inference from a Bayesian agent (she) to a motivated-reasoning agent (he) when they receive the same signal $x \in X$ about the probability that the event is T .¹¹ The Bayesian sets her posterior to be proportional to her prior times the likelihood of the signal:

$$\underbrace{\mathbb{P}(T|x)}_{\text{posterior}} \propto \underbrace{\mathbb{P}(T)}_{\text{prior}} \cdot \underbrace{\mathbb{P}(x|T)}_{\text{likelihood}}$$

Taking log odds ratios of both sides gives the Bayesian logit updating process:

$$\text{logit } \mathbb{P}(T|x) = \text{logit } \mathbb{P}(T) + \log \left(\frac{\mathbb{P}(x|T)}{\mathbb{P}(x|\neg T)} \right), \quad (1)$$

The motivated reasoner updates similarly, but he incorporates his prior, likelihood, and a motivated reasoning term:

$$\underbrace{\mathbb{P}(T|x)}_{\text{posterior}} \propto \underbrace{\mathbb{P}(T)}_{\text{prior}} \cdot \underbrace{\mathbb{P}(x|T)}_{\text{likelihood}} \cdot \underbrace{M(T)^{\varphi(x)}}_{\text{mot. reasoning}},$$

¹¹This can be straightforwardly generalized to any discrete state space of events $\{E_1, E_2, \dots\}$, where agents infer about the probability of events E_1 versus $\neg E_1$, E_2 versus $\neg E_2$, \dots

where $M(T) : \{T, \neg T\} \rightarrow \mathbb{R}_+$.¹² Define $m(T) \equiv \log M(T)$ and take log odds ratios to get the motivated-reasoning logit updating process, which will be central to the rest of this section:

$$\text{logit } \mathbb{P}(T|x) = \text{logit } \mathbb{P}(T) + \log \left(\frac{\mathbb{P}(x|T)}{\mathbb{P}(x|\neg T)} \right) + \varphi(x)(m(T) - m(\neg T)). \quad (2)$$

The motivated reasoner acts as if he receives both the actual signal (x) and a signal whose relative likelihood corresponds to how much he is motivated to believe the state is T . $m(T) : \{T, \neg T\} \rightarrow \mathbb{R}$ is denoted the **motive** function.

We assume that the motive function does not depend on the signal structure. Motives may also be indirect; for instance, an agent may be motivated to believe that a news source is truthful because it reports something in support of her political party. It will also be useful to treat the motive function cardinally in order to study distributions of beliefs. That is, m can be thought of as an *expected* motive function to mirror the standard expected utility function u .

The agent weights the motive signal by parameter $\varphi(x) \geq 0$, called **susceptibility**. When $\varphi(x) = 0$, the agent is Bayesian; when $\varphi(x) > 0$, the agent motivatedly reasons. φ may be a function of signal x and the *perceived informativeness* of x , but does not depend on m .¹³

Closing the model requires additional assumptions on $\varphi(x)$. In the main text of this paper, we will not probe further and instead focus on one particular type of signal structure. For further discussion of a specific definition of φ that depends on the noisiness of the updating process, see Appendix B. Experimentally, this paper studies one type of signal structure, but a future experiment could expand the space of signals to identify perceptions of informativeness by exogenously varying φ .

2.2 Identifying Motivated Reasoning

We now use the above framework to identify φ when we assume something about people's motives. We consider an environment in which priors are fixed and Bayesians do not infer anything, but motivated reasoning can play a role.

¹²Note that there is also a change in the proportionality constant between Bayes and motivated reasoning, but this is not a function of T . A similar definition arises for a continuous state ω . Bayes rule sets $f(\omega|z) \propto p(z|\omega) \cdot f(\omega)$, and motivated reasoning sets $f(\omega|z) \propto p(z|\omega) \cdot f(\omega) \cdot m(\omega)^{\varphi(z)}$.

¹³This can be different from the *actual* informativeness of x in important ways. The experiment shows an environment in which signals are uninformative, but are perceived as informative, and still lead to motivated reasoning. Within the class of uninformative signals, there is heterogeneity in perceptions, and this can drive susceptibility.

Consider an agent with prior $F(\theta)$ about a state in Θ . Denote by $\mu \equiv F^{-1}(1/2)$ the median of $F(\theta)$. For simplicity, we assume that F has no atom at μ and that $\mathbb{P}(\mu = \theta) = 0$. That is, the agent believes that the answer has probability zero of being exactly equal to μ , and the true probability is indeed zero.

To preview the experimental design that is developed in Section 3, suppose the agent now receives a message from one of two news sources, True News (TN) or Fake News (FN), and does not know which. Both news sources send a binary message $x^{TN}, x^{FN} \in \{G, L\}$ that compares θ to μ . G says that θ is *greater than* μ and L says that θ is *less than* μ . TN always sends the “true” message and FN always sends the “fake” message:

| | $\theta > \mu$ | $\theta < \mu$ |
|-----------------|----------------|----------------|
| True News sends | G | L |
| Fake News sends | L | G |

The agent has a prior about the news source $p \equiv \mathbb{P}(TN)$ that does not depend on θ , and infers about $\mathbb{P}(TN)$ given the message received. The agent receives quadratic utility from stating probability a :

$$u(a|TN) = 1 - (1 - a)^2 \text{ and}$$

$$u(a|FN) = 1 - a^2,$$

such that she maximizes utility by stating her subjective belief a .

We can now look at how a Bayesian and a motivated reasoner update their beliefs about the news source. Given message G , the Bayesian updates according to Equation (1):

$$\begin{aligned} \text{logit } a|G &= \text{logit } \mathbb{P}(TN|G) = \text{logit } \mathbb{P}(TN) + \log \left(\frac{\mathbb{P}(G|TN)}{\mathbb{P}(G|FN)} \right) \\ &= \text{logit } p + \log \left(\frac{\mathbb{P}(\theta > \mu)}{\mathbb{P}(\theta < \mu)} \right) \\ &= \text{logit } p. \end{aligned}$$

$$\text{Therefore: } a|G = p = a|L.$$

Since the Bayesian thinks that both messages are equally likely ex ante, she doesn’t update in any direction. In the experiment, this will be the main null hypothesis, and the hypothesis for unmotivated topics: $a|G = a|L$.

However, the motivated reasoner updates according to Equation (2):

$$\begin{aligned}\text{logit } a|G &= \text{logit } \mathbb{P}(TN) + \log \left(\frac{\mathbb{P}(G|TN)}{\mathbb{P}(G|FN)} \right) + \varphi(m(\theta|\theta > \mu) - m(\theta|\theta < \mu)) \\ &= \text{logit } p + \varphi(m(\theta|\theta > \mu) - m(\theta|\theta < \mu)).\end{aligned}$$

This implies the following:

Fact 1 (Identifying motivated reasoning using news veracity assessments)

The procedure above identifies motivated reasoning from Bayesian updating:

- For a Bayesian ($\varphi = 0$), $a|G = a|L$.
- For a motivated reasoner ($\varphi > 0$), $a|G > a|L \iff m(\theta|\theta > \mu) > m(\theta|\theta < \mu)$.

More specifically, this design identifies whether agents have greater expected motive for believing that the true state is above their median belief μ or for believing that the true state is below μ .

In this paper, states are real numbers and motives are typically assumed to be monotonic in the state, so that $\text{sign}\left(\frac{\partial m}{\partial \theta}\right)$ does not depend on θ . For simplicity, we will sometimes make the further restriction that motives are *linear*. In the linear case, $m(\theta) = m \cdot \theta$, so that the prediction does not rely on the distribution $F(\theta)$: that is, $a|G > a|L$ if and only if $m \cdot \varphi(x) > 0$.¹⁴

Predictions involve jointly hypothesizing that agents motivatedly reason and hypothesizing something about their motive function. In the context of the experiment, the main hypothesis will be that observables (such as political preferences) predict $m(\theta|\theta > \mu) - m(\theta|\theta < \mu)$, and therefore predict $\text{logit}(a|G) - \text{logit}(a|L)$.

It is worth noting that the null hypothesis is the same for many *non-Bayesian* models of inference. Consider the following class of updating rules defined by general misweighting of priors or likelihoods:

$$\begin{aligned}\text{logit } a|G &= \zeta \text{logit } \mathbb{P}(TN) + \kappa \log \left(\frac{\mathbb{P}(G|TN)}{\mathbb{P}(G|FN)} \right) \\ &= \zeta \text{logit } p + \kappa \cdot 0, \text{ and} \\ \text{logit } a|L &= \zeta \text{logit } p \text{ as well.}\end{aligned}$$

¹⁴Strictly monotonic motives posit that people are more motivated to hold extreme beliefs. An example of a more “moderate” motive function is *quadratic loss*: $m(\theta) = -m_{\text{quad}}(\theta^* - \theta)^2$, where $m_{\text{quad}} > 0$ so that θ^* is the highest-motive belief. One parametrization sets θ^* equal to μ ; this motive suggests a similar psychology to prior-confirming bias. Experimentally, the quadratic term could be identified by giving people binary messages that say that the answer is within or outside their 50-percent confidence interval.

This class of updating rules includes a form of prior-confirming bias ($\zeta > 1$), conservatism ($\kappa < 1$), base-rate neglect ($\zeta < 1$), and over-inference ($\kappa > 1$). In all these cases, there is no differential updating from G and L . These biases may also affect inference in many settings in which motivated reasoning plays a role. In such cases, the motivated reasoning term can simply be separately added to other models.

2.3 Inferring Motives from Beliefs

When motives are unobservable, an experimenter can learn about agents' motives by looking at their initial beliefs μ . Conceptually, an agent's error in beliefs can be partly explained by motivated reasoning, and therefore the direction of the error predicts the direction of the motive function. A motivated reasoner with an increasing motive function will be more likely to hold a belief that $\mu > \theta$, and a motivated reasoner with a decreasing motive function will be more likely to hold a belief that $\mu < \theta$, if they receive a signal drawn from the same distribution. This implies that an agent who believes $\mu > \theta$ is more likely to have an increasing motive function than is an agent who believes $\mu < \theta$.

When the two agents then make news assessments using the structure above, agents will trust news that *reinforces* the error in their beliefs more than news that *mitigates* the error. This occurs even though signals are designed exactly so that their interpretation is distinct from μ .

More formally, there is a state $\theta \in \mathbb{R}$. Consider a Bayesian (she) and a motivated reasoner (he) with the same prior $\theta \sim F_\theta$ and who receive a public signal $z \sim F_z$. We assume that the motivated reasoner has motive $m(\theta')$ that is strictly monotonic in θ' , and $\varphi(z, F_z) > 0$. We also assume that the signal leads the Bayesian's posterior median μ_B to take values close to θ with positive probability, but $\mathbb{P}(\mu_B = \theta) = 0$. That is, for all $\delta > 0$, there exists some $\delta' > 0$ such that $\mathbb{P}(|\mu_B - \theta| < \delta) > \delta'$.

Without loss of generality, consider a motivated reasoner who has $m(\theta')$ strictly increasing in θ' . Since the log-likelihood of the motive is strictly increasing, his posterior distribution first-order stochastically dominates the Bayesian's posterior distribution. In addition, for every such motive function, there exists a δ such that for all signals leading to the Bayesian having a posterior median $\mu_B \in (\theta - \delta, \theta)$, the motivated reasoner has posterior median $\mu_M > \theta$. Since there is a probability of at least $\delta' > 0$ of such a signal, this high- θ -motivated reasoner is *strictly* more likely than the Bayesian to state $\mu > \theta$. By the same argument, a low- θ motivated reasoner is strictly less likely than the Bayesian to state $\mu > \theta$.

Now suppose that μ is observable and the true θ is known, but z and $m(\theta)$ are unobservable. If some people have monotonically-increasing motives and others have monotonically-

decreasing motives, then:

$$\mathbb{P}(m(\theta) \text{ increasing} \mid \mu > \theta) > \mathbb{P}(m(\theta) \text{ increasing} \mid \mu < \theta).$$

If we look at how agents respond to the procedure above to a new message G or L , this implies that $\mathbb{E}[a|G, \mu > \theta] > \mathbb{E}[a|G, \mu < \theta]$ and $\mathbb{E}[a|L, \mu > \theta] < \mathbb{E}[a|L, \mu < \theta]$ when motives are heterogeneous.

Now, recall that message G says that $\theta > \mu$ and L says $\theta < \mu$. Since G and L are equally likely, the prediction is that subjects trust error-reinforcing messages more than error-mitigating messages when motivated reasoning plays a role.

In this design, error-mitigating messages are exactly True News and error-reinforcing messages are exactly Fake News. Therefore, agents give higher assessments to Fake News than True News, with and without controlling for observable party preference:

Fact 2 (Motivated reasoning leads to over-trusting Fake News, under-trusting True News)

Suppose that agents motivatedly reason with a strictly monotonic motive. Then:

- $a|Fake\ News > a|True\ News.$
- $a|Fake\ News; Pro\text{-}Party\ news \geq a|True\ News; Pro\text{-}Party\ news.$
- $a|Fake\ News; Anti\text{-}Party\ news \geq a|True\ News; Anti\text{-}Party\ news.$

Suppose also that the sign of the slope of the motive function is heterogeneous within party. That is, the probability of an agent having $\frac{\partial m(\theta)}{\partial \theta} > 0$ is strictly between 0 and 1, conditional on the agent's party. Then:

- $a|Fake\ News; Pro\text{-}Party\ news > a|True\ News; Pro\text{-}Party\ news.$
- $a|Fake\ News; Anti\text{-}Party\ news > a|True\ News; Anti\text{-}Party\ news.$

The stark result that motivated reasoners will trust Fake News more than True News is particular to the un informativeness of the messages. However, the prediction that agents will trust Fake News more than a *Bayesian* will is quite general, only relying on unobservable inputs into current beliefs. It is also worth noting that this prediction only holds for motivated states, psychologically differentiating this theory from unmotivated explanations of over-trusting Fake News (such as a general prior-confirming bias). Practically, it suggests that excessive trust in disinformation will be more prominent when people hold stronger motivated beliefs.

2.4 Motivated Reasoning, Overprecision, and Overconfidence

There are two ways in which motivated reasoners may have excess confidence in their beliefs compared to Bayesians in this setting. First, motivated reasoners may form miscalibrated confidence intervals about the initial questions: *overprecision*. Second, motivated reasoners may form more extreme beliefs about the veracity of the news sources, leading them to overestimate their news veracity assessment accuracy: *overconfidence*.

These consequences of motivated reasoning require functional form assumptions. Unlike the previous subsection, we now suppose that agents have a normally-distributed prior $\theta \sim \mathcal{N}(\mu_0, 1/\tau_0^2)$, and that agents receive a noisy signal $z = \theta + \epsilon_z$, where $\epsilon_z \sim \mathcal{N}(0, 1/\tau_z^2)$.

Suppose also that motivated reasoners have $m(\theta) = m \cdot \theta$ and $\varphi(z) = \varphi(\tau_z)$. That is, agents have a linear motive and signals only affect susceptibility through their level of precision.¹⁵ In the political context, $|m|$ can be thought of as increasing in political partisanship.

A Bayesian forms the posterior:

$$f(\theta|z) = \mathcal{N}\left(\frac{\tau_0\mu_0 + \tau_z z}{\tau_0 + \tau_z}, \tau_0 + \tau_z\right),$$

and a motivated reasoner forms the posterior:

$$f(\theta|z) = \mathcal{N}\left(\frac{\tau_0\mu_0 + \tau_z z + \varphi(\tau_z) \cdot m}{\tau_0 + \tau_z}, \tau_0 + \tau_z\right).$$

Notably, the two agents have the same posterior variance, but the motivated reasoner's distribution is miscalibrated. Consider their $(1 - Q)/2$ - and $(1 + Q)/2$ -quantile beliefs, and call this the *Q-confidence interval*. Then:

Fact 3 (Motivated reasoning and overprecision)

Suppose that a motivated reasoner has normally-distributed priors and receives a signal normally distributed with mean equal to θ , as above. When $\varphi > 0$, the probability that his Q-confidence interval contains θ is equal to Q for $m = 0$ and strictly decreases in $|m|$.

Since Bayesian updating is equivalent to motivated reasoning with $m = 0$, this says that Bayesians are appropriately precise and motivated reasoners are overprecise. Note that the direction of overprecision relies not just on linear motives, but also on the normal-normal functional form.¹⁶

¹⁵One appealing functional form is $\varphi(z) = \min\{\varphi \cdot \tau_z, \bar{\varphi}\}$. Using this form, the susceptibility of two weak signals is equal to the sum of their precisions, but there is a maximum level of susceptibility.

¹⁶For instance, suppose that the state space contains two values and a Bayesian infers from a signal that either one value has a $(1 + Q)/2$ likelihood of occurring or the other value has a $(1 - Q)/2$ likelihood of

Next, we consider underperformance and overconfidence. Recall that this theory posits that agents who motivatedly reason may do so at a cost to their utility.¹⁷ Specifically, motivated-reasoning agents underperform by having lower decision utility from their assessments than Bayesians do. This expected utility decreases as the motive function becomes steeper. However, *anticipated* expected utility often will *increase* in motive steepness, since agents become (erroneously) more confident about their assessments. This discrepancy leads to overconfidence.

Using the quadratic utility from above, agents’ assessments lead them to attain utility that is decreasing in $|m|$. This implies that motivated reasoners underperform compared to Bayesians, who update the same way as motivated reasoners who have $m = 0$.

Fact 4 (Motivated reasoning and underperformance)

For all $\varphi > 0$ and priors $p \in (0, 1)$, $\mathbb{E}[u(a; m)]$ decreases in $|m|$.

Though agents with steeper motives will receive lower utility on average, they will *expect* to receive *higher* utility, denoted by $\tilde{\mathbb{E}}$, as long as their priors on news veracity are not too extreme.

Fact 5 (Motivated reasoning and confidence)

For all $\varphi > 0$, $\tilde{\mathbb{E}}[u(a; m)]$ increases in $|m|$ if $p \in [\frac{1}{2} - \frac{\sqrt{3}}{6}, \frac{1}{2} + \frac{\sqrt{3}}{6}] \approx [0.211, 0.789]$.

The proof involves more algebra than insight, so it is relegated to Appendix A.1.

To intuitively understand why this is true, consider a partisan (with a steeper motive) and a moderate (with a less steep motive). The partisan will move her assessments substantially upwards when she receives Pro-Party news and expect to score highly, and she will move her assessments substantially downward when she receives Anti-Party news — and still expect to score highly. The moderate will have more tempered expectations given that his assessments are less extreme. Exceptions can occur when p is close to 0 or 1 and φ is not too large, because when partisans update more from Pro-Party (Anti-Party) news, their posteriors may end up below (above) $1/2$.

We can conceptually combine these two results by defining overconfidence as the agent’s anticipated expected utility minus her actual expected utility. The implication is that political partisans become more overconfident in the accuracy of their news veracity assessments because of motivated reasoning.

occurring. Then, her confidence interval would contain one point, and a motivated reasoner may have a confidence interval that contains both points.

¹⁷This is in contrast to models in which people deviate from Bayes’ rule because they choose *utility-maximizing beliefs* and strategically self-deceive, as in Brunnermeier and Parker 2005; Benabou and Tirole 2002; and Mobius et al. 2014.

3 Experimental Design

3.1 Summary, Timeline, and Topics

This section details the experiment — introduced in Section 2.2 — that is designed to test predictions of the motivated-reasoning model. This design focuses on how subjects infer the veracity of a message that says that their current median belief is erroneously high or erroneously low.

To fix ideas, consider the following question, taken verbatim from the experiment:

Some people believe that the Obama administration was too soft on crime and that violent crime increased during his presidency, while others believe that President Obama’s pushes towards criminal justice reform and reducing incarceration did not increase violent crime.

This question asks how murder and manslaughter rates changed during the Obama administration. In 2008 (before Obama became president), the murder and manslaughter rate was 54 per million Americans.

In 2016 (at the end of Obama’s presidency), what was the per-million murder and manslaughter rate?

The main test of motivated reasoning involves three steps:

1. **Beliefs:** Subjects are asked to guess the answers to politicized questions like the one above. Importantly, they are asked and incentivized to guess their median belief (i.e. such that find it equally likely for the answer to be above or below their guess). They are also asked and incentivized for their interquartile range. Screenshots of instruction pages are in the Online Appendix.
2. **News:** Subjects receive a binary message from one of two randomly-chosen news sources: True News and Fake News. The message from True News is always correct, and the message from Fake News is always incorrect. This is the main (within-subject) treatment variation.

The message says either “The answer is **greater than** your previous guess of [previous guess].” or “The answer is **less than** your previous guess of [previous guess].” Note that the exact messages are *different* for each subject since subjects have different guesses. These customized messages are designed so that they have the same *subjective* likelihood of occurring.

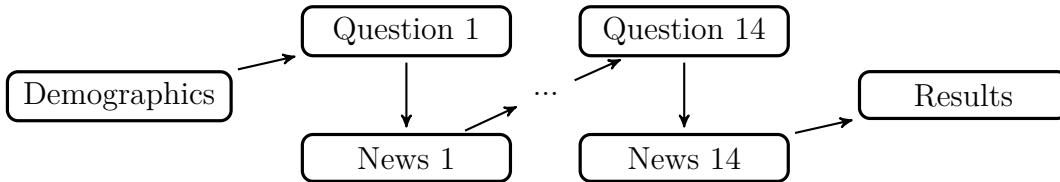
For the Crime Under Obama question above, “greater than” corresponds to Pro-

Republican News and “less than” to Pro-Democratic News. For subjects who support the Republican Party than the Democratic Party, “greater than” is Pro-Party news and “less than” is Anti-Party news, and vice versa for subjects who support the Democratic Party more.

3. **Assessment:** After receiving the message, subjects assess the probability that the message came from True News using a scale from 0/10 to 10/10, and are incentivized to state their true belief. This news veracity assessment is the main outcome measure. The effect of variation in news direction on veracity assessments is the primary focus for much of this paper. An example of the News / Assessment page is in the Online Appendix.

Since subjects receive messages that compare the answer to their median, a Bayesian would not change her assessment based on the message. Likewise, general over- and under-weighting of priors and likelihoods (such as forms of prior-confirming biases and conservatism) do not predict a treatment effect of message direction on assessment.

Subjects see 14 questions in the experiment. 13 are in Table 1 and one is a comprehension check. The experiment has the following general structure:



The Demographics page includes questions about party ratings (which will be used to determine subjects’ relative party preference), party affiliation, ideology, gender, age, race and ethnicity, annual income, highest education level, state or territory of residence, religion, nine opinion questions (one each about eight topics in the study and one about Donald Trump’s performance), and a 4-item multiple-choice quiz about current events.

The Results page tells subjects what their overall performance was, what their score on each question and assessment was, and the correct answer to each question and assessment. Importantly, subjects are told that they will see this page at the beginning of the experiment, and they are forced to go through it before exiting the study and receiving payment.¹⁸ Being forced to learn the true answers at the end of the experiment substantially limits the scope for strategic self-deception, differentiating motivated reasoning from theories of utility-maximizing inference.

¹⁸Subjects spend an average of 71 seconds on the Results page, suggesting that they are indeed looking at it. They spend about as long on the Results page as on one Question page and one Info page combined.

The order of Questions 1-12 is randomized between subjects, but Questions 13 and 14 are the same for each subject. These last two questions are “meta-questions” that rely on previous questions: Question 13 asks subjects about their performance on the first 12 questions relative to 100 other (pilot) subjects, and Question 14 asks about other Democratic (pilot) subjects’ performance compared to other Republican (pilot) subjects’ performance on Questions 1-12.¹⁹

Each of the politicized and neutral topics are equally likely to be selected in each round, but the comprehension check is restricted to be between Question 2-11. This restriction is to make sure subjects are still paying attention after the first question, and to make sure the willingness-to-pay treatment (discussed in Appendix B.2), which occurs for Question 12, does not overlap with the comprehension check.

All of the specific question wordings are in Appendix C. Screenshots for every page are in the Online Appendix.

3.2 Pages and Scoring Rules

Overall Scoring Rule

At the end of the experiment, subjects earn a show-up fee of \$3 and either receive a bonus of an additional \$10 or nothing. As will be elaborated below, in each round of the experiment subjects earn between 0-100 “points” based on their performance. These points correspond to the probability that the subject wins the bonus: a score of x points corresponds to an $x/10$ percent chance of winning the bonus.²⁰

Questions Page

On question pages, subjects are given the round number (Question x of 14), the topic, the text of the question, and are asked to input three numbers about their initial beliefs:

- *My Guess*: This elicits the median of the subjects’ prior distribution.
- *My Lower Bound*: This elicits the 25th percentile of the subjects’ prior distribution.
- *My Upper Bound*: This elicits the 75th percentile of the subjects’ prior distribution.

The scoring rule for guesses is piecewise linear. Subjects are given $\max\{100 - |c - g|, 0\}$ points for a guess of g when the correct answer is c . Subjects maximize expected points

¹⁹Half of subjects are given the Democrats’ score and asked to predict the Republicans’; half are given the Republicans’ score and asked to predict the Democrats’.

²⁰This lottery system is designed to account for risk aversion; directly mapping points to earnings could lead to subjects hedging their guesses. The probability distribution is identical to randomly choosing a round for payment and subsequently playing the lottery based on the points in that round.

by stating the median of their belief distribution. They are told the scoring rule in the instructions and given the following message:

*It is in your best interest to guess an answer that is in the ‘middle’ of what you believe is likely. For example, if you think the answer is equally likely to be 10, 40, and 60, you should guess 40.*²¹

The scoring rule for bounds is piecewise linear with different slopes. For upper bound ub , subjects are given $\max\{100 - 3(c - ub), 0\}$ points if $c \geq ub$ and $\max\{100 - (ub - c), 0\}$ points if $c \leq ub$. For lower bound lb , subjects are given $\max\{100 - (c - lb), 0\}$ points if $c \geq lb$ and $\max\{100 - 3(lb - c), 0\}$ points if $c \leq lb$. Subjects maximize expected points by setting ub to be the 75th percentile and lb to be the 25th percentile of their belief distribution. They are told the scoring rule in the instructions and given the following message:

It is in your best interest to choose a lower bound such that you think it’s 3 times more likely to be above the bound than below it, and an upper bound such that it’s 3 times more likely to be below the bound than above it. For example, if you think the answer is equally likely to be any number from 100 to 200, you should set a lower bound of 125 and an upper bound of 175.

In addition, subjects are restricted to only give answers such that $\text{My Lower Bound} \leq \text{My Guess} \leq \text{My Upper Bound}$.

News Assessments Page

After submitting their initial beliefs, subjects are given a second page about the same question. At the top of the page is the exact text of the original question. Below the question is a message relating the correct answer to the number they submit for *My Guess*. This message says either:

“The answer is **greater than** your previous guess of [My Guess].” or

“The answer is **less than** your previous guess of [My Guess].”

Subjects are told that True News *always* tells the truth and Fake News *never* tells the truth, and that sources are iid. The message saying “greater than” or “less than” is the main treatment variation. Below the message, subjects are asked: “Do you think this information is from True News or Fake News?” and can choose one of eleven radio buttons that say “x/10 chance it’s True News, (10-x)/10 chance it’s Fake News” from each $x=0, 1, \dots, 10$ in increasing order.

The scoring rule for assessments is quadratic. For assessment a , subjects are given $100(1 - (1 - a)^2)$ points if the source is True News and $100(1 - a^2)$ points if it is Fake News. The

²¹This example is chosen intentionally because the mean and median are different.

optimal strategy is to answer with the closest multiple of 0.1 to the true belief. In the instructions, subjects are given a table with the points earned as a function of each assessment and news source.

Occasionally, a subject will correctly guess the answer. If this happens, she skips the news assessment page and moves on to the next question.²²

Second-Guess Treatment

Half of subjects are in the “Second Guess” treatment. For these subjects, immediately below the news assessment question they are asked an additional question: “After seeing this message and assessing its truthfulness, what is your guess of the answer to the original question?”

Subjects are given the same linear scoring rule as on the initial guess. They are given $\max\{100 - |c - g|, 0\}$ points for a guess of g when the correct answer is c . See the Online Appendix for a screenshot of the Crime Under Obama news assessment page that subjects in the Second Guess treatment see, with the second guess part highlighted.

Willingness-to-Pay (WTP) Treatment

The other half of subjects are in the WTP treatment. These subjects see an additional page between Question 12 and News 12, on which they are given instructions and asked to submit a WTP for a message. Results suggest that subjects (erroneously) value the message for the purpose of assessing veracity and that they do not differentially value messages on politicized and neutral topics (indicating naivete about their motivated reasoning). For more detailed instructions and results, see Appendix B.

3.3 Hypotheses

This subsection summarizes the predictions from Section 2 in the context of the experiment to generate testable hypotheses.

The main hypothesis is that a news veracity assessment will be larger when it leads to a higher motive. This is therefore a joint test that (1) people motivatedly reason, giving higher assessments to news in the direction of higher motives than to news in the direction of lower motives, and (2) the predicted direction of motives is as in Table 1. Since we will be mostly considering politicized topics, the degree of partisanship will affect the steepness of the motive function.

Hypothesis 1 (Motivated reasoning with political motives)

- $a|Pro\text{-}Party\ news > a|Anti\text{-}Party\ news.$

²²This is true except for the comprehension check question, where the message says “The answer is **equal** / **not equal** to your previous guess of [My Guess].”

- $a|Neutral\ topic\ news \in (a|Anti\text{-}Party\ news, a|Pro\text{-}Party\ news)$.
- $(a|Pro\text{-}Party\ news - a|Anti\text{-}Party\ news)$ increases in partisanship.

A similar prediction is that changes in beliefs are differentially affected by the news category, i.e. that people are more likely to follow the message if it is Pro-Party than Anti-Party. This is tested using the Second Guess subsample. The hypothesis is the same for Pro-Own Performance news and Anti-Own Performance news.

Second, we can test whether the direction of the error in subjects' beliefs can be explained in part by their motives. This implies that they will give higher assessments to error-reinforcing news compared to error-mitigating news, as in Fact 2. Recalling that error-reinforcing news is Fake News and error-mitigating news is True News, this leads to the following prediction:

Hypothesis 2 (Motivated reasoning and trust in Fake News)

- $a|Fake\ News > a|True\ News\ on\ politicized\ topics, but\ not\ on\ neutral\ topics.$
- $a|\{Fake\ News, Pro\text{-}Party\ news\} > a|\{True\ News, Pro\text{-}Party\ news\}.$
- $a|\{Fake\ News, Anti\text{-}Party\ news\} > a|\{True\ News, Anti\text{-}Party\ news\}.$

These are the main hypotheses of the experiment.

There are two secondary hypotheses that focus on the Second-Guess treatment. By comparing subjects' first and second guesses, we can replicate the main politically-motivated reasoning prediction and study a form of belief polarization.

First, there is an equivalent hypothesis to Hypothesis 1: controlling for news direction, subjects more frequently adjust their guesses in the direction of their political party preference. Second, by a similar logic to Hypothesis 2, motivated reasoning will lead subjects to be more likely to adjust their guesses towards the population mean than away from it on politicized topics.

Hypothesis 3 (Motivated reasoning and second guesses)

Define Follow Message as the ternary variable that takes value:

- 1 if the message says G and $\mu|G > \mu$ or if it says L and $\mu|L < \mu$;
- 0 if $\mu|message = \mu$; and
- -1 if the message says G and $\mu|G < \mu$ or if it says L and $\mu|L > \mu$.

Define Polarizing news as news that says G if μ is greater than the population mean guess or L if μ is less than the population mean guess. Define Anti-Polarizing news as the opposite.

- $Follow\ Message | Pro\text{-}Party\ news > Follow\ Message | Anti\text{-}Party\ news.$

- *Follow Message | Polarizing news > Follow Message | Anti-Polarizing news on politicized topics.*

Next, we consider the predictions from Section 2.4 about the consequences of motivated reasoning. Namely, the model predicts overprecision, underperformance, and overconfidence.

The overprecision hypothesis uses subjects' 50-percent confidence intervals, claiming that motivated reasoning can lead the belief distribution to become miscalibrated.

Hypothesis 4 (Overprecision and partisanship)

- *On politicized questions, subjects' 50-percent confidence intervals contain the correct answer less than 50 percent of the time.*
- *The likelihood that confidence intervals contain the correct answer decreases in partisanship.*

Next, as a direct implication of Hypothesis 2, motivated reasoners will earn fewer points in the experiment. In the political realm, the severity of underperformance is hypothesized to be increasing in partisanship. Additionally, it predicts that partisans will give more certain answers on assessments of politicized news, leading to greater confidence in answers. This is measured by subjects' predictions of their performance relative to others'.

Hypothesis 5 (Underperformance and overconfidence)

- *Average points scored on news assessments is less than the points earned by assessing that the probability of True News is 50 percent.*
- *Average points scored on news assessments is decreasing in partisanship on politicized topics.*
- *Predicted overconfidence — expected performance relative to other subjects minus actual performance — will be increasing in partisanship.*

In the theory, the last part of this hypothesis holds when subject priors on $P(\text{True})$ are between 0.21 and 0.79. In the experiment, nearly all subjects have average assessments within this range, including the ones who are not told explicitly that the probability of True News is $1/2$.

The main experiment tests each of these hypotheses. It is worth noting that while each of the primary results were hypothesized ex ante, some of the consequences results involved ex post analysis. As such, Appendix D discusses results from a replication exercise conducted one year later on a smaller sample. In the replication, I pre-registered each of the above hypotheses with the exception of overconfidence, due to insufficient statistical power. The replication results are very similar to the main results.

4 Data and Experiment Details

The experiment was conducted on June 25, 2018 on Amazon’s Mechanical Turk (MTurk) platform. MTurk is an online labor marketplace in which participants choose “Human Intelligence Tasks” to complete. MTurk has become a very popular way to run economic experiments (e.g. Horton, Rand, and Zeckhauser 2011; Kuziemko et al. 2015), and Levay, Freese, and Druckman (2016) find that participants generally tend to have more diverse demographics than students in university laboratories with respect to politics. The experiment was coded using oTree, an open-source software based on the Django web application framework developed by Chen, Schonger, and Wickens (2016).

The study was offered to MTurk workers currently living in the United States. 1,387 subjects were recruited and answered at least one question, and 1,300 subjects completed the study. Of these subjects, 987 (76 percent) passed simple attention and comprehension checks, and the rest are dropped from the analyses.²³

All subjects are asked to rate the Democratic Party and the Republican Party using a scale from 0-100; this scale is modeled after the feeling thermometer used in the American National Election Studies. 627 subjects (64 percent) give a higher rating to the Democratic Party; 270 (27 percent) give a higher rating to the Republican Party; and 90 (9 percent) give identical ratings to both parties.²⁴ These subjects are labeled as “Pro-Dem,” “Pro-Rep,” and “Neutral,” respectively, and for most analyses the Neutral subjects will be dropped. Results are similar if liberal-conservative ideology or party affiliation is used instead, though many more subjects are then classified as neutral. Results are also similar when weighting by party preference, ideology, or party registration, or when using demographic weights for gender, age categories, race, religion, and location to make the sample representative of the U.S. population.

Treatments were cross-randomized so that 2/3 of subjects would not receive a prior about the veracity of the news source, and 1/3 of subjects would be told that True News and Fake News were equally likely. Independently, 1/2 of subjects would receive the willingness-to-pay treatment and 1/2 would be in the second-guess treatment. Indeed, of the non-Neutral subjects, 66 percent do not receive a prior and 34 percent do; 49 percent are in the WTP treatment and 51 percent are in the second-guess treatment.

Each subject answers 13 questions; there are a total of 11,661 guesses to questions for

²³In order to pass these checks, subjects needed to perfectly answer the comprehension check question in Appendix C (by giving a correct answer, correct bounds, and answering the news assessment with certainty). In addition, many questions had clear maximum and minimum possible answers (such as percentages, between 0 and 100). Subjects were dropped if any of their answers did not lie within these bounds. The Online Appendix shows that main results are robust to inclusion of these subjects.

²⁴Levay, Freese, and Druckman (2016) also find that the MTurk subject pool is mostly Democratic.

the 897 non-neutral subjects. There are 11,443 news assessments. The discrepancy between these numbers is due to 143 subjects in the WTP treatment who did not receive a message in one round, and due to there being 75 (0.7 percent) correct guesses.²⁵ I drop these 218 observations for news assessment analyses. There are 7,902 news assessments on politicized topics, 891 on the question about own performance, and 2,650 on neutral topics.

The balance table for the Pro-Party / Anti-Party treatment is in Appendix A.5. Since this randomization is within subject, treatments are expected to be balanced across demographics. Importantly, the overall shares of Pro-Party and Anti-Party news are not noticeably different. This suggests that there was no differential attrition in the experiment by treatment.

5 Results

5.1 Raw Data

This subsection shows that the raw data supports the main predictions of the model, and the following subsections show the relevant regressions. To validate that these questions are politicized, Appendix A.4 compares initial guesses by party and finds that there are systematic differences in beliefs between Pro-Rep and Pro-Dem subjects in the direction predicted in Table 1. Recall Hypothesis 1 and Hypothesis 2: subjects will trust Pro-Party news more than Anti-Party news; this gap will be larger for partisans than moderates; Neutral news will lie in between; and error-accentuating Fake News will be trusted more than error-mitigating True News on politicized topics.

The mean assessment of Pro-Party news is 62.0 percent (s.e. 0.5 percent), the mean assessment of Neutral news is 57.9 percent (s.e. 0.6 percent), and the mean assessment of Anti-Party news is 52.9 percent (s.e. 0.5 percent).²⁶ The difference between every pair of these is highly significant ($p < 0.001$ each).²⁷

In support of Hypothesis 1, Figure 1 shows the subject-demeaned assessments by news direction (Pro-Party; Anti-Party; Neutral) and subject type (Partisan and Moderate, as defined by the absolute difference in party ratings). Subjects indeed give higher average

²⁵The low frequency of correct guesses is an indicator that the vast majority of subjects were not looking up the answers. It is also a sign that the model’s assumption of an atomless belief distribution is reasonable.

²⁶All standard errors are clustered at the individual level.

²⁷All these percentages are significantly greater than 50, even for subjects who are given a prior that True News and Fake News are equally likely. There are two potential explanations that are beyond the scope of this paper. First, perhaps subjects ignore the stated prior and set their own prior around 58 percent. Second, and more suggestively, subjects may motivatedly reason to trust what they are told. Further work can explore this latter channel.

assessments to Pro-Party than to Neutral news, and higher to Neutral than to Anti-Party news, and these differences are larger for partisans. Appendix Figure 5 shows the empirical distribution of assessments for Pro-Party and Anti-Party news on politicized topics. The empirical distribution of Pro-Party assessments first-order stochastically dominates the distribution of Anti-Party assessments.

In support of Hypothesis 2, Figure 2 shows the subject-demeaned assessments by news direction (Pro-Party; Anti-Party; Neutral) and news veracity (True News; Fake News). Subjects indeed give higher assessments to Fake News than to True News on politicized topics, but they do not on neutral topics.²⁸ Similar results hold if we look at where subjects' initial guesses lie compared to the median subject instead of compared to the truth. Appendix Figure 6 shows the empirical distribution of assessments for True News and Fake News on politicized questions. The empirical distribution of Fake News assessments first-order stochastically dominates the distribution of True News assessments.

5.2 Regression Specifications for News Assessments

The primary regression specifications are within subject; 892 of the 897 non-neutral subjects receive at least one piece of Pro-Party news, Anti-Party news, and Neutral news.²⁹

In particular, the main specification for politically-motivated reasoning is in Table 2, column 2. The regression looks at assessments a for subject i , question topic q , and round r with fixed effects for i , q , and r when all news is Pro-Party or Anti-Party:³⁰

$$a_{iqr} = \alpha + \beta \cdot 1(\text{Pro-Party})_{iqr} + \gamma FE_i + \delta FE_q + \zeta FE_r + \epsilon_{iqr}$$

Hypothesis 1 claims that the Pro-Party / Anti-Party gap is increasing in partisanship, so column 3 interacts partisanship (the absolute difference in party ratings) with Pro-Party news. It also claims that motivated reasoning leads to both higher assessments for Pro-Party news and lower assessments for Anti-Party news; as such, column 4 includes indicators for both Pro-Party (vs. Neutral) news and Anti-Party (vs. Neutral) news.

Hypothesis 2 claims that for politicized news, subjects will trust Fake News more than True News, so the final two specifications in Table 2 regress assessments on a dummy for True News, controlling for and not controlling for Pro-Party news.

²⁸If anything, assessments are higher for neutral True News than neutral Fake News. This suggests that reflecting on the question again may lead to adjusting estimates *towards* the truth in the absence of motivated beliefs.

²⁹Three subjects randomly receive no Pro-Party news; two subjects randomly receive no Anti-Party news; and all subjects receive some Neutral news.

³⁰As seen in the Online Appendix, all results are qualitatively identical if we use $\text{logit}(a_{iqr})$ instead of a_{iqr} . The linear specification is used for ease of interpretation.

Table 2 shows that Hypotheses 1 and 2 are strongly supported. Assessments for Pro-Party news are substantially higher than for Anti-Party news, and this effect increases in partisanship. There is evidence for motivated reasoning on both Pro-Party and Anti-Party news, and controlling for news type, Fake News assessments are significantly higher than True News assessments.

Next, to show that motivated reasoning is a general phenomenon across domains, we look at each topic separately by regressing on the interaction of topic dummies and news type.

Figure 3 shows that there is strong evidence to support politically-motivated reasoning on eight of the nine hypothesized topics. Each of these eight coefficients are statistically significant from zero at the $p = 0.001$ level. I also analyze placebo tests that Pro-Rep subjects support high answers for the neutral questions compared to Pro-Dem subjects, and find no evidence supporting a difference in assessments by party. On the performance topic, the average effect supports the hypothesis that people motivatedly reason towards believing they outperformed others.³¹

Consistent with hypotheses, partisans engage in at least as much politically-motivated reasoning than moderates on each topic where motivated reasoning plays a role. Appendix Figure 7 interacts the topic-by-topic treatment effects from Figure 3 with a dummy for being partisan and for being moderate. There is a consistent difference on politicized topics, but not on neutral topics.

5.3 Changing Guesses and Polarization

Recall that half of subjects are randomly assigned to give a second guess to the initial question after receiving news. While the predictions here are not as well-identified, motivated reasoning should play the same role. In particular, the related hypothesis is that subjects are more likely to update in the Pro-Party direction than in the Anti-Party direction. This test is useful as a robustness check, but also helps us better understand how these messages affect subjects' beliefs about these issues.

Table 3 shows that subjects are more likely to update in the direction of Pro-Party messages than they are from Anti-Party messages. As hypothesized, on politicized topics subjects are also more likely to change their guesses in the direction of a polarizing message (one that tells them that their guess is further away from the mean) than from an anti-polarizing message.

Columns 4-6 of Table 3 show that discrepancies in both motivated reasoning and belief polarization are largely explained by differences in news assessments. After controlling for

³¹Unlike on the politicized topics, this effect is entirely driven by men. See Section 6.2.

assessments, guess changes are not significantly affected by Pro-Party / Anti-Party messages, nor are they significantly affected by polarizing messages. This indicates that belief changes and news assessments are consistent with each other, validating the news assessment measure of motivated reasoning. That is, how someone assesses the veracity of a news source is the main determining predictor of how she directionally changes her beliefs.³²

More broadly, this gives a stark prediction about how people change their beliefs. Motivated reasoning leads people to engage in belief polarization from *uninformative* messages. This suggests that, in environments where signals serve to remind people of their motivated beliefs, not only do people not need different news sources to polarize their beliefs, informational content is not a necessary condition either.

5.4 Alternative Explanations and Robustness Checks

5.4.1 Misunderstanding “median” and skewed priors

It is reasonable to expect that subjects do not fully understand the concept of a median. For instance, they may answer with their mean belief instead. This would not directionally impact the news assessment results in a systematic direction, unless the prior distribution were notably skewed. We can use where the initial guess μ_q lies in subjects’ confidence intervals as a proxy for skewness, and see that the main results hold for subjects who have zero skewness.

When looking at the politicized questions, 32 percent of subjects’ guesses are exactly halfway between their upper and lower bounds. In the appendix, Table 8 uses the same within-subject specification as the main regression but interacts Pro-Party news, Anti-Party news, and True News with a dummy that equals 1 for such “unskewed” priors. The treatment effects are essentially both qualitatively and quantitatively identical, indicating that skewness does not directionally effect results.

5.4.2 The independence of news sources

The interpretation of $P(\text{True News})$ in the model and analysis assumes that subjects treat news sources as being drawn from independent distributions. While subjects are explicitly told to do this in the instructions, it is useful to show that they are not using previous pieces of news to update about current pieces of news.

³²It is worth noting that the converse is not true. For instance, after controlling for the direction of guess changes, subjects give statistically significantly higher assessments to Pro-Party news than to Anti-Party news.

In Appendix Table 9, I modify the main regression table to account for the relative number of Pro- and Anti-Party news in previous rounds. The effect of previous rounds’ Pro- and Anti-Party news have precisely zero effect on current beliefs, and the main coefficients of interest remain unchanged, suggesting that subjects indeed treat news sources as independent.

5.4.3 Misunderstanding “Fake News”

First, suppose that subjects believe that messages from Fake News are actually from “Random News” and are equally likely to send correct and incorrect messages, instead of *always* sending incorrect messages. In this experiment, that would not affect any predictions about assessments. A Bayesian would still have an ex-ante prior that Pro-Party and Anti-Party messages are equally likely, and would not infer anything about $P(\text{True News})$ given either message. A motivated reasoner who is motivated to believe that the answer is large would still infer that $P(\text{True} \mid \text{Pro-Party}) > P(\text{True} \mid \text{Anti-Party})$.

A more complicated situation involves subjects believing that messages from Fake News are actually from a news source that is biased against their party. That is, suppose that subjects believe that Fake News was politically asymmetric, and is more likely to report Anti-Party news given Pro-Party truth than Pro-Party news given Anti-Party truth.

To test this, we can again look at how subjects change their guesses in Table 3. In particular, suppose that subjects were Bayesian but had this asymmetrically wrong definition of Fake News. Then, they would find Pro-Party “Fake News” messages to be more informative than Anti-Party “Fake News” messages, since “Fake News” is expected to usually send the Anti-Party message. (The quotes here indicate that these subjects are using the wrong definition of Fake News.) So, such subjects would update more from Pro-Party than Anti-Party news, *conditional on their assessment of $P(\text{True News})$* .

In Table 3, we see that subjects are similarly likely to update from Pro-Party and Anti-Party news after controlling for their assessments. While the data are too imprecise to rule out that there may exist subjects who treat Fake News as biased, this explanation is insufficient to drive results.

5.4.4 Incorrect initial guesses

While it can sometimes be in subjects’ best interests to strategically misreport their median in order to earn more points on news assessment questions, I find no evidence of this.

In Round 1 of the experiment, subjects do not yet know that they will be seeing a news assessment page. If subjects were strategically mis-guessing to earn more assessment points, they would perform worse in Round 1 than subsequent rounds on assessments and better in

Round 1 than subsequent rounds on guesses.

There are no significant differences in assessment scores in Round 1. Subjects score 67.2 points (s.e. 0.9) in Round 1 and 66.4 points (s.e. 0.3) in Rounds 2-12;³³ the difference is 0.8 points (s.e. 1.0) and insignificant ($p = 0.383$). The null result remains when using within-subject tests, controlling for topic, and controlling for linear round trends.

There are also no significant differences in guess scores in Round 1. Subjects score 76.2 points (s.e. 1.0) in Round 1 and 75.9 points (s.e. 0.2) in Rounds 2-12; the difference is 0.3 points (s.e. 1.0) and insignificant ($p = 0.758$). Within-subject tests, controlling for topic, and controlling for linear round trends do not change the null result.

Non-strategic forms of incorrect initial guesses are more complicated to rule out. If there is symmetric noise such that the probability that a subject is equally likely to state her Q quantile and her $1 - Q$ quantile for $Q \neq 1/2$, then the main results do not change. Results are also not consistent with subjects biasing their initial guesses towards the population mean. While this behavior can explain why subjects trust error-reinforcing news more than error-mitigating news on politicized and performance topics (and why they trust Pro-Party news more than Anti-Party news), it incorrectly predicts the same pattern on neutral topics. The one form of misreporting that can be consistent with both Bayesian updating and results from the experiment involves subjects systematically misreporting medians in a way that is biased in the opposite direction from their party.

In theory, one potential reason for an Anti-Party-biased first guess is that subjects do not sufficiently think about the question; and, given more time, they update towards their true (more Pro-Party) belief. A version of this explanation in which purely time spent affects the extremity of beliefs seems unlikely to explain these results, as the main treatment effect does not noticeably affect time spent on the question page.³⁴ An alternative version in which seeing the second screen causes subjects to think harder about the original question, and thinking harder leads to more Pro-Party beliefs, is more plausible. The psychology behind this explanation is very similar to this theory of motivated reasoning, as the second page evokes the motive, and further work could better elucidate the contours of what qualifies as a signal for motivated reasoning.

5.4.5 Expressive preferences

Bursztyn et al. (2019) provides recent evidence showing that people in an experiment may forgo payment in order to make political statements. In this experiment, if subjects have

³³I exclude scoring on Rounds 13-14 since the questions are not randomly assigned in those rounds; the result is identical if they are included. I also exclude scoring on comprehension check questions.

³⁴The mean time spent on the assessment page with Pro-Party news is 14.6 seconds (s.e. 0.3 seconds), and the mean time spent on the assessment page with Anti-Party news is 14.8 seconds (s.e. 0.3 seconds).

a preference for stating Pro-Party signals, then both their initial guesses and their news assessments will be biased in the Pro-Party direction, consistent with the data. However, if they are Bayesian, how they *change* their guesses will not be directional, since they have already stated their preferred belief.

Recall that in Table 3, subjects are more likely to update their guesses in the Pro-Party direction than in the Anti-Party direction, even though they are equally likely to receive Pro-Party and Anti-Party messages. This is consistent with subjects genuinely trusting the Pro-Party messages more; it is not consistent with Bayesian updating and expressive preferences.

5.4.6 Motivated reasoning by treatment and round

It is possible to construct alternative hypotheses in which some treatments lead to more biased updating processes than others. For instance, perhaps the subjects who were not told in the instructions that $P(\text{True News}) = 1/2$ behave differently than those who are told this, and the latter group does not motivatedly reason because of this prior. Or perhaps the subjects who are told to give a second guess to the initial question are reminded of their initial median more and this leads to a correction of motivated reasoning.

In the Online Appendix, I restrict the regressions from Table 2 to subjects in the willingness-to-pay treatment, the second-guess treatment, the received-prior treatment, and the did-not-receive-prior treatment. Estimates naturally become noisier, but the direction of every estimate is identical. There is no evidence that any treatment significantly affected the observed magnitude of motivated reasoning.

It is also possible that subjects learn over the course of the experiment that they motivatedly reason and debias themselves. I find no evidence for this. In the Online Appendix, I interact the main effect with dummies for each round number; in every single round, subjects give larger assessments to Pro-Party news than Anti-Party news. I also restrict Table 2 to Rounds 1-6 and Rounds 7-12, and effects are in the same direction.

5.5 Motivated Reasoning and Initial Beliefs

The previous results have shown that subjects differentially update their beliefs about the veracity of news sources based on the direction of messages received, and that an observer can infer something more about people’s motives from their erroneous beliefs.

This subsection discusses two consequences of motivated reasoning that are manifested in beliefs about the questions themselves: polarization and overprecision. First, I show that variation in this experiment’s measure of motivated beliefs can explain a sizable fraction of

variation in actual beliefs about these questions.

I look at the relationship between motives and beliefs by correlating the normalized answers to politicized questions with the normalized differences in assessments between Pro-Rep and Pro-Dem news. For each politicized question, subjects' initial guesses are winsorized (at the 5-percent level), normalized, and signed; positive numbers correspond to more Pro-Rep. Next, for each subject, these normalized guesses are averaged (and re-normalized) to give a measure of how Pro-Rep her beliefs are. I correlate this value with the normalized average difference between Pro-Rep news assessments and Pro-Dem news assessments.³⁵

Variation in news assessments explain 13 percent of the variation in beliefs. By comparison, non-political demographics collected in this experiment — age, gender, race, education, logged income, whether one is religious, whether one is from a state that voted for Trump or Clinton in 2016 — explain 7 percent of the variance in beliefs.³⁶

In support of Hypothesis 4, there is evidence that subjects are overprecise in their initial beliefs about questions that evoke motivated beliefs, but no evidence for overprecision on neutral questions. On politicized topics, subjects' confidence intervals contain the correct answer 46.6 percent of the time (s.e. 0.6 percent); this is statistically significantly different from 50 percent ($p < 0.001$). Overprecision on these topics is primarily driven by partisans, whose intervals contain the correct answer 44.2 percent of the time (s.e. 0.9 percent). Moderates' intervals contain the correct answer 48.8 percent of the time (s.e. 0.8 percent). Partisans' level of overprecision is statistically significantly larger than moderates' ($p < 0.001$). On the performance question, subjects' confidence intervals contain the correct answer 42.0 percent of the time (s.e. 1.6 percent), which is also statistically significantly different from 50 percent ($p < 0.001$).

This evidence for overprecision cannot be explained by a more universal bias towards overly narrow confidence intervals. On the neutral topics, subjects are actually somewhat underprecise. A natural test looks at subjects' confidence intervals for the "Random Number" question, which asks them to guess what a random number drawn from 0 to 100 will equal. On this question, subjects' intervals contain the correct answer 54.6 percent of the time, which is statistically significantly *larger* than 50 ($p = 0.004$).³⁷

³⁵There are five subjects who, by chance, do not receive one of the two news types. I drop these subjects, but the estimate is exactly the same if they are instead set to zero.

³⁶These are unadjusted R^2 values. Adjusted R^2 is 13 percent for news assessments and 6 percent for demographics.

³⁷Similarly, the average interval subjects have is 56.4, while a correctly-calibrated subject would have an interval of 50. On the two other neutral questions, subjects exhibit moderate underprecision as well.

5.6 Motivated Reasoning, Underperformance, and Overconfidence

Next, we consider implications discussed in Hypothesis 5: underperformance and overconfidence. On news assessment questions, subjects typically score worse than if they had ignored the message entirely. This is primarily explained by two factors:

1. **Noisy updating lowers performance.** Subjects score worse on neutral topic news assessments than if they had always guessed their prior $P(\text{True})$.
2. **Motivated beliefs lower performance.** Subjects score worse on news assessments about politicized topics than about neutral topics. This is a logical consequence of Hypothesis 2, since subjects are more likely to believe Fake News than True News on politicized topics compared to neutral topics.

If subjects had always answered $P(\text{True}) = 1/2$ on news assessment questions, they would score 75 points. Yet, on average, subjects score lower than 75 points on every question. Table 6 shows that scores are especially lower for politicized topics compared to neutral topics.

The lower-than-75 scores on neutral topics can be explained by subjects updating with noise.³⁸ The further gap between neutral and politicized topics can be explained by motivated reasoning. The difference in subjects' news assessment scores between politicized and neutral topics increases in subjects' partisanship.

In fact, partisanship can explain nearly the entirety of subjects' scoring gap between politicized and neutral questions. In Table 6, column 1 shows that scores are lower for politicized topics than neutral topics, column 2 shows that the gap between neutral and political assessment scores increases in partisanship and column 3 shows that this is due to decreasing political scores more than increasing neutral scores.

Similarly, subjects' average scores across all pages are negatively correlated with their partisanship. These scores are hard to interpret on their own, but they are compared to 100 pilot participants to establish a Relative Performance percentile.³⁹ On the relative performance question, subjects are asked to predict how many of these 100 they outscored. Hypothesis 5 posits that more partisan subjects will have lower Performance scores and be more overconfident in how they scored relative to others.

Table 7 gives evidence for both parts of this hypothesis. Expected performance significantly increases in partisanship. Points scored significantly decrease in partisanship, though

³⁸An alternative explanation is that prior beliefs about $P(\text{True})$ may be substantially different from $1/2$ for some subjects. However, even subjects whose average assessment is exactly $1/2$ score significantly lower than 75 points on both partisan and neutral questions.

³⁹These overall scores are an average of scores on assessments, guesses, bounds, and either second guesses or the willingness-to-pay round. They are calculated after round 12.

the Relative Performance percentile is a noisy estimate of this, so this measure is only significant at the 10% level. There does not appear to be substantial overconfidence overall; subjects on average expect to perform at the median. But, partisans on score worse than the median and expect to score better than the median on average.

5.7 Discussion

These results strongly support the hypothesis of motivated reasoning with politically-motivated beliefs compared to Bayesian updating. Subjects significantly over-trust Pro-Party news and Fake News in an environment with uninformative signals, real monetary stakes, and little room for self-deception. This bias leads to other errors and biases such as underperformance, overconfidence, and overprecision.

Motivated reasoning may explain one form of prior-confirming bias, one in which people update further in the direction of their prior than a Bayesian would. Evidence supporting this prior-confirming bias would show a positive correlation between over-updating and prior beliefs. Motivated reasoning suggests that prior beliefs are often reflective of motivated beliefs, and that detection of prior-confirming biases may in fact be detecting motivated reasoning.

The results in Section 5.3 also relate to the effect of motivated reasoning on political polarization. Not only do subjects polarize in beliefs about the veracity of news, they polarize in their beliefs about the questions themselves, despite receiving uninformative news. Gentzkow and Shapiro (2011) find only modest differences in the media that liberals and conservatives consume, and motivated reasoning can help explain why people polarize even if they consume similar media outlets.

Results also suggest that motivated beliefs are *even further apart* than current beliefs, and that people have not yet reached their highest-motive beliefs. The reason for this is that the amount of distortion in updating is constrained by the actual informational content of signals. Motivated reasoners who receive precise signals would in fact become less polarized.

Methodologically, news assessments seem to be a more precise measure of motivated reasoning than changing guesses. With a continuous state, there is much heterogeneity in how *Bayesian* subjects would update their beliefs from information, so the null hypothesis is harder to reject and the magnitude of bias is hard to compare across domains. By using this experimental paradigm, subjects' priors are standardized, heterogeneity across issues and subjects is testable, and the Bayesian null is more easily falsifiable.

6 Demographic Heterogeneity

6.1 Heterogeneity in Motivated Reasoning

There are two types of heterogeneity to consider: heterogeneity in the direction of motivated reasoning, and heterogeneity in its magnitude. The main finding of this section is that motivated reasoning on the politicized topics does not noticeably depend on any non-political demographics, and that we can rule out even moderately large effects.

First, we consider the direction of heterogeneity. To do this, Table 4 runs a horse race regression that regresses news assessments on the interaction of the political direction of the news (Pro-Rep vs. Pro-Dem) and observable demographics. Non-political demographics in this study are race, gender, income, age, education, whether the subject’s state voted for Trump or Clinton in 2016, and religious affiliation. Controlling for party preference, *none* of the other demographics have any significant effect on the direction of motivated reasoning.

Not only are other demographics not statistically significantly different from zero, they are all statistically significantly different from ± 0.05 . This does not seem to be an artifact of aggregating across questions; even on questions about particular demographics (e.g. gender and math ability; racial discrimination), there are not statistically significant demographic effects.

Next, we consider the *magnitude* of motivated reasoning, acknowledging that this design does not enable us to disentangle magnitude of bias and strength of motive. Table 5 runs another horse race regression, regressing the news assessments on the interaction of the motivated direction of the news (Pro-Party / Pro-Performance vs. Anti-Party / Anti-Performance) and observable demographics.

There is strong evidence that partisans of both parties motivatedly reason; the discrepancy between partisans and moderates seems to be a difference in motive strength, not in the level of bias. Interestingly, there is a notable difference between Pro-Rep and Pro-Dem moderates, the former of which do not motivatedly reason in the predicted direction on average. This party difference may be better explained by direction instead of magnitude of bias, as the sample is non-representative *conditional on party*. For instance, only 76 percent of Republicans in this sample approved of President Trump’s performance; in a Gallup poll conducted contemporaneously (from June 25-July 1), 87 percent of Republicans approved of his performance (Gallup 2018b).

As with the direction of motivated reasoning, non-political demographics do not notably affect the magnitude of the bias; all effects are again between ± 0.05 once party preference is controlled for.

These results suggest that the degree of bias of motivated reasoning is somewhat consis-

tent across demographics, but that the direction of motivated beliefs are heterogeneous. In particular, the sign of the slope of the motive function about many of these issues is exactly the opposite for Democrats and Republicans.

6.2 Gender, Performance-Motivated Reasoning, and Confidence

Section 6.1 showed that the direction of motivated reasoning was similar across non-party demographics on politicized topics, but this is not the case for performance-motivated reasoning. Overall, men significantly motivatedly reason in the direction of believing they outperformed others, while women do not systematically motivatedly reason in either direction.

Figure 4 shows gender differences in the magnitude of the treatment effect by question. On the performance topic, men give Pro-Performance news 11 percentage points higher assessments than Anti-Party news (s.e. 2 percent) and women give Pro-Performance news 0.2 percentage points lower assessments than Anti-Performance news (s.e. 2 percent). But on the politicized topics, men give Pro-Party news 9 percentage points higher assessments than Anti-Party news (s.e. 0.9 percentage points), and women give Pro-Party news 10 percentage points higher assessments than Anti-Party news (s.e. 0.9 percentage points).

Similar patterns emerge for overconfidence. Table 7 shows that men are more overconfident than women. In fact, only men are overconfident. The magnitude of the overconfidence discrepancy is especially stark when comparing expected performance by gender when controlling for actual performance, as seen in Appendix Figure 8. Except for the highest-performing women, women of all performance levels expect to score below the median, and men of all performance levels expect to score above the median.

These results suggest that gender differences in confidence are related to gender differences in motivated reasoning. In particular, there is a clear gender asymmetry in the magnitude of both biases: women are not systematically biased about either performance-related motivated reasoning nor confidence on average, while men are systematically biased about both in the direction of believing they outperformed others.

7 Conclusion

Motivated reasoning plays a substantial role in people’s assessment of the veracity of news and helps explain why people form inaccurate and polarized beliefs. This paper demonstrates its importance across numerous varied topics with a novel experimental design, showing that motivated reasoning is a unique phenomenon from Bayesian updating, prior- and likelihood-

misweighting biases, and utility-maximizing beliefs. Furthermore, these results have shown how motivated reasoning leads to further belief polarization, overprecision, and an excess trust in Fake News.

One interpretation of this paper is unambiguously bleak: people form polarized and biased beliefs because of motivated reasoning, motivatedly reason even farther in the polarized direction in the experiment, and make particularly biased inferences on issues they find important. However, there is another, complementary, interpretation of this paper: this experimental design takes a step towards better identifying and understanding motivated reasoning, and makes it easier for future work to attenuate the bias. Using this design, we can identify and estimate the magnitude of the bias; future projects that use interventions to debias people can use this estimated magnitude as a dependent variable. Since the bias often decreases utility, people may have demand for such interventions.

A potential path to attenuate the bias involves understanding the determinants of susceptibility. There is no evidence that susceptibility depends much on an individual’s characteristics; however, it could depend on the signal structure. Intuitively, an agent who receives an arbitrarily precise signal or a clearly irrelevant signal will likely have very low susceptibility, while an agent who receives a hard-to-interpret signal will likely have higher susceptibility and deviate more from Bayes’ rule. Future work can experimentally and empirically estimate this parameter in contexts with fixed motives but varying signal structures. And, if we can decrease susceptibility, we can limit the bias in people’s updating process.

Many of these results also suggest further exploration of what motives actually represent. This paper identifies a few specific parts of the motive function distribution, but extending this design can identify the shape of the distribution and generate utility-like properties such as concavity and risk motives. It also can provide insight on how motives and choices interact.

Finally, while one definition of motivated beliefs posits that they are beliefs that increase utility, this paper provides no evidence that people are motivated to believe “good things” about the world, and such an interpretation gives perverse implications about peoples’ preferences. What does it mean if Republicans are motivated to believe that more Americans were murdered during Obama’s presidency? What does it mean if Democrats are motivated to believe that there is rampant racial discrimination in labor markets? These are controversial questions, but they are ones that are crucial for understanding how people form beliefs in a highly politicized society.

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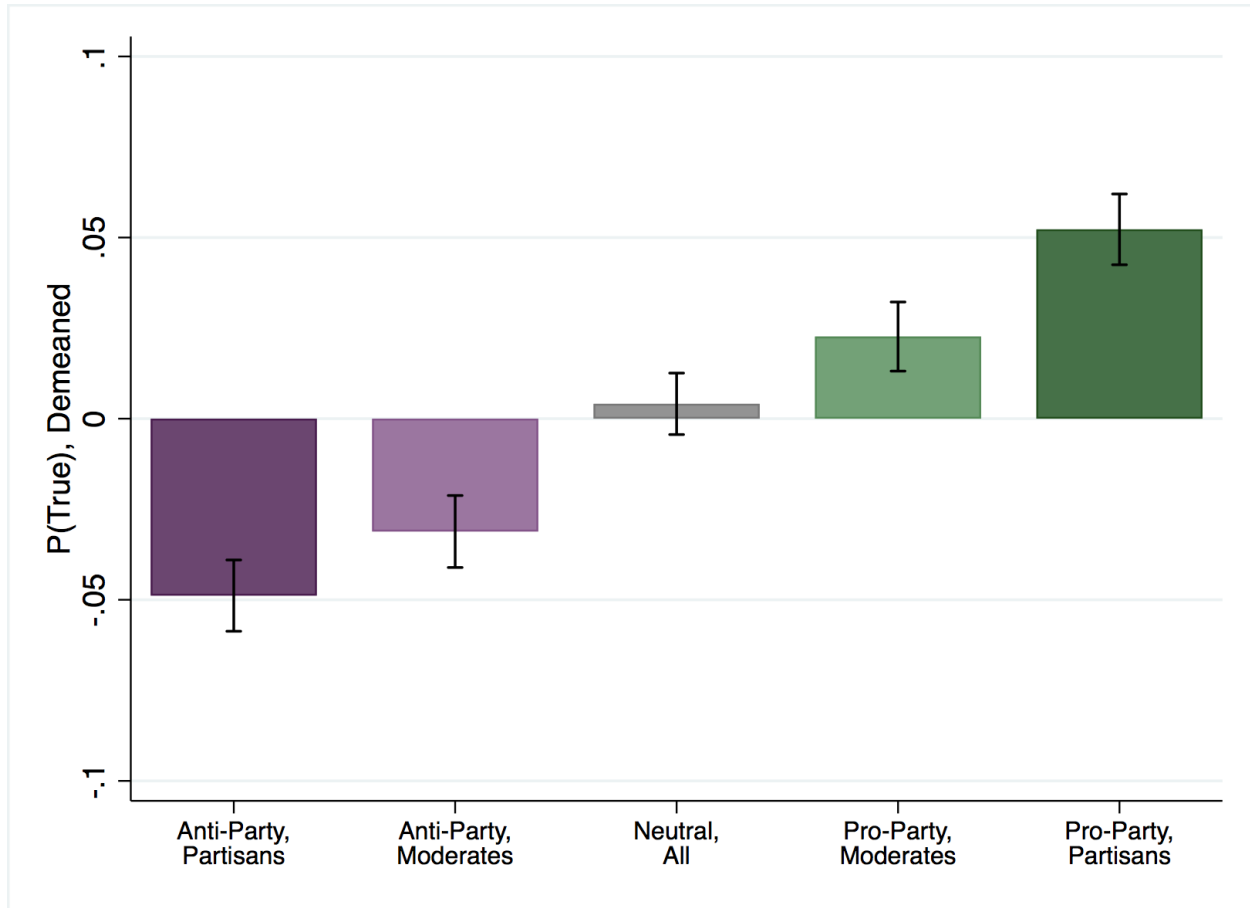
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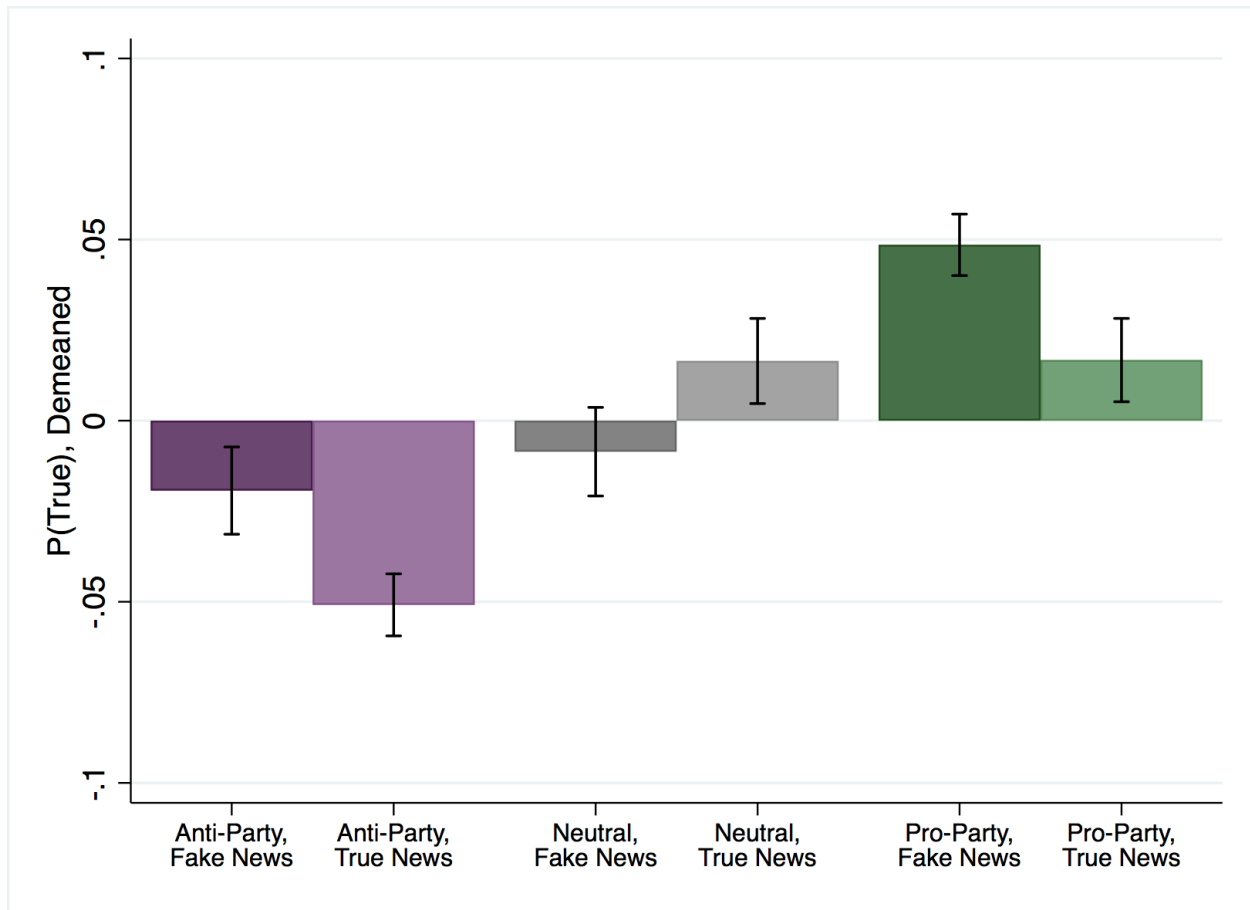
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Figure 1: Politically-Motivated Reasoning: Perceived Veracity by News Direction and Subject Partisanship



Notes: The y-axis is stated $P(\text{True})$, demeaned at the subject level. News on partisan topics is classified as Pro-Party (Anti-Party) if it is more (less) representative of the subject's preferred political party, as defined in Table 1. A subject who is above the median value for $\text{abs}(\text{Republican Party rating} - \text{Democratic Party rating})$ is classified as Partisan; a subject who is not is classified as Moderate. Error bars correspond to 95 percent confidence intervals.

Figure 2: Motivated Reasoning and Trust in Fake News: Perceived Veracity by News Direction and Actual Veracity



Notes: The y-axis is stated $P(\text{True})$, demeaned at the subject level. News on partisan topics is classified as Pro-Party (Anti-Party) if it is more (less) representative of the subject's preferred political party, as defined in Table 1. Fake News sends messages that reinforce the direction of subjects' error; True News sends messages that mitigate subjects' error. Error bars correspond to 95 percent confidence intervals.

Table 2: The Effect of News Direction and Actual Veracity on Perceived Veracity

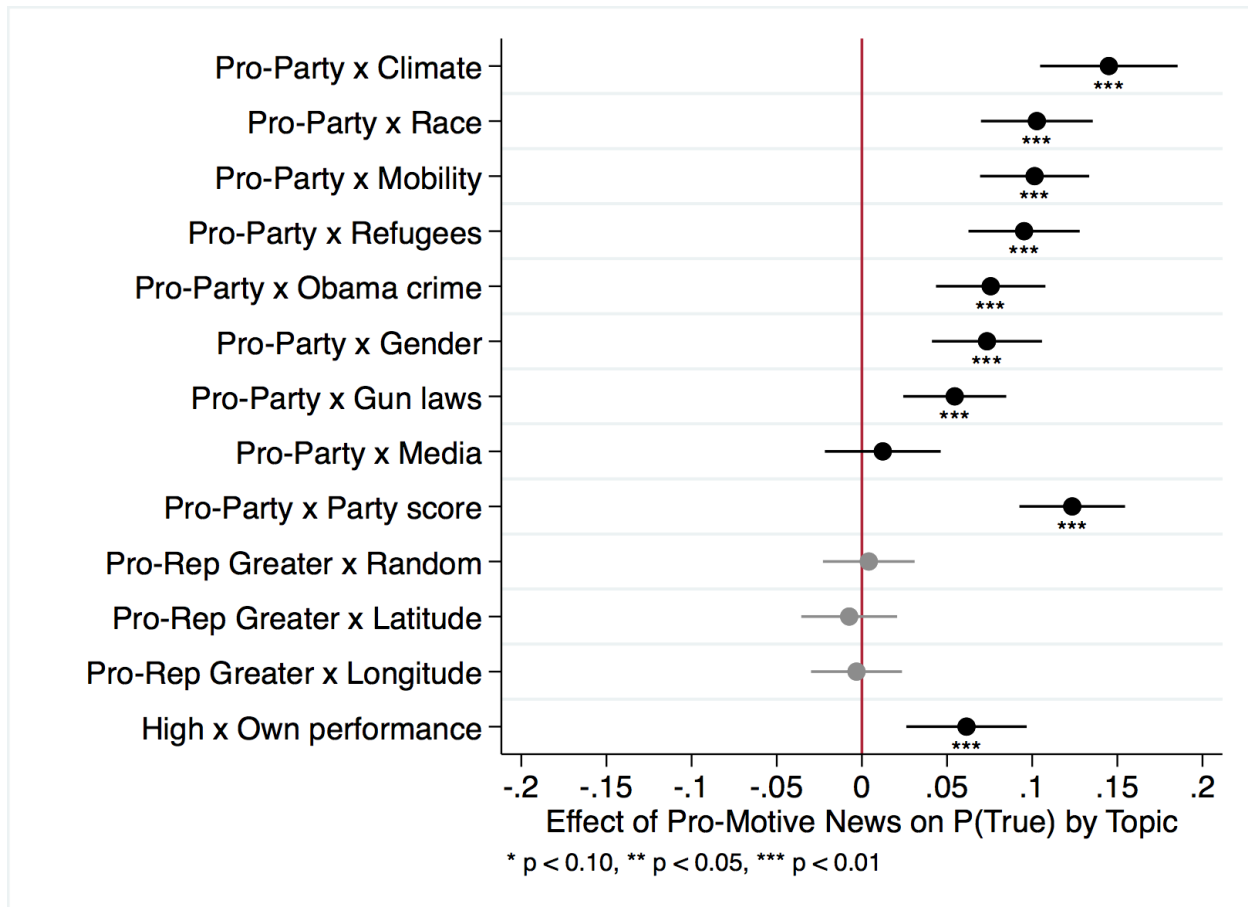
| | (1) | (2) | (3) | (4) | (5) | (6) |
|-----------------------------|---------------------|---------------------|---------------------|----------------------|----------------------|----------------------|
| Pro-Party News | 0.092*** (0.006) | 0.088*** (0.007) | 0.040*** (0.013) | 0.037*** (0.007) | | 0.077*** (0.007) |
| Partisanship x Pro-Party | | | 0.050*** (0.012) | | | |
| Anti-Party News | | | | -0.048*** (0.007) | | |
| True News | | | | | -0.059*** (0.006) | -0.034*** (0.007) |
| Neutral News | No | No | No | Yes | No | No |
| Question FE | Yes | Yes | Yes | No | Yes | Yes |
| Round FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Subject controls | Yes | No | No | No | No | No |
| Subject FE | No | Yes | Yes | Yes | Yes | Yes |
| Observations | 7902 | 7902 | 7902 | 10552 | 7902 | 7902 |
| R^2 | 0.05 | 0.25 | 0.25 | 0.21 | 0.23 | 0.25 |
| Mean | 0.573 | 0.573 | 0.573 | 0.574 | 0.573 | 0.573 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS, errors clustered at subject level. Neutral News indicates that Pro-Party / Anti-Party news assessments are compared to assessments on Neutral topics. These classifications are defined in Table 1. Controls: race, gender, log(income), years of education, religion, and whether state voted for Trump or Clinton in 2016. Partisanship is the absolute difference between ratings of the Republican and Democratic parties.

Figure 3: Motivated Reasoning Across Topics: Effect of Pro-Party News on Perceived Veracity by Topic



Notes: OLS regression coefficients, errors clustered at subject level. FE included for round number and topic. Pro-Party (vs. Anti-Party) news is defined in Table 1. Pro-Rep Greater is a placebo check to test whether Pro-Rep and Pro-Dem subjects give different assessments on neutral topics. Error bars correspond to 95 percent confidence intervals.

Table 3: Changing Guess to Follow Message Given News Direction

| | (1) | (2) | (3) | (4) | (5) | (6) |
|-----------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| Pro-Party News | 0.122*** (0.021) | | 0.114*** (0.021) | 0.018 (0.018) | | 0.024 (0.018) |
| Polarizing News | | 0.061*** (0.019) | 0.032* (0.019) | | -0.017 (0.016) | -0.022 (0.016) |
| P(True) | | | | 1.126*** (0.062) | 1.139*** (0.061) | 1.131*** (0.063) |
| Question FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Round FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Subject FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4085 | 4085 | 4085 | 4085 | 4085 | 4085 |
| R^2 | 0.28 | 0.28 | 0.28 | 0.45 | 0.45 | 0.45 |
| Mean | 0.659 | 0.659 | 0.659 | 0.659 | 0.659 | 0.659 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS, errors clustered at subject level. Only subjects from the Second-Guess treatment. Only Pro-Party / Anti-Party news observations, as defined in Table 1. Polarizing News is defined as news that tells subjects that, compared to their initial guess, the answer is in the opposite direction from the population mean. Dependent variable is 1 if subjects change their guess upwards when the message says “Greater Than” or downwards when the message says “Less Than,” -1 if they change their guess in the opposite direction, and 0 if they do not change their guess.

Table 4: Heterogeneity in the Partisan Direction of Motivated Reasoning: Horse Race Regression

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|----------------------|-------------------|----------------|----------------|-----------------|----------------|-----------------|-----------------|-------------------|-------------------|
| Rep News x Pro-Rep | 0.13*** (0.01) | | | | | | | | 0.12*** (0.01) |
| Rep News x (Age>32) | | 0.00 (0.01) | | | | | | | -0.01 (0.01) |
| Rep News x Male | | | 0.00 (0.01) | | | | | | 0.00 (0.01) |
| Rep News x White | | | | 0.03* (0.02) | | | | | 0.02 (0.02) |
| Rep News x College | | | | | 0.01 (0.01) | | | | 0.02 (0.01) |
| Rep News x (Inc>50K) | | | | | | -0.01 (0.01) | | | -0.02 (0.01) |
| Rep News x Red State | | | | | | | 0.02* (0.01) | | 0.01 (0.01) |
| Rep News x Religious | | | | | | | | 0.05*** (0.01) | 0.02 (0.01) |
| Rep News | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Question FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Round FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 7902 | 7902 | 7902 | 7902 | 7902 | 7902 | 7902 | 7902 | 7902 |
| R^2 | 0.26 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.26 |
| Mean | 0.57 | 0.57 | 0.57 | 0.57 | 0.57 | 0.57 | 0.57 | 0.57 | 0.57 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS regression coefficients, errors clustered at subject level. FE included for round number and topic. Only Pro-Party / Anti-Party news observations, as defined in Table 1. Pro-Rep: higher rating for Republican than Democratic Party. Red State: coted for Trump in 2016. Religious: subject affiliates with any religion.

Table 5: Heterogeneity in the Magnitude of Motivated Reasoning: Horse Race Regression

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|------------------------|---------|--------|--------|--------|--------|---------|--------|----------|---------|
| Pro-Motive x Pro-R | 0.06*** | | | | | | | | 0.08*** |
| x Partisan | (0.02) | | | | | | | | (0.03) |
| Pro-Motive x Pro-R | -0.02 | | | | | | | | 0.00 |
| x Moderate | (0.01) | | | | | | | | (0.03) |
| Pro-Motive x Pro-D | 0.11*** | | | | | | | | 0.12*** |
| x Moderate | (0.01) | | | | | | | | (0.02) |
| Pro-Motive x Pro-D | 0.13*** | | | | | | | | 0.14*** |
| x Partisan | (0.01) | | | | | | | | (0.02) |
| Pro-Motive x (Age>32) | | 0.00 | | | | | | | 0.01 |
| | | (0.01) | | | | | | | (0.01) |
| Pro-Motive x Male | | | 0.00 | | | | | | 0.01 |
| | | | (0.01) | | | | | | (0.01) |
| Pro-Motive x White | | | | -0.02 | | | | | -0.01 |
| | | | | (0.01) | | | | | (0.01) |
| Pro-Motive x College | | | | | 0.01 | | | | 0.01 |
| | | | | | (0.01) | | | | (0.01) |
| Pro-Motive x (Inc>50K) | | | | | | -0.02** | | | -0.02* |
| | | | | | | (0.01) | | | (0.01) |
| Pro-Motive x Red State | | | | | | | -0.02* | | -0.01 |
| | | | | | | | (0.01) | | (0.01) |
| Pro-Motive x Religious | | | | | | | | -0.04*** | -0.01 |
| | | | | | | | | (0.01) | (0.01) |
| Pro-Motive News | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes | No |
| Question FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Round FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 8793 | 8793 | 8793 | 8793 | 8793 | 8793 | 8793 | 8793 | 8793 |
| R^2 | 0.24 | 0.23 | 0.23 | 0.23 | 0.23 | 0.23 | 0.23 | 0.23 | 0.24 |
| Mean | 0.58 | 0.58 | 0.58 | 0.58 | 0.58 | 0.58 | 0.58 | 0.58 | 0.58 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS regression coefficients, errors clustered at subject level. FE for round number and topic. Only observations relevant to motives as defined in Table 1. Pro-Motive indicates Pro-Party or Pro-Performance. Pro-R: higher rating for Rep than Dem Party. Partisan: above median for abs(Rep rating - Dem rating). Red State: state voted for Trump in 2016. Religious: subject affiliates with any religion.

Table 6: The Effect of Topic and Partisanship on News Assessment Scores

| | (1) | (2) | (3) |
|----------------------------------|--------------------|-------------------|--------------------|
| Politicized Topic | -4.14*** (0.62) | -1.92* (1.08) | -1.92* (1.03) |
| Partisanship x Politicized Topic | | -5.09** (1.98) | -3.58*** (1.14) |
| Partisanship x Neutral Topic | | | 1.53 (1.62) |
| Round FE | Yes | Yes | Yes |
| Subject FE | Yes | Yes | No |
| Observations | 11612 | 11612 | 11612 |
| R^2 | 0.12 | 0.12 | 0.01 |
| Mean | 69.47 | 69.47 | 69.47 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS, errors clustered at subject level. Party-indifferent subjects included. News assessment scores range from 0 to 100; subjects can guarantee a score of 75 by saying that the source is equally likely to be True News or Fake News. Partisanship is the absolute difference between subjects' ratings of the Republican and Democratic parties. Politicized topics and neutral topics as defined in Table 1. Subject controls are party preference, age, race, gender, log(income), education, religion, and whether state voted for Trump or Clinton in 2016.

Table 7: Performance and Expected Performance by Partisanship

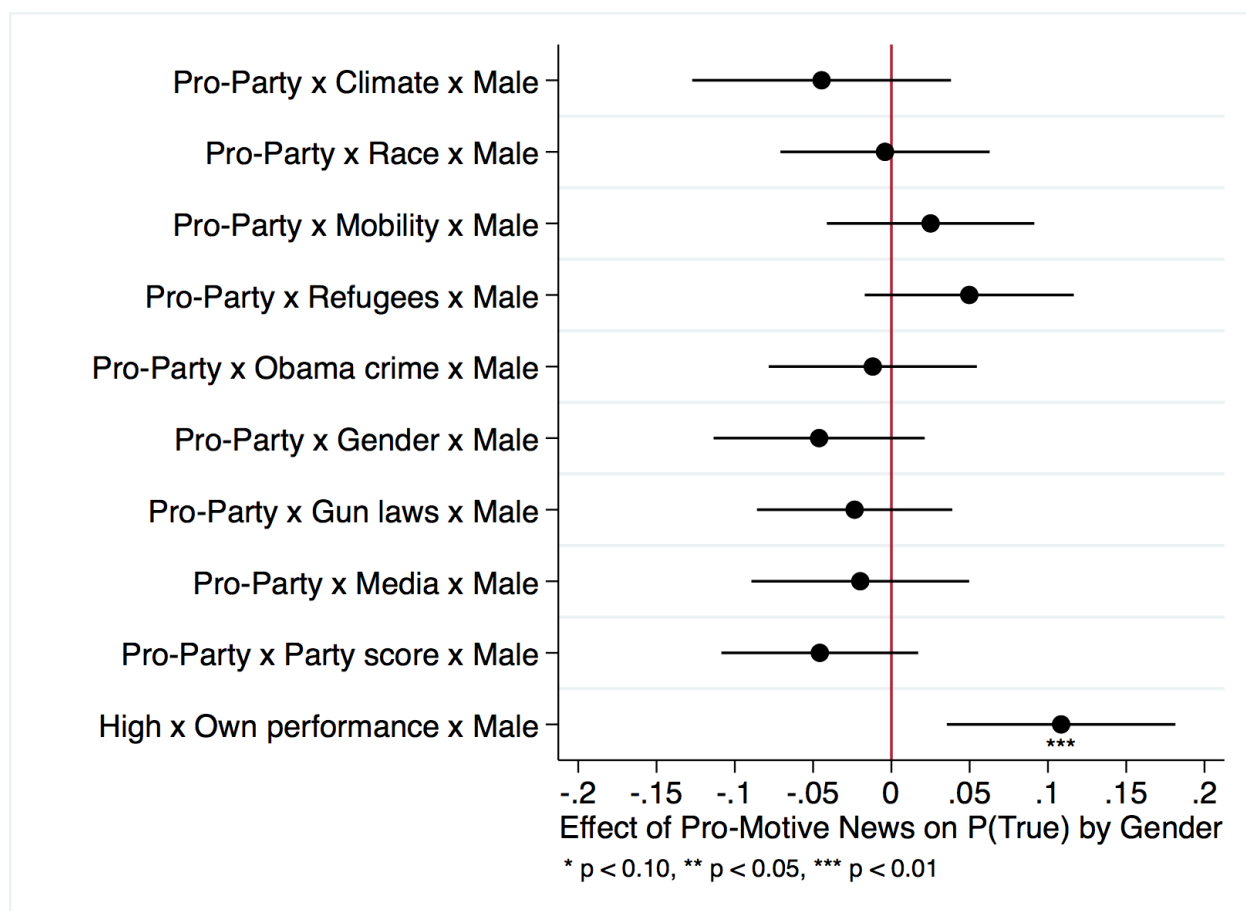
| | News Pts | | Performance | | Expectation | |
|------------------|--------------------|--------------------|------------------|------------------|-------------------|--------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Partisanship | -3.58*** (1.13) | -3.53*** (1.15) | -4.74* (2.60) | -4.89* (2.68) | 6.13*** (2.18) | 8.19*** (2.16) |
| Male | | -0.81 (0.71) | | 3.65** (1.70) | | 11.98*** (1.31) |
| Subject controls | No | Yes | No | Yes | No | Yes |
| Observations | 8696 | 8696 | 987 | 987 | 987 | 987 |
| R^2 | 0.00 | 0.00 | 0.00 | 0.04 | 0.01 | 0.13 |
| Mean | 69.01 | 69.01 | 47.64 | 47.64 | 50.36 | 50.36 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS. Party-indifferent subjects included. A subject's News Pts is her points scored on news questions on politicized topics. A subject's Performance is equal to how many pilot subjects (out of 100) she outscored. Calculations are made after round 12 of the experiment. A subject's Expectation is equal to her median belief of how many pilot subjects (out of 100) she outscored. Partisanship is the absolute difference between subjects' ratings of the Republican and Democratic parties. Subject controls are party preference, age, race, gender, log(income), education, religion, and whether state voted for Trump or Clinton in 2016.

Figure 4: Gender Heterogeneity in Motivated Reasoning Across Topics: Effect of News Direction on Perceived Veracity by Topic and Gender



Notes: OLS regression coefficients, errors clustered at subject level. FE included for round number and topic, interacted with gender. Only subjects who identify as male or female included. Only news observations that are relevant to motives as defined in Table 1. Figure shows interaction between Pro-Party / Pro-Performance news and male, controlling for Pro-Party / Pro-Performance news. Error bars correspond to 95 percent confidence intervals.

A Supplementary Appendix: Additional Results

A.1 Proof of Hypothesis 5

First, we calculate the expected utility that an agent anticipates receiving (*agent-expected utility*), given her assessment a :

$$\begin{aligned}\tilde{\mathbb{E}}[u(a)|a] &= a \cdot (1 - (1 - a)^2) + (1 - a) \cdot (1 - a^2) \\ &= 1 - a(1 - a) \\ &= 3/4 + (a - 1/2)^2.\end{aligned}$$

Agent-expected utility increases in $(a - 1/2)^2$.

Next, we calculate the average agent-expected utility $\tilde{\mathbb{E}}[u(a)]$, given her motivated reasoning. The agent motivatedly reasons as follows:

$$\begin{aligned}\text{logit } a|G &= \text{logit } p + \varphi m (\mathbb{E}[\theta|\theta > \mu(m)] - \mathbb{E}[\theta|\theta < \mu(m)]) . \\ \text{logit } a|L &= \text{logit } p - \varphi m (\mathbb{E}[\theta|\theta > \mu(m)] - \mathbb{E}[\theta|\theta < \mu(m)]) .\end{aligned}$$

The average agent-expected utility is $(\tilde{\mathbb{E}}[u(a|G)] + \tilde{\mathbb{E}}[u(a|L)]) / 2$.

Define $\Delta_m \equiv \varphi m (\mathbb{E}[\theta|\theta > \mu(m)] - \mathbb{E}[\theta|\theta < \mu(m)])$. Note that since the standard deviation of agents' beliefs does not depend on m , Δ_m is linear in m . Now, take the inverse logit function of both sides, $\text{logit}^{-1}(x) = \frac{e^x}{1+e^x}$, and average:

$$\begin{aligned}1 - \tilde{\mathbb{E}}[u(a)] &= \frac{1}{4} - P(G)\mathbb{E} \left[\left(\text{logit}^{-1}(\text{logit } p + \Delta_m) - 1/2 \right)^2 \right] \\ &\quad - P(L)\mathbb{E} \left[\left(\text{logit}^{-1}(\text{logit } p - \Delta_m) - 1/2 \right)^2 \right] \\ &= \frac{1}{4} - \frac{1}{2}\mathbb{E} \left[\left(\text{logit}^{-1}(\text{logit } p + \Delta_m) - 1/2 \right)^2 \right] \\ &\quad - \frac{1}{2}\mathbb{E} \left[\left(\text{logit}^{-1}(\text{logit } p - \Delta_m) - 1/2 \right)^2 \right]\end{aligned}$$

Therefore, average agent-expected utility equals:

$$3/4 + 1/2 \left(\text{logit}^{-1}(\text{logit } p + \Delta_m) - 1/2 \right)^2 + 1/2 \left(\text{logit}^{-1}(\text{logit } p - \Delta_m) - 1/2 \right)^2 .$$

We can rewrite this using the hyperbolic tan function, $\tanh(x) \equiv \frac{\exp(x) - \exp(-x)}{\exp(x) + \exp(-x)}$:

$$3/4 + 1/8 \left[\tanh(\text{logit } p + \eta_i \Delta_m)/2 \right]^2 + 1/8 \left[\tanh(\text{logit } p - \eta_i \Delta_m)/2 \right]^2$$

Taking the derivative with respect to Δ_m — which is linear in m — and setting equal to zero gives the following:

$$|\varphi\Delta_m| = 2\cosh^{-1} \left[1/2 \sqrt{\operatorname{sech}(\logit p)(2\cosh(\logit p) + \cosh(2 \logit p) - 3)} \right],$$

where $\cosh(x) \equiv 1/2(e^x + e^{-x})$ and $\operatorname{sech}(x) \equiv (\cosh(x))^{-1}$.

The right-hand side is real only if the term in the square brackets is at least 1, in which case there is such a solution p ; that is, if $\operatorname{sech}(\logit p)(2\cosh(\logit p) + \cosh(2 \logit p) - 3) < 4$, then the first-order condition is never satisfied and anticipated expected utility is always monotonic in $|m|$. In this case, the second-order condition shows that average agent-expected utility is increasing in $|m|$. This condition is met iff $p \in \left(\frac{1}{2} - \frac{\sqrt{3}}{6}, \frac{1}{2} + \frac{\sqrt{3}}{6}\right)$.

A.2 Raw Data: Pro-Party and Anti-Party News Assessments

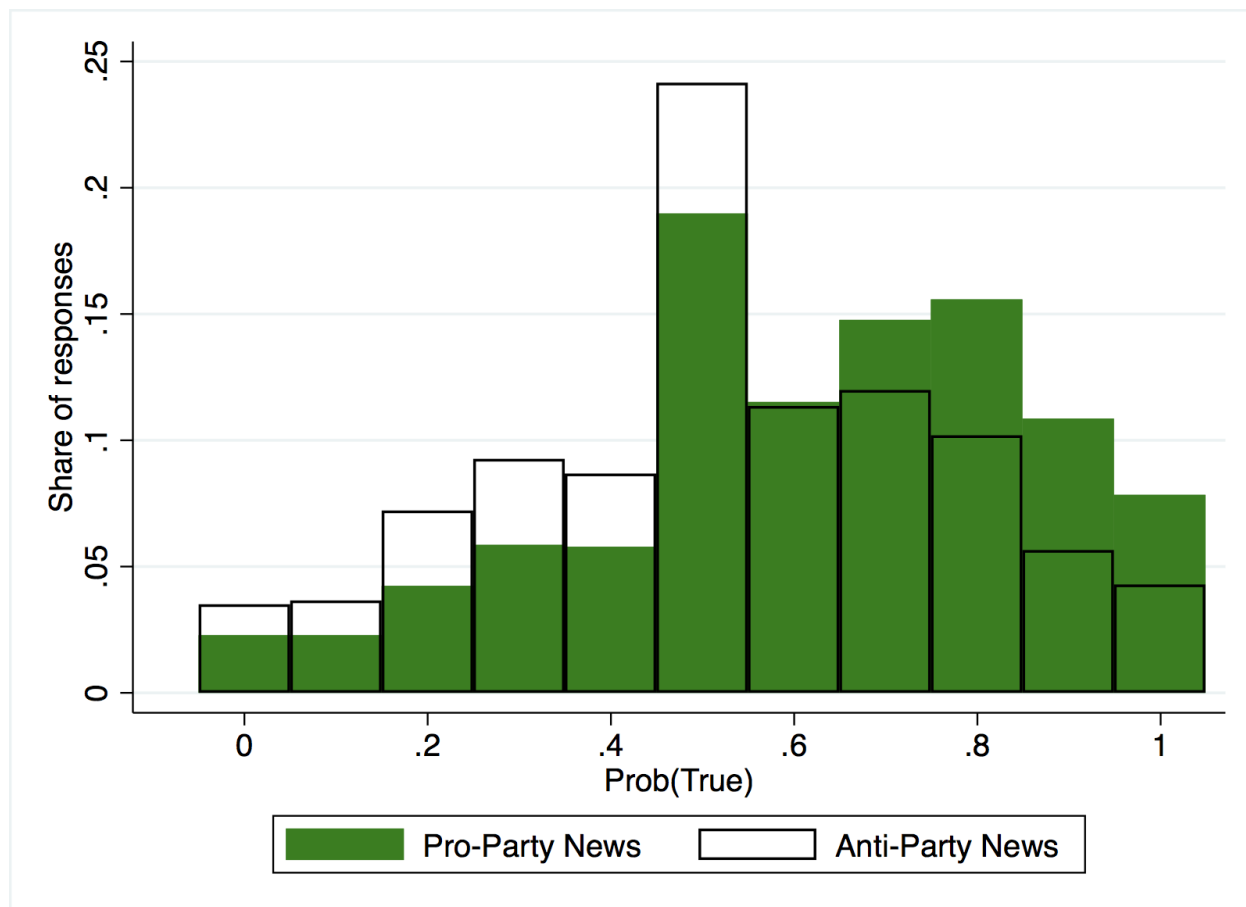


Figure 5: Histogram of Perceived Veracity of Pro-Party and Anti-Party News.

Notes: Only Pro-Party / Anti-Party news observations, as defined in Table 1. Messages are customized so that Bayesians give the same assessment for Pro-Party and Anti-Party news.

A.3 Raw Data: True News and Fake News Assessments

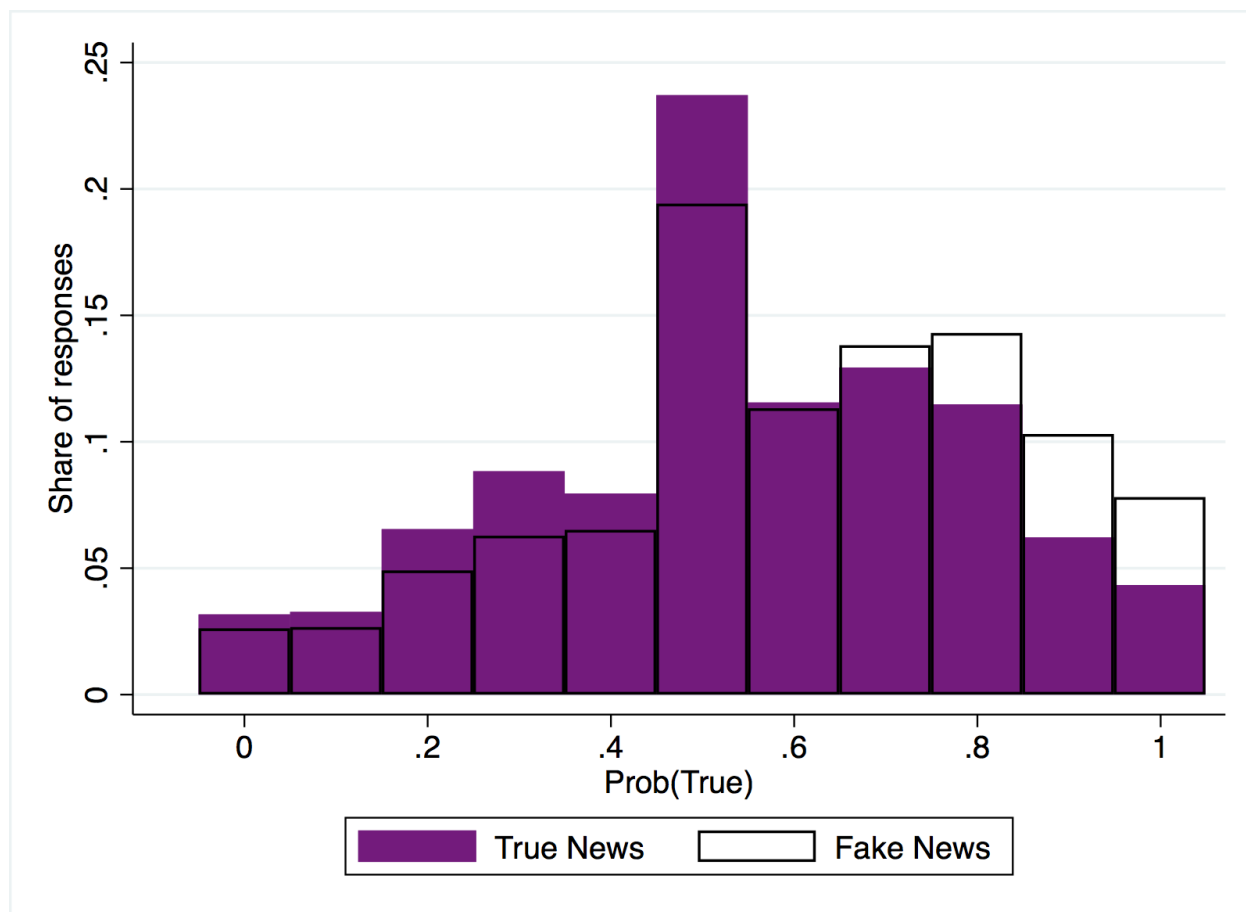


Figure 6: Histogram of Perceived Veracity of True News and Fake News on Politicized Topics.

Notes: Only Pro-Party / Anti-Party news observations, as defined in Table 1. Messages are customized so that Bayesians give the same assessment for Pro-Party and Anti-Party news.

A.4 Relative Prior Beliefs by Party

| | Pro-Rep | Pro-Dem | Difference | Answer |
|-------------------|-----------------------|-----------------------|-----------------------|--------|
| Obama Crime Guess | 55.907*** (0.765) | 49.560*** (0.391) | 6.348*** (0.858) | 53 |
| Mobility Guess | 30.185*** (1.048) | 22.152*** (0.611) | 8.034*** (1.211) | 64.9 |
| Race Guess | 12.349*** (0.874) | 8.051*** (0.436) | 4.298*** (0.975) | 6.45 |
| Gender Guess | 3.059*** (0.015) | 3.086*** (0.008) | -0.027 (0.017) | 3.15 |
| Refugees Guess | 287.640*** (5.894) | 239.004*** (2.353) | 48.637*** (6.335) | 228.2 |
| Climate Guess | 75.226*** (1.056) | 85.366*** (0.572) | -10.140*** (1.200) | 87 |
| Gun Laws Guess | 230.013*** (5.950) | 184.478*** (3.914) | 45.535*** (7.113) | 318.6 |
| Media Guess | 36.656*** (1.211) | 41.850*** (0.599) | -5.195*** (1.349) | 19.8 |
| Rep Score Guess | 71.563*** (0.787) | 61.933*** (0.614) | 9.630*** (0.997) | 70.83 |
| Dem Score Guess | 64.671*** (0.771) | 73.277*** (0.415) | -8.606*** (0.875) | 72.44 |
| Observations | 2430 | 5643 | 8073 | |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

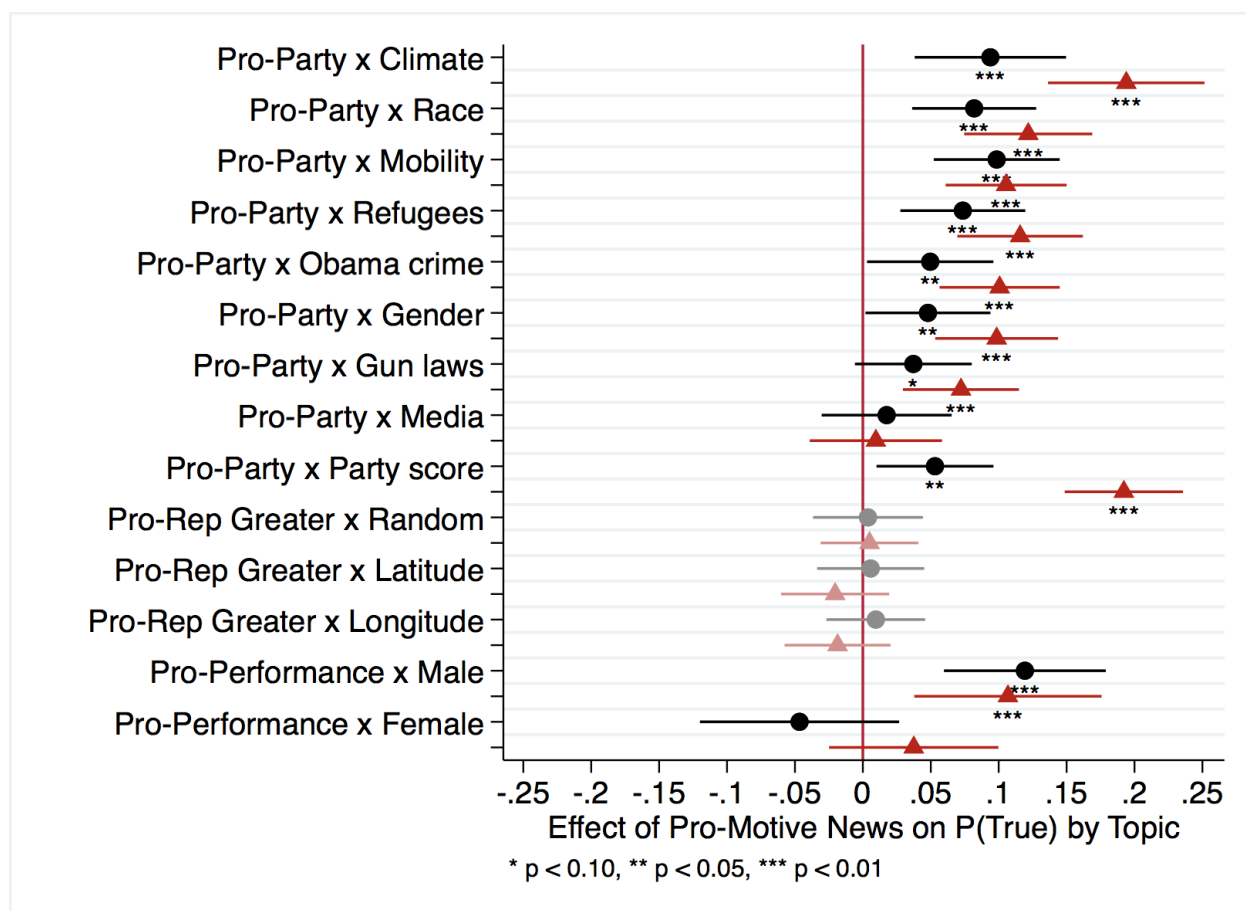
Notes: OLS, robust standard errors. Guesses are winsorized at the 5-percent level. Third column represents mean Pro-Rep guess minus mean Pro-Dem guess. The sign of every coefficient points in the predicted motive direction from Table 1.

A.5 Balance Table

| | Anti-Party News | Pro-Party News | Anti vs. Pro | p-value |
|---------------|-------------------|-------------------|-------------------|---------|
| Partisanship | 0.484 (0.005) | 0.478 (0.005) | 0.007 (0.007) | 0.312 |
| Rep vs. Dem | -0.237 (0.008) | -0.236 (0.008) | -0.001 (0.011) | 0.937 |
| Male | 0.532 (0.008) | 0.534 (0.008) | -0.002 (0.011) | 0.881 |
| Age | 35.261 (0.175) | 35.400 (0.173) | -0.139 (0.246) | 0.573 |
| Education | 14.716 (0.029) | 14.765 (0.030) | -0.049 (0.042) | 0.242 |
| Log(income) | 10.725 (0.012) | 10.748 (0.013) | -0.024 (0.018) | 0.182 |
| White | 0.752 (0.007) | 0.760 (0.007) | -0.008 (0.010) | 0.430 |
| Black | 0.075 (0.004) | 0.081 (0.004) | -0.006 (0.006) | 0.303 |
| Hispanic | 0.066 (0.004) | 0.062 (0.004) | 0.004 (0.006) | 0.499 |
| Religious | 0.443 (0.008) | 0.457 (0.008) | -0.014 (0.011) | 0.214 |
| Red State | 0.567 (0.008) | 0.558 (0.008) | 0.009 (0.0011) | 0.431 |
| WTP elicited | 0.490 (0.008) | 0.476 (0.008) | 0.014 (0.011) | 0.213 |
| Told 1/2 True | 0.333 (0.007) | 0.344 (0.008) | -0.011 (0.011) | 0.309 |
| <i>N</i> | 3961 | 3941 | 7902 | |

Notes: Standard errors in parentheses. Rep vs. Dem is the rating of the Republican Party minus the rating of the Democratic Party and is between -1 and 1. Partisanship is the absolute difference in these ratings. Education is in years. Religious is 1 if subject in any religious group. Red State is 1 if state voted for Trump in 2016 election. WTP elicited is 1 if subject in the willingness-to-pay treatment and 0 if in the second-guess treatment. Told 1/2 True is 1 if subject is told that P(True News) is 1/2 and 0 if subject is not.

Figure 7: Motivated Reasoning Across Topics: Effect of Pro-Party News on Perceived Veracity by Topic and Partisanship



Notes: OLS regression coefficients, errors clustered at subject level. Black circles are coefficients for moderates, red triangles are coefficients for partisans. FE included for round number and topic. Pro-Party (vs. Anti-Party) news is defined in Table 1. Pro-Rep Greater is a placebo check to test whether Pro-Rep and Pro-Dem subjects give different assessments on neutral topics. Error bars correspond to 95 percent confidence intervals.

Table 8: The Effect of News Direction, Actual Veracity, and Skewed Prior Distributions on Perceived Veracity

| | (1) | (2) | (3) | (4) |
|-------------------------------------|---------------------|---------------------|----------------------|----------------------|
| Unskewed | -0.011 (0.010) | -0.003 (0.014) | -0.019* (0.011) | 0.002 (0.013) |
| Pro-Party News | 0.084*** (0.008) | 0.041*** (0.015) | 0.028*** (0.008) | 0.075*** (0.008) |
| Unskewed x Pro-Party | 0.014 (0.013) | -0.002 (0.024) | 0.021 (0.014) | 0.006 (0.013) |
| Partisanship x Pro-Party | | 0.044*** (0.014) | | |
| Unskewed x Partisanship x Pro-Party | | 0.017 (0.022) | | |
| Anti-Party News | | | -0.052*** (0.008) | |
| Unskewed x Anti-Party | | | 0.006 (0.014) | |
| True News | | | | -0.027*** (0.008) |
| Unskewed x True News | | | | -0.021 (0.014) |
| Neutral News | No | No | Yes | No |
| Question FE | Yes | Yes | No | Yes |
| Round FE | Yes | Yes | Yes | Yes |
| Subject FE | Yes | Yes | Yes | Yes |
| Observations | 7902 | 7902 | 10552 | 7902 |
| R^2 | 0.25 | 0.25 | 0.21 | 0.25 |
| Mean | 0.573 | 0.573 | 0.574 | 0.573 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS, errors clustered at subject level. Neutral News indicates that Pro-Party / Anti-Party compared to Neutral News, as defined in Table 1. Controls: race, gender, log(income), education (in years), religion, whether state voted for Trump or Clinton in 2016. Partisanship is absolute difference between Republican and Democratic ratings. Unskewed is 1 if initial guess is exactly halfway between lower / upper bounds and 0 otherwise.

Table 9: The Effect of News Direction, Actual Veracity, and Previous News Directions on Perceived Veracity

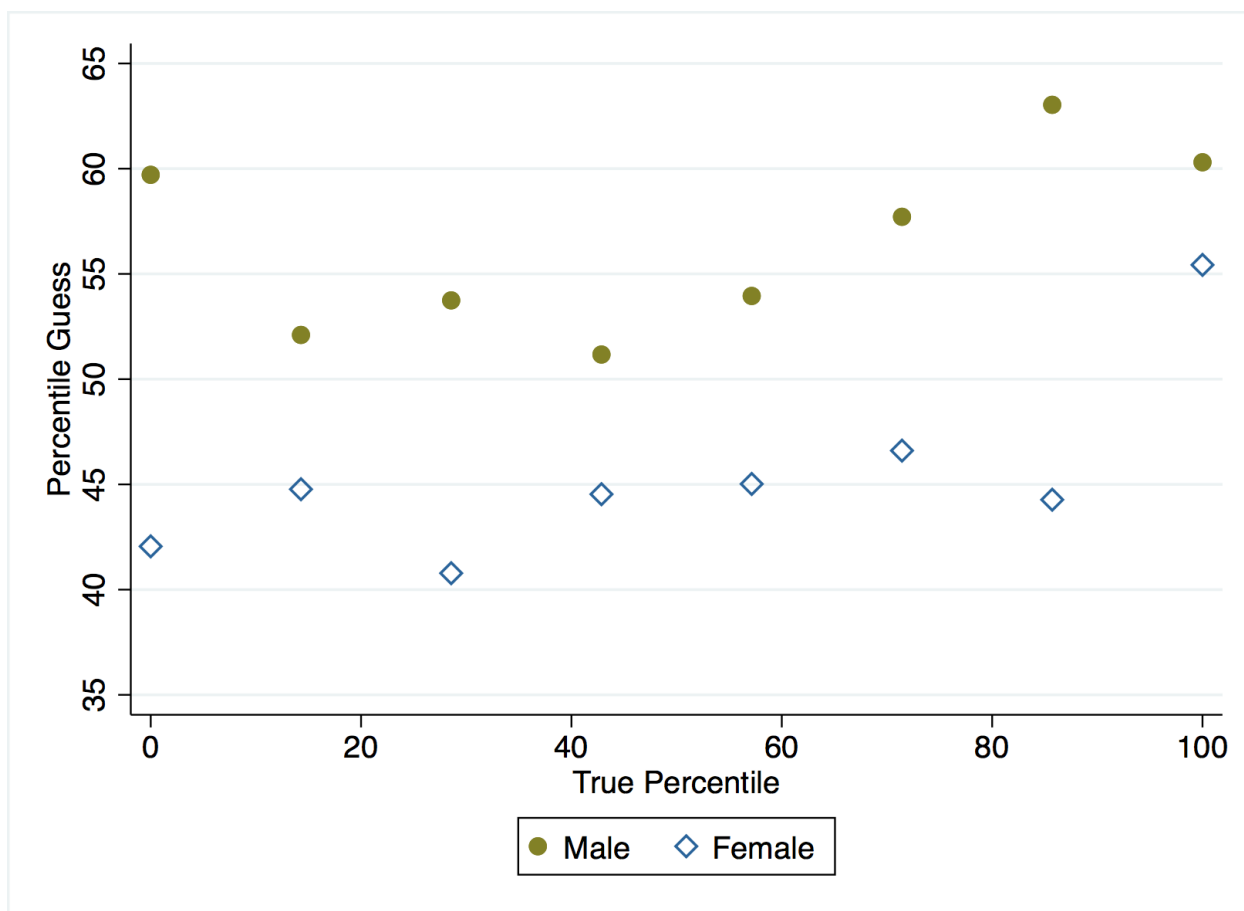
| | (1) | (2) | (3) | (4) |
|--------------------------|---------------------|---------------------|----------------------|----------------------|
| Previous Pro-Party | -0.001 (0.002) | -0.001 (0.002) | -0.002 (0.002) | -0.002 (0.002) |
| Pro-Party News | 0.087*** (0.007) | 0.039*** (0.013) | 0.036*** (0.007) | 0.076*** (0.007) |
| Partisanship x Pro-Party | | 0.050*** (0.012) | | |
| Anti-Party News | | | -0.048*** (0.007) | |
| True News | | | | -0.034*** (0.007) |
| Neutral News | No | No | Yes | No |
| Question FE | Yes | Yes | No | Yes |
| Round FE | Yes | Yes | Yes | Yes |
| Subject FE | Yes | Yes | Yes | Yes |
| Observations | 7902 | 7902 | 10552 | 7902 |
| R^2 | 0.25 | 0.25 | 0.21 | 0.25 |
| Mean | 0.573 | 0.573 | 0.574 | 0.573 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS, errors clustered at subject level. Neutral News indicates that Pro-Party / Anti-Party compared to Neutral News, as defined in Table 1. Controls: race, gender, log(income), education (in years), religion, whether state voted for Trump or Clinton in 2016. Partisanship is the absolute difference between Republican and Democratic ratings. Previous Pro-Party is the number of all previous pieces of news that are Pro-Party minus the number that are Anti-Party.

Figure 8: Bin-Scatter Plot of Expected Performance by Gender and True Performance



Notes: Party-indifferent subjects included. True Percentile compares subjects' score on rounds 1-12 to the scores of 100 pilot subjects. Percentile Guess is subjects' prediction of their True Percentile. Subjects binned by gender into eight True Percentile groups.

B Supplementary Appendix: Demand for News, susceptibility, and Structurally Estimating Motives

This appendix section discusses awareness of motivated reasoning and susceptibility. First, we consider subjects’ demand for a message by eliciting willingness to pay (WTP); correlations are consistent with the notion that subjects are aware that they will update from information, but not aware that they motivatedly reason in a way that decreases earnings.

Much of this section relies on an extension of the main model, making the additional assumption that susceptibility is related to the noisiness of the updating process. In particular, we modify Equation (2) as follows:

$$\text{logit } \mathbb{P}(\theta|x) = \text{logit } \mathbb{P}(\theta) + \log \left(\frac{\mathbb{P}(x|\theta)}{\mathbb{P}(x|\neg\theta)} \right) + \varphi(m(\theta) - m(\neg\theta)) + \epsilon, \quad (3)$$

where $\epsilon \sim \mathcal{N}(0, \varphi^2)$.

Agents update with noise that depends on the signal structure but is independent of the motive. The noise term is normally distributed and its standard deviation is the updated definition of susceptibility.⁴⁰

B.1 WTP Treatment Details

In round 12, half of subjects are told that they will either receive the usual message or the message with a black bar over the words “Greater Than” / “Less Than,” and are given an example of the black bar message.

They are then asked for their WTP to remove the black bar from the message. WTP is elicited by a standard Becker-DeGroot-Marschak mechanism. The units of payment are points; average points across all rounds in the experiment determine the probability of winning a \$10 bonus in the experiment.⁴¹ Subjects can choose any valuation between -25 points and 25 points. A noninteger is then chosen uniformly randomly from -25 to 25. If this number is greater than the valuation, it is added to the points on the next page and subjects see a black bar; otherwise, no points are added and the standard message is revealed.

⁴⁰If susceptibility is instead assumed linear in φ , it is hard to identify this linear multiple from a linear multiple of the motive function, which is why the extra parameter is not introduced here. Normal noise is used for simplicity, and the choice is fairly arbitrary. Results are qualitatively the same when noise is assumed to be uniform across $[-\varphi, \varphi]$, for instance.

⁴¹More technically, points are added to or subtracted from the news assessment score of that round.

Subjects are told the above, and told that positive numbers indicate that they prefer to see the message, while negative numbers indicate that they prefer not to. Since subjects see the true answers soon after this question, WTP seems to be a reasonable metric for signal valuation. Importantly, these subjects are *not* asked to give a second guess, so the only value of the message is in inferring the veracity of the news source.

B.2 Susceptibility and Demand for Messages

This subsection aims to use variance in assessments and demand for messages (WTP) to show that susceptibility, φ , is positive, and to argue that subjects are unaware of their directionally-motivated reasoning. This uses the parametrization from Equation (3); in this case, susceptibility can be empirically defined using the standard deviation of the noise in updating about topics absent motivated reasoning.

Importantly, none of the subjects in the WTP treatment is ever asked to give a second guess to any question, as this treatment was intended to capture how subjects valued messages insofar as they provide signals for news assessments. Subjects also know that they soon learn the correct answer, so the only value in seeing the message is for improving their news assessments.

This test helps show that susceptibility is positive and *expected* susceptibility is positive. If $\varphi = 0$, subjects will have $WTP = 0$ and not vary their answers. If subjects expect to have $\varphi = 0$ but actually have $\varphi > 0$, they will have $WTP = 0$ but vary their answers. If subjects expect to have $\varphi > 0$ and do have $\varphi > 0$, but don't realize that this is an error, then they will have positive WTP since they expect to perform better with the message.

Meanwhile, there is no evidence that subjects are aware of the motive part of their politically-motivated reasoning. This would come through in differences in WTP from politicized and neutral news: if subjects expected to motivatedly reason about politicized news and that this would lead to underperformance, they would have a lower WTP for these signals.

Subjects' WTP are positive and do not seem smaller for politicized topics. 71% of subjects have a strictly positive WTP. Partisanship does not lead to a significantly larger WTP for politicized topic messages. However, a larger standard deviation of previous assessments is highly correlated with WTP, suggesting that subjects genuinely expect to find these messages useful.

There are three main observations from the WTP question, all suggesting that subjects pay for messages based on their perceived expected usefulness but are not aware of the effect of politically-motivated reasoning:

1. WTP is significantly greater than zero for politicized and neutral topics, indicating that subjects do expect messages to be informative. The mean is 9 points (s.e. 1 point); this magnitude is similar to the WTP if subjects expected to move from a prior of $P(\text{True}) = 1/2$ to the empirical $P(\text{True} \mid \text{message})$ distribution (7 points, s.e. 0.2 points).
2. WTP is similar for politicized and neutral topics; that is, in this environment there is no evidence of moral wiggling or awareness about motivated reasoning.
3. WTP significantly increases in variance of $P(\text{True} \mid \text{message})$; that is, subjects are aware of their belief susceptibility.⁴²

This adds to the broader literature on meta-awareness of biases, as categorized by Gagnon-Bartsch, Rabin, and Schwartzstein 2018 and Schwartzstein 2014. The literature analyzing sophistication and naivete of other biases include base-rate neglect and present bias (for examples, see Dan Benjamin, Bodoh-Creed, and Rabin 2019, Augenblick and Rabin 2015, and O'Donoghue and Rabin 2001). This result indicates a mixed view of sophistication, in that subjects seem aware that their $\varphi > 0$ but not aware of what their m is.

⁴²Similarly, it significantly increases in the measure of subject-expected points in point 1 above.

B.3 Structural Estimation

The more precise measure of susceptibility allows for an analytical structural estimation of Equation (3). In particular, we restrict to *linear* motive functions $m(\theta) = m \cdot \theta$ and define susceptibility φ as the standard deviation of noise in subjects' updating process as above.

Then, we can estimate m up to a linear multiple under the following additional assumptions:

1. $m(\theta) = 0$ for neutral topics. This allows for identification of φ through variance in assessments on neutral topics.
2. $\varphi(x)$ is fixed across questions and individuals. The former assumes that noisiness is a function of priors and signal likelihood, but not the topic or direction of the message; this assumption is necessary to separately identify $m(\theta)$ and $\varphi(x)$.⁴³ This assumption posits that subjects first set their φ as a function of the *true* likelihood before considering their motive, and only then bias their updating. If $\varphi(x)$ is allowed to vary across individuals, the model is exactly identified and estimates are unstable.⁴⁴

Assuming that subjects have normally-distributed priors, Equation (3) can be rewritten as

$$\epsilon_{iq} = \text{logit } a_{iq} - \text{logit } \hat{p}_i - \hat{\varphi} \hat{m}_{iq} R_{iq},$$

where $\epsilon \sim \mathcal{N}(0, \hat{\varphi}^2)$,

where hatted variables are the ones to be estimated, and where $R_{iq} \equiv \mathbb{E}_i[\theta_q | \theta_q > \mu_q] - \mathbb{E}_i[\theta_q | \theta_q < \mu_q]$ is proportional to the difference between the subject's upper and lower bound guesses.⁴⁵

That is, we maximize the following log-likelihood function:

$$\begin{aligned} \sum_{i,q} \log f_{iq} &= \frac{IQ \log(2\pi)}{2} \log \hat{\varphi} \\ &+ \frac{1}{2\hat{\varphi}^2} \sum_i \left[\sum_n (\text{logit } a_{in} - \text{logit } \hat{p}_i)^2 + \sum_y (\text{logit } a_{iy} - \text{logit } \hat{p}_i - \hat{\varphi} \hat{m}_{iy} R_{iy})^2 \right], \end{aligned} \tag{4}$$

⁴³That is, $\varphi(\text{Greater Than message}) = \varphi(\text{Less Than message})$ for each question, but only because the likelihood of receiving each signal is 1/2.

⁴⁴For instance, the maximum likelihood estimate does not exist for agents who happen to give the same assessments for the three neutral questions, as the supremum of the likelihood is achieved when φ_i is arbitrarily small and $|m|$ is arbitrarily large.

⁴⁵ $R_{iq} \equiv (\text{Upper Bound}_{iq} - \text{Lower Bound}_{iq}) \cdot \frac{\sqrt{\pi}}{\text{Erfc}^{-1}(1/2)} \approx (\text{Upper Bound}_{iq} - \text{Lower Bound}_{iq}) \cdot 1.183$, where Erfc^{-1} is the inverse complementary error function.

where $i = 1, \dots, I$ indexes subjects, $q = 1, \dots, Q$ indexes all questions, $y = 1, \dots, Y$ indexes motivated questions, and $n = 1, \dots, N$ indexes neutral questions.⁴⁶

To maximize this, we take partial derivatives with respect to the parameters \hat{m}_{iq} , logit \hat{p}_i , and $\hat{\varphi}$. The following are the equations for each parameter; details are in Appendix B.5.

We end up with the following estimates:

$$\begin{aligned}\hat{m}_{iy} &= \frac{\text{logit } a_{iy} - \text{logit } \hat{p}_i}{\hat{\varphi} R_{iy}}. \\ \text{logit } \hat{p}_i &= \frac{1}{N} \sum_n \text{logit } a_{in} \\ \hat{\varphi}^2 &= \frac{1}{IQ} \sum_{i,n} (\text{logit } a_{in} - \text{logit } \hat{p}_i)^2.\end{aligned}\tag{5}$$

Estimated motives are proportional to the change from logit assessment and logit prior, and decrease in susceptibility. Estimated priors are equal to the average logit assessments on neutral questions. Estimated susceptibility is the sum of second moments of a_{iq} about the priors \hat{p}_i , divided by the total number of individuals and questions, IQ .⁴⁷

Now, we can solve the set of equations in Equation (5) for each i and q . \hat{m}_{iq} are discussed in the next section below. $\hat{\varphi}$ is estimated at 0.47. The mean estimated prior \hat{p}_i is 0.58 (s.e. 0.006), and 80 percent of subjects have estimated priors between $\frac{1}{2} - \frac{\sqrt{3}}{6} \equiv 0.211$ and $\frac{1}{2} + \frac{\sqrt{3}}{6} \equiv 0.789$, the bounds necessary for the hypothesis that confidence increases in partisanship from Hypothesis 5.

B.4 Comparing Estimated Motives Across Questions

As expected, topic-by-topic results are similar to the more reduced-form measure. We see this in Table 11 using three variants of the main predictions. First, the sign of the estimated motives are in the hypothesized direction from Table 1 on almost every question. Secondly, estimated motives are different for Pro-Rep and Pro-Dem subjects in the hypothesized direction on almost every question. Thirdly, estimated motives are positively correlated with initial guesses on almost every question.

The heterogeneity of estimated motives for one's performance compared to others are stark. The Own Performance motive is only greater than zero for male Pro-Rep subjects (0.040, s.e. 0.012, $p = 0.001$) while almost exactly zero for all other subjects (-0.004, s.e.

⁴⁶Technically, these are Q_i, Y_i , and N_i , since some subjects happen to see slightly different numbers of questions. I don't index to make the structural estimate equations easier to understand.

⁴⁷We divide by IQ instead of IN because, in maximizing the likelihood, each politicized question explains variance in posteriors entirely by motives instead of susceptibility. This feature depends on the motive function chosen.

0.008, $p = 0.592$).⁴⁸

In general, there is no interpretation of the slope of linear motives, just as there is no interpretation of the slope of a linear utility function. However, we can compare motive slopes to each other. For instance, the average $|m_{i,\text{Refugees and crime}}|$ is 0.045, the average $|m_{i,\text{Obama and crime}}|$ is 0.126, and the average $|m_{i,\text{Guns and crime}}|$ is 0.026.⁴⁹ This indicates that a 1-unit increase in crime under Barack Obama is given approximately three times the weight as a 1-unit increase in crime due to Germany’s refugee laws, and five times the weight as a 1-unit increase in crime after Australia’s gun laws.

Note that these are different scales, however. The refugee question asked about the impact on the per-100,000 violent crime rate in Germany, the Obama question asked about the per-million murder and manslaughter rate in the United States, and the gun laws question asked about the average number of victims in a 5-year period. This indicates that the *signal* of the change in crime is more important than the *number* of victims. While (after adjusting for population) the motives regarding the absolute Germany and United States crime amounts are similarly in magnitude (after correcting for population size), the number of gun deaths in Australia is so comparably small that “motives over number of deaths” would be orders of magnitude larger.

In some sense, this is reassuring, since it indicates that Republicans are not motivated to believe people are being violently attacked (due to refugees or Obama’s policies) but instead that partisans are motivated to believe in signals that their party is correct. On the other hand, it is telling that partisans have stronger motives over party signals compared to motives over loss of human lives.

⁴⁸In fact, the median estimated motive for subjects in all other gender-party subgroups are exactly zero.

⁴⁹Motives here winsorized at the 5% level due to a few extreme outliers.

B.5 Structural Estimation Calculation Details

Recall the log likelihood:

$$\begin{aligned} \sum_{i,q} \log f_{iq} &= \frac{IQ \log(2\pi)}{2} \log \hat{k} \\ &+ \frac{1}{2\hat{k}^2} \sum_i \left[\sum_n (\text{logit } a_{in} - \text{logit } \hat{p}_i)^2 + \sum_y (\text{logit } a_{iy} - \text{logit } \hat{p}_i - \hat{k}\hat{m}_{iy}R_{iy})^2 \right], \end{aligned} \quad (6)$$

where $i = 1, \dots, I$ indexes subjects, $q = 1, \dots, Q$ indexes all questions, $y = 1, \dots, Y$ indexes motivated questions, and $n = 1, \dots, N$ indexes neutral questions

Solving with respect to \hat{m}_{iq} :

$$\begin{aligned} \frac{\partial (\sum \log f_{iq})}{\partial \hat{m}_{iq}} &= 0 = \frac{1}{2\hat{\varphi}^2} (-2\hat{\varphi}R_{iy})(\text{logit } a_{iy} - \text{logit } \hat{p}_i - \hat{k}\hat{m}_{iy}R_{iy}) = 0 \\ \implies \hat{m}_{iy} &= \frac{\text{logit } a_{iy} - \text{logit } \hat{p}_i}{\hat{\varphi}R_{iy}}. \end{aligned} \quad (7)$$

Solving with respect to $\text{logit } \hat{p}_i$:

$$\begin{aligned} \frac{\partial (\sum \log f_{iq})}{\partial (\text{logit } \hat{p}_i)} &= 0 \\ &= \frac{1}{2\hat{\varphi}^2} \left[-\sum_n 2(\text{logit } a_{in} - \text{logit } \hat{p}_i) - \sum_y 2(\text{logit } a_{iy} - \text{logit } \hat{p}_i - \hat{\varphi}\hat{m}_{iy}R_{iy}) \right] \\ \implies \text{logit } \hat{p}_i &= \frac{1}{Q} \left[\sum_q \text{logit } a_{iq} - \hat{\varphi} \sum_y \hat{m}_{iy}R_{iy} \right]. \end{aligned}$$

Plugging in the estimate for \hat{m}_{iy} shows that priors are entirely identified by neutral assessments:

$$\text{logit } \hat{p}_i = \frac{1}{N} \sum_n \text{logit } a_{in}. \quad (8)$$

Solving with respect to $\hat{\varphi}$:

$$\begin{aligned}
\frac{\partial (\sum \log f_{iq})}{\partial \hat{\varphi}} &= 0 = \frac{IQ}{\hat{\varphi}} \\
&- \sum_i \left[\frac{1}{\hat{\varphi}^3} \sum_n (\text{logit } a_{in} - \text{logit } \hat{p}_i)^2 + \frac{1}{\hat{\varphi}^3} \sum_y [(\text{logit } a_{iy} - \text{logit } \hat{p}_i)(\text{logit } a_{iy} - \text{logit } \hat{p}_i - \hat{\varphi} \hat{m}_{iy} R_{iy})] \right] \\
&\implies IQ \hat{\varphi}^2 + \left[\sum_{i,y} \hat{m}_{iy} R_{iy} (\text{logit } a_{iy} - \text{logit } \hat{p}_i) \right] \hat{\varphi} \\
&- \sum_i \left[\sum_n (\text{logit } a_{in} - \text{logit } \hat{p}_i)^2 - \sum_y (\text{logit } a_{iy} - \text{logit } \hat{p}_i)^2 \right] = 0 \\
&\implies \hat{\varphi} = -\frac{1}{2IQ} \sum_{i,y} \hat{m}_{iy} R_{iy} (\text{logit } a_{iy} - \text{logit } \hat{p}_i) \\
&+ \sqrt{\left(\frac{1}{2IQ} \sum_{i,y} \hat{m}_{iy} R_{iy} (\text{logit } a_{iy} - \text{logit } \hat{p}_i) \right)^2 + \frac{1}{IQ} \sum_{i,q} (\text{logit } a_{iq} - \text{logit } \hat{p}_i)^2}.
\end{aligned}$$

Plugging in the estimate for \hat{m}_{iy} and \hat{p}_i simplifies this greatly and shows that φ is also entirely identified by neutral assessments:

$$\hat{\varphi}^2 = \frac{1}{IQ} \sum_{i,n} \left(\text{logit } a_{in} - \frac{1}{N} \sum_{i,n'} \text{logit } a_{in'} \right)^2 = \frac{1}{IQ} \sum_{i,n} (\text{logit } a_{in} - \text{logit } \hat{p}_i)^2. \quad (9)$$

Tables for Appendix B

Table 10: Determinants of Willingness-To-Pay

| | (1) | (2) | (3) | (4) |
|--------------------|---------------------|----------------------|----------------------|---------------------|
| Assessment SD | | 22.655*** (8.421) | 22.605*** (8.470) | 19.809** (8.688) |
| Politicized topics | 1.093 (1.697) | | 1.052 (1.701) | |
| Constant | 8.448*** (1.498) | 4.234** (2.078) | 3.466 (2.436) | 10.504* (5.968) |
| Question FE | No | No | No | Yes |
| Subject controls | No | No | No | Yes |
| Observations | 482 | 482 | 482 | 482 |
| R^2 | 0.00 | 0.02 | 0.02 | 0.06 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS, robust standard errors. Dependent variable is Willingness-To-Pay; this occurs in round 12. Party-indifferent subjects included. Assessment SD is the standard deviation of the subject's news veracity assessments in all other rounds. Politicized topics defined in Table 1.

Table 11: Estimated Motives: By Direction, By Party, and By Prior

| | Hyp. direction (1) | Pro-R vs. Pro-D (2) | Diff. by prior (3) |
|-----------------------|-----------------------|------------------------|-----------------------|
| Climate topic | 0.083*** (0.010) | 0.068*** (0.019) | 0.085*** (0.009) |
| Race topic | 0.075*** (0.019) | 0.029 (0.041) | 0.059*** (0.009) |
| Mobility topic | 0.032*** (0.005) | 0.039*** (0.011) | 0.021*** (0.005) |
| Refugees topic | 0.010*** (0.002) | 0.017*** (0.005) | 0.004** (0.002) |
| Obama crime topic | 0.026*** (0.006) | 0.043*** (0.013) | 0.009* (0.005) |
| Gender topic | 0.605*** (0.192) | 0.534 (0.413) | 0.279* (0.149) |
| Gun laws topic | 0.003** (0.001) | 0.001 (0.003) | 0.002 (0.001) |
| Media topic | 0.001 (0.004) | 0.018* (0.009) | 0.020*** (0.004) |
| Rep score topic | 0.029*** (0.006) | 0.073*** (0.014) | 0.021*** (0.007) |
| Dem score topic | 0.032*** (0.007) | 0.050*** (0.014) | 0.025*** (0.007) |
| Own performance topic | 0.007** (0.003) | | 0.016*** (0.004) |
| Question FE | No | Yes | Yes |
| Observations | 8785 | 7902 | 8785 |
| R^2 | 0.01 | 0.03 | 0.03 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: For each topic, estimated motives winsorized at the 5% level. Columns correspond to different independent and dependent variables. Column 1 measures the mean estimated motive by question in the direction hypothesized in Table 1. Estimated motives are multiplied by 1 for Pro-Motive and -1 for Anti-Motive. Column 2 regresses estimated motives on a dummy for Pro-Rep for each question, multiplying by the direction in Table 1. Column 2 regresses estimated motives on the z score of the initial guess for each question; the guess is winsorized at the 5% level.

C Study Materials: Exact Question Wordings

Crime Under Obama

Some people believe that the Obama administration was too soft on crime and that violent crime increased during his presidency, while others believe that President Obama's pushes towards criminal justice reform and reducing incarceration did not increase violent crime.

This question asks how murder and manslaughter rates changed during the Obama administration. In 2008 (before Obama became president), the murder and manslaughter rate was 54 per million Americans.

In 2016 (at the end of Obama's presidency), what was the per-million murder and manslaughter rate?

Correct answer: 53.

Source linked on results page: <http://bit.ly/us-crime-rate>

Upward Mobility

In 2017, Donald Trump signed into law the largest tax reform bill since Ronald Reagan's 1981 and 1986 bills. Some people believe that Reagan's reforms accelerated economic growth and allowed lower-income Americans to reap the benefits of lower taxes, while other people believe that this decreased the government's spending to help lower-income Americans get ahead.

This question asks whether children who grew up in low-income families during Reagan's tenure were able to benefit from his tax reforms.

Of Americans who were born in the lowest-income (bottom 20%) families from 1980-1985, what percent rose out of the lowest-income group as adults?

(Please guess between 0 and 100.)

Correct answer: 64.9.

Source linked on results page: <http://bit.ly/us-upward-mobility> (page 47)

Racial Discrimination

In the United States, white Americans have higher salaries than black Americans on average. Some people attribute these differences in income to differences in education, training, and culture, while others attribute them more to racial discrimination.

In a study, researchers sent fictitious resumes to respond to thousands of help-wanted ads in newspapers. The resumes sent had identical skills and education, but the researchers

gave half of the (fake) applicants stereotypically White names such as Emily Walsh and Greg Baker, and gave the other half of the applicants stereotypically Black names such as Lakisha Washington and Jamal Jones.

9.65 percent of the applicants with White-sounding names received a call back. What percent of the applicants with Black-sounding names received a call back?

(Please guess between 0 and 100.)

Correct answer: 6.45.

Source linked on results page: <http://bit.ly/labor-market-discrimination>

Gender and Math GPA

In the United States, men are more likely to enter into mathematics and math-related fields. Some people attribute this to gender differences in interest in or ability in math, while others attribute it to other factors like gender discrimination.

This question asks whether high school boys and girls differ substantially in how well they do in math classes. A major testing service analyzed data on high school seniors and compared the average GPA for male and female students in various subjects.

Male students averaged a 3.04 GPA (out of 4.00) in math classes. What GPA did female students average in math classes?

(Please guess between 0.00 and 4.00.)

Correct answer: 3.15.

Source linked on results page: <http://bit.ly/gender-hs-gpa>

Refugees and Violent Crime

Some people believe that the U.S. has a responsibility to accept refugees into the country, while others believe that an open-doors refugee policy will be taken advantage of by criminals and put Americans at risk.

In 2015, German leader Angela Merkel announced an open-doors policy that allowed all Syrian refugees who had entered Europe to take up residence in Germany. From 2015-17, nearly one million Syrians moved to Germany. This question asks about the effect of Germany's open-doors refugee policy on violent crime rates.

In 2014 (before the influx of refugees), the violent crime rate in Germany was 224.0 per hundred-thousand people.

In 2017 (after the entrance of refugees), what was the violent crime rate in Germany per hundred-thousand people?

Correct answer: 228.2.

Sources linked on results page: Main site: <http://bit.ly/germany-crime-main-site>. 2014 and 2015 data: <http://bit.ly/germany-crime-2014-2015>. 2016 and 2017 data: <http://bit.ly/germany-crime-2016-2017>.

Climate change

Some people believe that there is a scientific consensus that human activity is causing global warming and that we should have stricter environmental regulations, while others believe that scientists are not in agreement about the existence or cause of global warming and think that stricter environmental regulations will sacrifice jobs without much environmental gain.

This question asks about whether most scientists think that global warming is caused by humans. A major nonpartisan polling company surveyed thousands of scientists about the existence and cause of global warming.

What percent of these scientists believed that “Climate change is mostly due to human activity”?

(Please guess between 0 and 100.)

Correct answer: 87.

Source linked on results page: <http://bit.ly/scientists-climate-change>

Gun Reform

The United States has a homicide rate that is much higher than other wealthy countries. Some people attribute this to the prevalence of guns and favor stricter gun laws, while others believe that stricter gun laws will limit Americans’ Second Amendment rights without reducing homicides very much.

After a mass shooting in 1996, Australia passed a massive gun control law called the National Firearms Agreement (NFA). The law illegalized, bought back, and destroyed almost one million firearms by 1997, mandated that all non-destroyed firearms be registered, and required a lengthy waiting period for firearm sales.

Democrats and Republicans have each pointed to the NFA as evidence for/against stricter gun laws. This question asks about the effect of the NFA on the homicide rate in Australia.

In the five years before the NFA (1991-1996), there were 319.8 homicides per year in Australia. In the five years after the NFA (1998-2003), how many homicides were there per year in Australia?

Correct answer: 318.6.

Sources linked on results page: <http://bit.ly/australia-homicide-rate> (Suicides declined substantially, however. For details: <http://bit.ly/impact-australia-gun-laws>.)

Media Bias

Some people believe that the media is unfairly biased towards Democrats, while some believe it is balanced, and others believe it is biased towards Republicans.

This question asks whether journalists are more likely to be Democrats than Republicans.

A representative sample of journalists were asked about their party affiliation. Of those either affiliated with either the Democratic or Republican Party, what percent of journalists are Republicans?

(Please guess between 0 and 100.)

Correct answer: 19.8.

Source linked on results page: <http://bit.ly/journalist-political-affiliation>

Party Relative Performance

Subjects are randomly assigned to see either the Democrats' score (and asked to predict the Republicans' score) or to see the Republicans' score (and asked to predict the Democrats' score).

Democrats' Relative Performance

This question asks whether you think Democrats or Republicans did better on this study about political and U.S. knowledge. I've compared the average points scored by Democrats and Republicans among 100 participants (not including yourself).

The Republicans scored 70.83 points on average.

How many points do you think the Democrats scored on average?

(Please guess between 0 and 100)

Correct answer: 72.44.

Republicans' Relative Performance

This question asks whether you think Democrats or Republicans did better on this study about political and U.S. knowledge. I've compared the average points scored by Democrats and Republicans among 100 participants (not including yourself).

The Democrats scored 72.44 points on average.

How many points do you think the Republicans scored on average?
(Please guess between 0 and 100)

Correct answer: 70.83.

Own Relative Performance

How well do you think you performed on this study about political and U.S. knowledge? I've compared the average points you scored for all questions (prior to this one) to that of 100 other participants.

How many of the 100 do you think you scored higher than?
(Please guess between 0 and 100.)

Correct answer: Depends on participant's performance.

Random Number

A computer will randomly generate a number between 0 and 100. What number do you think the computer chose?

(As a reminder, it is in your best interest to guess an answer that is close to the computer's choice, even if you don't perfectly guess it.)

Correct answer: Randomly generated for each participant.

Latitude of Center of the United States

The U.S. National Geodetic Survey approximated the geographic center of the continental United States. (This excludes Alaska and Hawaii, and U.S. territories.)

How many degrees North is this geographic center?

(Please guess between 0 and 90. The continental U.S. lies in the Northern Hemisphere, the Equator is 0 degrees North, and the North Pole is 90 degrees North.)

Correct answer: 39.833.

Source linked on results page: <http://bit.ly/center-of-the-us>

Longitude of Center of the United States

The U.S. National Geodetic Survey approximated the geographic center of the continental United States. (This excludes Alaska and Hawaii, and U.S. territories.)

How many degrees West is this geographic center?

(Please guess between 0 and 180. The continental U.S. lies in the Western Hemisphere, which ranges from 0 degrees West to 180 degrees West.)

Correct answer: 98.583.

Source linked on results page: <http://bit.ly/center-of-the-us>

Comprehension Check: Current Year

In 1776 our fathers brought forth, upon this continent, a new nation, conceived in Liberty, and dedicated to the proposition that all men are created equal.

What is the year right now?

This is not a trick question and the first sentence is irrelevant; this is a comprehension check to make sure you are paying attention. For this question, your lower and upper bounds should be equal to your guess if you know what year it currently is.

Correct answer: 2018.

Source linked on results page: <http://bit.ly/what-year-is-it>

D Replication

I preregistered a replication for the findings from this paper. In particular, I ran this in conjunction with a debiasing treatment; the replication tests whether the control group from that sample satisfies the hypotheses from this experiment. This section reports all replication results that were specified in the pre-analysis plan in Thaler (2019).

There are a few differences between the replication sample and the original sample. The replication was conducted approximately one year later, on July 8-9, 2019. The replication questions included additional topics and variants of the original questions.⁵⁰ There were no neutral questions.

The sample includes 1,050 subjects recruited from Amazon’s Mechanical Turk platform that passed pre-specified comprehension checks that are akin to those in the original experiment. 356 subjects never received a treatment and 694 subjects received a treatment after the end of round 3. As such, the control group includes 1,050 subjects for the first three rounds, and 356 subjects in the remaining rounds. The debiasing treatment group observations are dropped from all analyses. There are 982 subjects who are either Pro-Rep or Pro-Dem, and these subjects give 5,314 news veracity assessments on politicized topics.

D.1 Primary Outcomes

The most important primary outcome results are strongly replicated. As seen in the first column of Table 12, subjects give statistically significantly higher assessments to Pro-Party news than to Anti-Party news ($p < 0.001$).⁵¹ The second column shows that this gap is increasing in partisanship ($p = 0.006$).

The next-most important primary outcome results are strongly replicated. Table 12 shows that subjects give statistically significantly higher assessments to Fake News than to True News. This holds both when Pro-Party / Anti-Party news is not controlled for (column 3) and when Pro-Party / Anti-Party news is controlled for (column 4); both results are significant at $p < 0.001$.

⁵⁰In particular, two new politicized topics were added: Wage Growth and Healthcare. On six of the politicized topics, subjects received different versions of the original question as part of a separate experiment on positivity-motivated reasoning.

⁵¹The coefficient is smaller in the replication, due in large part to the new added questions. On the questions with the exact same wording as the original study, the treatment effect for is 7.1 percentage points (s.e. 1.2 percentage points). On other politicized questions, the treatment effect is 3.5 percentage points (s.e. 1.0 percentage points). Of the original questions, the effects on the following topics were significant at $p < 0.05$ in the predicted direction: Climate Change, Race, Refugees, Gun Laws, Party Performance, Own Performance. The effects on the following topics were not significant at $p < 0.05$: Obama and Crime, Gender, Media.

The main alternative measure of motivated reasoning is suggestively replicated. As seen in the first column of Table 13, results suggest that subjects are more likely to update in the direction of the Pro-Party message compared to the Anti-Party message ($p = 0.055$).⁵² The third column shows that, as in Section 5.4, this difference vanishes once the news veracity assessment measure is controlled for.

D.2 Secondary Outcomes

The underperformance result is strongly replicated. Subjects score 66.3 points (s.e. 0.4 points) on politicized news assessments and 65.5 points (s.e. 1.6 points) on performance news assessments on average. Both of these are statistically significantly lower than 75 points, the score that subjects would receive if they had answered “5/10 chance the message came from True News” ($p < 0.001$).

The result that subjects’ confidence intervals are overprecise is strongly replicated. On politicized topics, subjects’ 50 percent confidence intervals contain the correct answer 44.1 percent of the time (s.e. 0.8 percent); this is statistically significantly different from 50 percent ($p < 0.001$). As seen in Table 14, the result that this measure of overprecision is increasing in partisanship is suggestive ($p = 0.066$).

The two polarization results are replicated. On politicized topics, Table 13 shows that subjects are statistically significantly more likely to follow Polarizing news than anti-Polarizing news ($p = 0.031$).⁵³ Subjects also state initial medians that are more likely to be in the Pro-Party direction ($p < 0.001$).

D.3 Untested Replications

I did not register replication tests for other results. Given the limited sample size, there would be insufficient statistical power for detecting effect sizes similar to the ones in the original experiment. Performance-driven motivated reasoning and overconfidence tests were not pre-specified.⁵⁴ Demographic heterogeneity, robustness exercises, and minor results were also not tested. Further work can test whether these results replicate on a larger sample.

⁵²As with the main effect, the coefficient is smaller in the replication, due in large part to the new questions. On the questions with the exact same wording as the original study, the treatment effect for is 5.7 percentage points (s.e. 2.6 percentage points). On other politicized questions, the treatment effect is 2.0 percentage points (s.e. 2.6 percentage points).

⁵³As in Section 5.4, this difference vanishes once the news assessment measure is controlled for.

⁵⁴Results, however, are broadly similar to those in the main experiment. For instance, subjects assess Pro-Performance news to be 8.0 percentage points higher than Anti-Performance news (s.e. 2.6 percentage points; $p = 0.003$). Subjects expect to place 7.2 percentiles higher than they actually place relative to 100 pilot subjects (s.e. 1.6 percentiles; $p < 0.001$). Both of these are only significant for male subjects.

Replication Tables

Table 12: The Effect of News Direction and Actual Veracity on Perceived Veracity: Replication

| | (1) | (2) | (3) | (4) |
|-----------------------------|---------------------|---------------------|----------------------|----------------------|
| Pro-Party News | 0.053*** (0.009) | 0.010 (0.018) | | 0.046*** (0.009) |
| Partisanship x Pro-Party | | 0.044*** (0.016) | | |
| True News | | | -0.043*** (0.009) | -0.033*** (0.009) |
| Question FE | Yes | Yes | Yes | Yes |
| Round FE | Yes | Yes | Yes | Yes |
| Subject FE | Yes | Yes | Yes | Yes |
| Observations | 5314 | 5314 | 5314 | 5314 |
| R^2 | 0.32 | 0.32 | 0.32 | 0.33 |
| Mean | 0.578 | 0.578 | 0.578 | 0.578 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS, errors clustered at subject level. Only Pro-Party / Anti-Party news observations. Partisanship is the absolute difference between ratings of the Republican and Democratic parties.

Table 13: Changing Guess to Follow Message Given News Direction: Replication

| | (1) | (2) | (3) | (4) |
|-----------------|---------|---------|----------|----------|
| Pro-Party News | 0.038* | | -0.020 | |
| | (0.020) | | (0.018) | |
| Polarizing News | | 0.040** | | -0.018 |
| | | (0.019) | | (0.017) |
| P(True) | | | 1.108*** | 1.107*** |
| | | | (0.055) | (0.055) |
| Question FE | Yes | Yes | Yes | Yes |
| Round FE | Yes | Yes | Yes | Yes |
| Subject FE | Yes | Yes | Yes | Yes |
| Observations | 5314 | 5314 | 5314 | 5314 |
| R^2 | 0.34 | 0.34 | 0.48 | 0.48 |
| Mean | 0.654 | 0.654 | 0.654 | 0.654 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS, errors clustered at subject level. Partisanship is the absolute difference between ratings of the Republican and Democratic parties. Only Pro-Party / Anti-Party news observations. Polarizing News is defined as news that tells subjects that, compared to their initial guess, the answer is in the opposite direction from the population mean. Dependent variable is 1 if subjects change their guess upwards when the message says “Greater Than” or downwards when the message says “Less Than,” -1 if they change their guess in the opposite direction, and 0 if they do not change their guess.

Table 14: Overprecision and Partisanship: Replication

| | (1) | (2) |
|------------------|---------|---------|
| Partisanship | 0.055* | 0.055* |
| | (0.030) | (0.030) |
| Subject controls | No | Yes |
| Observations | 5314 | 5314 |
| R^2 | 0.00 | 0.01 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS, errors clustered at subject level. Only politicized topics included. Partisanship is the absolute difference between ratings of the Republican and Democratic parties. Subject controls are race, gender, age, log(income), education, religion, and whether home state voted for Trump or Clinton in 2016.

E Online Appendix: Additional Robustness for Table 2

This section presents additional robustness checks for the main results in Table 2. These results are similar for each treatment, if subjects who fail comprehension checks are included instead of excluded, and if the dependent variable is the logit probability of news veracity assessments instead of the assessments themselves.

Main Results by Treatment

First, we look at Table 2 by treatment; recall that there are two independent treatment arms. For the first treatment arm, half of subjects are asked to give a second guess to the original question in addition to their news veracity assessment after receiving the message; the other half do not, but have one round in which their willingness-to-pay for a message is elicited.

For the second treatment arm, one-third of subjects are told in the instructions that “Whether you get your message from True News or Fake News is random *and each source is equally likely*.” The other two-thirds are told that “Whether you get your message from True News or Fake News is random.” That is, one-third of subjects are given a 50-50 prior, and the other two-thirds are not.

The main takeaway is that neither treatment arm substantially affects the main results, and neither arm affects the mean veracity assessment.

Table 15: The Effect of News Direction and Actual Veracity on Perceived Veracity: Second-Guess Treatment

| | (1) | (2) | (3) | (4) | (5) | (6) |
|-----------------------------|---------------------|---------------------|---------------------|----------------------|----------------------|----------------------|
| Pro-Party News | 0.090*** (0.009) | 0.092*** (0.010) | 0.040** (0.019) | 0.031*** (0.009) | | 0.081*** (0.010) |
| Partisanship x Pro-Party | | | 0.055*** (0.018) | | | |
| Anti-Party News | | | | -0.057*** (0.010) | | |
| True News | | | | | -0.061*** (0.009) | -0.035*** (0.009) |
| Neutral News | No | No | No | Yes | No | No |
| Question FE | Yes | Yes | Yes | No | Yes | Yes |
| Round FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Subject controls | Yes | No | No | No | No | No |
| Subject FE | No | Yes | Yes | Yes | Yes | Yes |
| Observations | 4085 | 4085 | 4085 | 5455 | 4085 | 4085 |
| R^2 | 0.05 | 0.24 | 0.25 | 0.20 | 0.23 | 0.25 |
| Mean | 0.577 | 0.577 | 0.577 | 0.580 | 0.577 | 0.577 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS, errors clustered at subject level. Neutral News indicates that Pro-Party / Anti-Party news assessments are compared to assessments on Neutral topics. These classifications are defined in Table 1. Controls: race, gender, log(income), years of education, religion, and state. Partisanship is the absolute difference between ratings of the Republican and Democratic parties. Observations only for Second-Guess treatment.

Table 16: The Effect of News Direction and Actual Veracity on Perceived Veracity: Willingness-to-Pay Treatment

| | (1) | (2) | (3) | (4) | (5) | (6) |
|-----------------------------|---------------------|---------------------|---------------------|----------------------|----------------------|----------------------|
| Pro-Party News | 0.095*** (0.009) | 0.085*** (0.009) | 0.040** (0.018) | 0.043*** (0.010) | | 0.074*** (0.009) |
| Partisanship x Pro-Party | | | 0.045*** (0.015) | | | |
| Anti-Party News | | | | -0.039*** (0.010) | | |
| True News | | | | | -0.056*** (0.009) | -0.032*** (0.009) |
| Neutral News | No | No | No | Yes | No | No |
| Question FE | Yes | Yes | Yes | No | Yes | Yes |
| Round FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Subject controls | Yes | No | No | No | No | No |
| Subject FE | No | Yes | Yes | Yes | Yes | Yes |
| Observations | 3817 | 3817 | 3817 | 5097 | 3817 | 3817 |
| R^2 | 0.05 | 0.25 | 0.25 | 0.22 | 0.24 | 0.26 |
| Mean | 0.569 | 0.569 | 0.569 | 0.568 | 0.569 | 0.569 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS, errors clustered at subject level. Neutral News indicates that Pro-Party / Anti-Party news assessments are compared to assessments on Neutral topics. These classifications are defined in Table 1. Controls: race, gender, log(income), years of education, religion, and state. Partisanship is the absolute difference between ratings of the Republican and Democratic parties. Observations only for Willingness-to-Pay treatment.

Table 17: The Effect of News Direction and Actual Veracity on Perceived Veracity: Given 50-50 Prior Treatment

| | (1) | (2) | (3) | (4) | (5) | (6) |
|-----------------------------|---------------------|---------------------|---------------------|----------------------|----------------------|---------------------|
| Pro-Party News | 0.090*** (0.011) | 0.088*** (0.011) | 0.068*** (0.021) | 0.046*** (0.011) | | 0.078*** (0.012) |
| Partisanship x Pro-Party | | | 0.021 (0.019) | | | |
| Anti-Party News | | | | -0.040*** (0.013) | | |
| True News | | | | | -0.056*** (0.011) | -0.029** (0.012) |
| Neutral News | No | No | No | Yes | No | No |
| Question FE | Yes | Yes | Yes | No | Yes | Yes |
| Round FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Subject controls | Yes | No | No | No | No | No |
| Subject FE | No | Yes | Yes | Yes | Yes | Yes |
| Observations | 2674 | 2674 | 2674 | 3568 | 2674 | 2674 |
| R^2 | 0.06 | 0.27 | 0.27 | 0.22 | 0.25 | 0.27 |
| Mean | 0.572 | 0.572 | 0.572 | 0.571 | 0.572 | 0.572 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS, errors clustered at subject level. Neutral News indicates that Pro-Party / Anti-Party news assessments are compared to assessments on Neutral topics. These classifications are defined in Table 1. Controls: race, gender, log(income), years of education, religion, and state. Partisanship is the absolute difference between ratings of the Republican and Democratic parties. Observations only for Given 50-50 Prior treatment.

Table 18: The Effect of News Direction and Actual Veracity on Perceived Veracity:
Not Given 50-50 Prior Treatment

| | (1) | (2) | (3) | (4) | (5) | (6) |
|-----------------------------|---------------------|---------------------|---------------------|----------------------|----------------------|----------------------|
| Pro-Party News | 0.093*** (0.008) | 0.088*** (0.008) | 0.024 (0.016) | 0.033*** (0.008) | | 0.077*** (0.008) |
| Partisanship x Pro-Party | | | 0.065*** (0.014) | | | |
| Anti-Party News | | | | -0.052*** (0.009) | | |
| True News | | | | | -0.061*** (0.008) | -0.037*** (0.008) |
| Neutral News | No | No | No | Yes | No | No |
| Question FE | Yes | Yes | Yes | No | Yes | Yes |
| Round FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Subject controls | Yes | No | No | No | No | No |
| Subject FE | No | Yes | Yes | Yes | Yes | Yes |
| Observations | 5228 | 5228 | 5228 | 6984 | 5228 | 5228 |
| R^2 | 0.05 | 0.24 | 0.24 | 0.20 | 0.22 | 0.24 |
| Mean | 0.574 | 0.574 | 0.574 | 0.576 | 0.574 | 0.574 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS, errors clustered at subject level. Neutral News indicates that Pro-Party / Anti-Party news assessments are compared to assessments on Neutral topics. These classifications are defined in Table 1. Controls: race, gender, log(income), years of education, religion, and state. Partisanship is the absolute difference between ratings of the Republican and Democratic parties. Observations only for Not Given 50-50 Prior treatment.

Results Without Comprehension Checks

The main results do not include subjects who fail attention and comprehension checks. As such, 313 of 1300 subjects are removed from the analysis. This subsection does the analysis without remove any subjects. Results are directionally identical when all subjects are included.

Table 19: The Effect of News Direction and Actual Veracity on Perceived Veracity: Including Subjects Who Fail Comprehension Checks

| | (1) | (2) | (3) | (4) | (5) | (6) |
|-----------------------------|---------------------|---------------------|---------------------|----------------------|----------------------|----------------------|
| Pro-Party News | 0.075*** (0.005) | 0.071*** (0.006) | 0.027*** (0.010) | 0.031*** (0.006) | | 0.064*** (0.006) |
| Partisanship x Pro-Party | | | 0.048*** (0.010) | | | |
| Anti-Party News | | | | -0.038*** (0.006) | | |
| True News | | | | | -0.043*** (0.006) | -0.026*** (0.006) |
| Neutral News | No | No | No | Yes | No | No |
| Question FE | Yes | Yes | Yes | No | Yes | Yes |
| Round FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Subject controls | Yes | No | No | No | No | No |
| Subject FE | No | Yes | Yes | Yes | Yes | Yes |
| Observations | 10478 | 10478 | 10478 | 13991 | 10478 | 10478 |
| R^2 | 0.03 | 0.30 | 0.30 | 0.27 | 0.29 | 0.30 |
| Mean | 0.560 | 0.560 | 0.560 | 0.561 | 0.560 | 0.560 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS, errors clustered at subject level. Neutral News indicates that Pro-Party / Anti-Party news assessments are compared to assessments on Neutral topics. These classifications are defined in Table 1. Controls: race, gender, log(income), years of education, religion, and state. Partisanship is the absolute difference between ratings of the Republican and Democratic parties. Observations *include* subjects who failed comprehension checks.

Results Using Logit Veracity Assessments

The model suggests that the relevant dependent variable is $\text{logit}(P(\text{True}))$ instead of $P(\text{True})$. Table 20 is the same as Table 2 but with this new dependent variable. Technically, since $\text{logit}(0)$ and $\text{logit}(1)$ are undefined, they are replaced here with $\text{logit}(0.025)$ and $\text{logit}(0.975)$.⁵⁵

Table 20: The Effect of News Direction and Actual Veracity on Perceived Veracity: Logit Veracity Assessments

| | (1) | (2) | (3) | (4) | (5) | (6) |
|-----------------------------|---------------------|---------------------|---------------------|----------------------|----------------------|----------------------|
| Pro-Party News | 0.507*** (0.037) | 0.486*** (0.039) | 0.208*** (0.076) | 0.165*** (0.041) | | 0.423*** (0.040) |
| Partisanship x Pro-Party | | | 0.287*** (0.068) | | | |
| Anti-Party News | | | | -0.302*** (0.044) | | |
| True News | | | | | -0.330*** (0.038) | -0.193*** (0.038) |
| Neutral News | No | No | No | Yes | No | No |
| Question FE | Yes | Yes | Yes | No | Yes | Yes |
| Round FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Subject controls | Yes | No | No | No | No | No |
| Subject FE | No | Yes | Yes | Yes | Yes | Yes |
| Observations | 7902 | 7902 | 7902 | 10552 | 7902 | 7902 |
| R^2 | 0.04 | 0.25 | 0.25 | 0.21 | 0.23 | 0.25 |
| Mean | 0.391 | 0.391 | 0.391 | 0.405 | 0.391 | 0.391 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Dependent variable is $\text{logit}(P(\text{True}))$. OLS, errors clustered at subject level. Neutral News indicates that Pro-Party / Anti-Party news assessments are compared to assessments on Neutral topics. These classifications are defined in Table 1. Controls: race, gender, $\log(\text{income})$, years of education, religion, and state. Partisanship is the absolute difference between ratings of the Republican and Democratic parties.

⁵⁵Subjects choose $P(\text{True}) = 0$ to maximize expected earnings if and only if they believe $P(\text{True}) \in [0, 0.05]$. 0.025 is the midpoint of this range. Results are similar if 0.05 is chosen or if these observations are removed.

Table 21: The Effect of News Direction and Actual Veracity on Perceived Veracity: Rounds 1-6

| | (1) | (2) | (3) | (4) | (5) | (6) |
|-----------------------------|---------------------|---------------------|--------------------|----------------------|----------------------|---------------------|
| Pro-Party News | 0.080*** (0.009) | 0.077*** (0.011) | 0.047** (0.021) | 0.030*** (0.010) | | 0.069*** (0.011) |
| Partisanship x Pro-Party | | | 0.031* (0.019) | | | |
| Anti-Party News | | | | -0.045*** (0.011) | | |
| True News | | | | | -0.046*** (0.011) | -0.024** (0.011) |
| Neutral News | No | No | No | Yes | No | No |
| Question FE | Yes | Yes | Yes | No | Yes | Yes |
| Round FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Subject controls | Yes | No | No | No | No | No |
| Subject FE | No | Yes | Yes | Yes | Yes | Yes |
| Observations | 3521 | 3521 | 3521 | 4919 | 3521 | 3521 |
| R^2 | 0.04 | 0.36 | 0.36 | 0.28 | 0.35 | 0.36 |
| Mean | 0.562 | 0.562 | 0.562 | 0.563 | 0.562 | 0.562 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS, errors clustered at subject level. Neutral News indicates that Pro-Party / Anti-Party news assessments are compared to assessments on Neutral topics. These classifications are defined in Table 1. Controls: race, gender, log(income), years of education, religion, and state. Partisanship is the absolute difference between ratings of the Republican and Democratic parties. Observations only for rounds 1-6.

Table 22: The Effect of News Direction and Actual Veracity on Perceived Veracity: Rounds 7-12

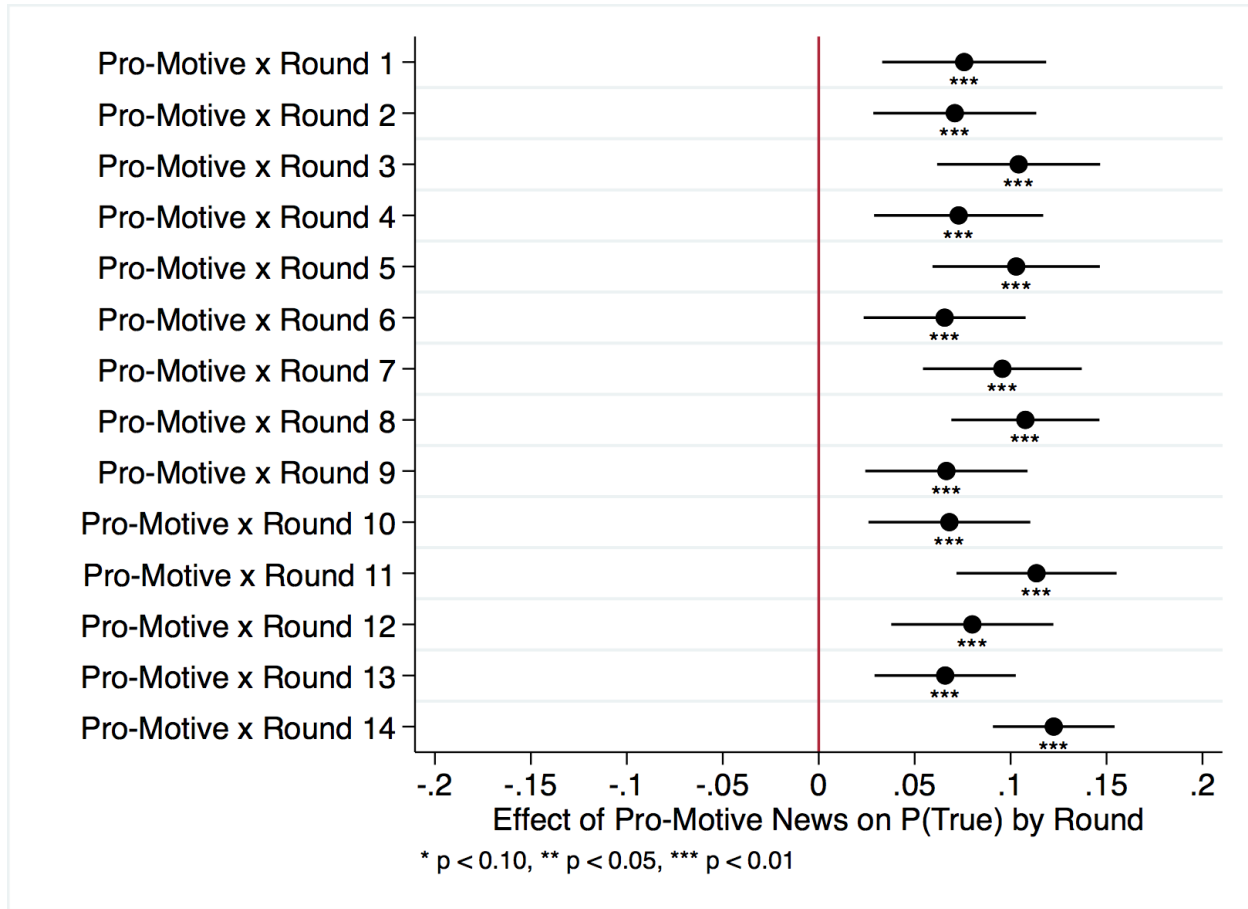
| | (1) | (2) | (3) | (4) | (5) | (6) |
|-----------------------------|---------------------|---------------------|---------------------|----------------------|----------------------|----------------------|
| Pro-Party News | 0.095*** (0.009) | 0.090*** (0.011) | 0.042* (0.022) | 0.040*** (0.010) | | 0.078*** (0.011) |
| Partisanship x Pro-Party | | | 0.050*** (0.019) | | | |
| Anti-Party News | | | | -0.046*** (0.011) | | |
| True News | | | | | -0.067*** (0.011) | -0.044*** (0.011) |
| Neutral News | No | No | No | Yes | No | No |
| Question FE | Yes | Yes | Yes | No | Yes | Yes |
| Round FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Subject controls | Yes | No | No | No | No | No |
| Subject FE | No | Yes | Yes | Yes | Yes | Yes |
| Observations | 3485 | 3485 | 3485 | 4737 | 3485 | 3485 |
| R^2 | 0.04 | 0.37 | 0.37 | 0.30 | 0.36 | 0.37 |
| Mean | 0.586 | 0.586 | 0.586 | 0.587 | 0.586 | 0.586 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS, errors clustered at subject level. Neutral News indicates that Pro-Party / Anti-Party news assessments are compared to assessments on Neutral topics. These classifications are defined in Table 1. Controls: race, gender, log(income), years of education, religion, and state. Partisanship is the absolute difference between ratings of the Republican and Democratic parties. Observations only for rounds 7-12.

Figure 9: Round-by-Round Effects of News Direction on Perceived Veracity



Notes: OLS regression coefficients, errors clustered at subject level. FE included for round number and topic. Pro-Motive (vs. Anti-Motive) news is defined in Table 1. Error bars correspond to 95 percent confidence intervals.

F Online Appendix: Study Materials

F.1 Flow of Experiment

Subjects see a series of pages in the following order:

- Introduction and Consent
- Demographics and Current Events Quiz
- Opinions
- Instructions for Question Pages
- Question 1
- Instructions for News Assessment Pages
- News Assessment 1
- Question 2, News Assessment 2, . . . , Question 14, News Assessment 14
- Feedback
- Results and Payment

Screenshots for each of the pages are in the following subsection. Exact question wordings are in the following subsection. Red boxes are not shown to subjects and are included for illustration purposes only. Results pages here are cut off after three questions, but all results are shown to subjects. Choices on the Demographics page and statements on the Opinions page are randomly ordered.

Subjects in the Willingness-To-Pay treatment see the News Valuation page between Question 12 and News Assessment 12. They see the black bar page if their elicited valuation is lower than the random number.

Subjects in the Second Guess treatment see the version of the News Assessment page with the message “After seeing this message and assessing its truthfulness, what is your guess of the answer to the original question?”

F.2 Study Materials

Introduction

You are invited to participate in this online study on political attitudes. This is a research project being conducted by Michael Thaler, a PhD student in economics at Harvard University.

Your participation in this survey is entirely voluntary. You may refuse to take part in the research or exit the survey at any time without penalty.

If you choose to be in the study, you will complete a series of questions related to issues affecting the United States today. The study should take approximately 20 minutes to complete, but you may take up to 45 minutes. You will have a chance to earn a bonus of \$10.00 in addition to your participation earnings.

Your specific answers will not be shared with anyone, and for the purpose of privacy please do not include your name or other personally identifiable information in your responses. Please make sure to mark your Amazon Profile as private if you do not want it to be accessible via your Mechanical Turk Worker ID.

If you have any questions or concerns, please contact Michael Thaler at michaelthaler@g.harvard.edu.

You may print or save a copy of this information sheet for your own records. **Please do not press the back button, refresh, or leave the page at any time or else you might have a server error; if this happens, you will not be able to reenter the study or earn your payment.**

If you wish to participate in the study, please indicate below that you have read the instructions and enter your Mechanical Turk Worker ID for payment.

What is your MTurk Worker ID number? This is required for payment.

☐ I have read the above information and would like to participate in the study.

Next

Demographic Information and Current Events Quiz

It is important for this study that you answer these questions honestly.

Your earnings and bonus are not affected by your answers to these questions.

What is your age?

What is your gender?

- ☐ Male
- ☐ Female
- ☐ Other / Prefer not to answer

What is your race/ethnicity?

- ☐ Hispanic or Latino
- ☐ Asian
- ☐ White
- ☐ American Indian
- ☐ Black or African American
- ☐ Two or more of these
- ☐ Other / Prefer not to answer

What is the highest level of education you have completed?

- ☐ Did not graduate high school
- ☐ High school graduate or GED
- ☐ Began college, no degree
- ☐ Associate's degree
- ☐ Bachelor's degree
- ☐ Postgraduate or professional degree

What religious group do you consider yourself affiliated with?

- ☐ Mainline Protestant
- ☐ Historically black Protestant
- ☐ Evangelical Protestant
- ☐ Catholic
- ☐ Other Christian
- ☐ Jewish
- ☐ Muslim
- ☐ Other religion or faith
- ☐ Atheist
- ☐ Agnostic
- ☐ Unaffiliated

Which US state or territory do you currently live in?

What was your total household income before taxes during the past 12 months?

- ☐ Less than \$20,000
- ☐ \$20,000 to \$29,999
- ☐ \$30,000 to \$39,999
- ☐ \$40,000 to \$49,999
- ☐ \$50,000 to \$69,999
- ☐ \$70,000 to \$99,999
- ☐ \$100,000 to \$149,999
- ☐ \$150,000 or more

In politics today, do you consider yourself a Republican, a Democrat, or an Independent?

- ☐ Democrat
- ☐ Republican
- ☐ Independent

Where do you see yourself on the liberal/conservative spectrum?

- ☐ Extremely liberal
- ☐ Liberal
- ☐ Slightly liberal
- ☐ Moderate
- ☐ Slightly conservative
- ☐ Conservative
- ☐ Extremely conservative

Please rate how you feel about the Republican Party using a scale of 0 to 100. The higher the number, the more favorable you feel toward the Republican Party.



Please rate how you feel about the Democratic Party using a scale of 0 to 100. The higher the number, the more favorable you feel toward the Democratic Party.



Who is the current President of France?

- ☐ Theresa May
- ☐ Charles de Gaulle
- ☐ Emmanuel Macron
- ☐ Marine Le Pen
- ☐ Justin Trudeau

Who won the recent special election in Alabama for the U.S. Senate?

- ☐ Doug Jones
- ☐ Roy Moore
- ☐ Richard Shelby
- ☐ Luther Strange
- ☐ Thad Cochran

Who was Hillary Clinton's running mate in the 2016 presidential election?

- ☐ Martin O'Malley
- ☐ Jim Webb
- ☐ Joe Biden
- ☐ Bernie Sanders
- ☐ Tim Kaine

Who is the most recently-appointed Supreme Court Justice?

- ☐ Merrick Garland
- ☐ Anthony Kennedy
- ☐ John Roberts
- ☐ Stephen Breyer
- ☐ Neil Gorsuch

Next

Opinions

For each of the following statements, please indicate whether you agree or disagree.

Your earnings and bonus are not affected by your answers to these questions.

| | | | | | |
|---|--------------------------------------|--------------------------------------|--|---|---|
| Donald Trump is doing a good job as president. | <input type="radio"/> Strongly agree | <input type="radio"/> Somewhat agree | <input type="radio"/> Neither agree nor disagree | <input type="radio"/> Somewhat disagree | <input type="radio"/> Strongly disagree |
| The United States media tends to be biased in favor of Democrats over Republicans. | <input type="radio"/> Strongly agree | <input type="radio"/> Somewhat agree | <input type="radio"/> Neither agree nor disagree | <input type="radio"/> Somewhat disagree | <input type="radio"/> Strongly disagree |
| One reason why there are more men than women working in science, technology, engineering, and math is that men are inherently more interested in these fields. | <input type="radio"/> Strongly agree | <input type="radio"/> Somewhat agree | <input type="radio"/> Neither agree nor disagree | <input type="radio"/> Somewhat disagree | <input type="radio"/> Strongly disagree |
| The Obama administration did a good job at dealing with violent crime. | <input type="radio"/> Strongly agree | <input type="radio"/> Somewhat agree | <input type="radio"/> Neither agree nor disagree | <input type="radio"/> Somewhat disagree | <input type="radio"/> Strongly disagree |
| The United States has a responsibility to accept refugees into the country. | <input type="radio"/> Strongly agree | <input type="radio"/> Somewhat agree | <input type="radio"/> Neither agree nor disagree | <input type="radio"/> Somewhat disagree | <input type="radio"/> Strongly disagree |
| Racial discrimination is a major reason why many black people can't get ahead these days. | <input type="radio"/> Strongly agree | <input type="radio"/> Somewhat agree | <input type="radio"/> Neither agree nor disagree | <input type="radio"/> Somewhat disagree | <input type="radio"/> Strongly disagree |
| Gun laws should be more strict than they are today. | <input type="radio"/> Strongly agree | <input type="radio"/> Somewhat agree | <input type="radio"/> Neither agree nor disagree | <input type="radio"/> Somewhat disagree | <input type="radio"/> Strongly disagree |
| There is solid evidence that the Earth is getting warmer and that this is due to human activity. | <input type="radio"/> Strongly agree | <input type="radio"/> Somewhat agree | <input type="radio"/> Neither agree nor disagree | <input type="radio"/> Somewhat disagree | <input type="radio"/> Strongly disagree |
| The recent tax reform bill will help lower-income Americans get ahead. | <input type="radio"/> Strongly agree | <input type="radio"/> Somewhat agree | <input type="radio"/> Neither agree nor disagree | <input type="radio"/> Somewhat disagree | <input type="radio"/> Strongly disagree |

Next

Instructions for Question Pages

Throughout this study, you will see several types of pages, including 14 Question pages.

On each of the Question pages, you will be asked to guess the answer to a factual question; each question has a correct numerical answer. In addition to your guaranteed HIT payment, you will have a chance to win an additional bonus of \$10.00 based on your guesses to these questions and questions on other pages. At least one question is an "attention check" for which the correct answer will be obvious.

You will also be asked to provide an upper bound and lower bound for your guess. You should choose these bounds in a way such that you think the answer has a 50% chance of falling between your bounds. The more confident you are, the smaller the difference should be between your upper and lower bound.

The details of the point system used to determine your chance of winning the prize are a bit complicated, but explained below if you are interested. **What is important to know is that the way your earnings are determined ensures that your chances of winning the bonus are maximized by carefully and honestly answering these questions.**

At the end of the study, the points you receive on all choices you make will be averaged, and this will determine the chance (out of 1000) that you win the bonus. For example, if you earn 90 points on average, you will have a 90 out of 1000 chance of winning the bonus.

Your final score, whether you won the prize, and a list of correct answers and sources will be provided at the end of the study.

You will see a Question page on the next screen.

Point system for your guess:

You will receive between 0 and 100 points for each guess you give. The closer your guess is to the correct answer, the more likely it is that you'll win the prize.

If you guess the answer correctly, you will receive 100 points (the maximum) for that question.

If your guess is more than 100 away from the answer, you will receive 0 points for that question.

If your guess is less than 100 away from the answer, you will receive points equal to 100 minus the distance from your guess to the correct answer.

It is in your best interest to guess an answer that is in the "middle" of what you believe is likely. For example, if you think the answer is equally likely to be 10, 40, and 60, you should guess 40.

Point system for your bounds:

*If the answer is **above** your **upper** bound, you will receive points equal to 100 minus 3 times the distance from your guess to the correct answer.*

*If the answer is **below** your **upper** bound, you will receive points equal to 100 minus the distance from your guess to the correct answer.*

*If the answer is **above** your **lower** bound, you will receive points equal to 100 minus the distance from your guess to the correct answer.*

*If the answer is **below** your **lower** bound, you will receive points equal to 100 minus 3 times the distance from your guess to the correct answer.*

You cannot earn negative points. All negative point values will be rounded up to zero.

It is in your best interest to choose a lower bound such that you think it's 3 times more likely to be above the bound than below it, and an upper bound such that it's 3 times more likely to be below the bound than above it. For example, if you think the answer is equally likely to be any number from 100 to 200, you should set a lower bound of 125 and an upper bound of 175.

Question

Question 1 of 14: Crime Under Obama

Some people believe that the Obama administration was too soft on crime and that violent crime increased during his presidency, while others believe that President Obama's pushes towards criminal justice reform and reducing incarceration did not increase violent crime.

This question asks how murder and manslaughter rates changed during the Obama administration. In 2008 (before Obama became president), the murder and manslaughter rate was 54 per million Americans.

In 2016 (at the end of Obama's presidency), what was the per-million murder and manslaughter rate?

My guess:

My lower bound:

My upper bound:

Please choose your bounds so that you think there's a 50% chance that the answer is between the bounds.

Next

Figure 10: Crime Under Obama question page.

Instructions for News Assessment Pages

After most Question pages, you will see a News Assessment page.

There has been a growing debate about the accuracy of news sources, with both the left and the right accusing each other's primary media of spreading "Fake News." News sources like CNN and Fox News have reported extensively on topics such as crime, global warming, and gun laws; some give factual information, while others may distort the truth or lie outright. This part of the study is testing whether people can recognize Fake News and True News.

On each News Assessment page, you will see the previous Question page and be given a message related to your previous guess from either a True News source or Fake News source. In addition to your guaranteed HIT payment, you will have a chance to win an additional bonus of \$10.00 based on your answers to these questions and questions on other pages. The message will say either "The answer is *greater than* your previous guess" or "The answer is **less than** your previous guess."

The True News source will *always* tell you the truth, while the Fake News source will *never* tell the truth.

If the answer truly is greater than your previous guess, True News will tell you "The answer is *greater than* your previous guess" and Fake News will tell you "The answer is *less than* your previous guess."

If the answer truly is less than your previous guess, True News will tell you "The answer is *less than* your previous guess" and Fake News will tell you "The answer is *greater than* your previous guess."

Whether you get your message from True News or Fake News is random; different messages may come from different sources. Seeing Fake News on one page does not affect the chances of seeing Fake News on any other page.

After each question, you will assess whether you think it is more likely that the source is True News or Fake News on a scale of 0/10 to 10/10, and your assessment will determine how many points you will earn for that page.

The details of the point system to determine your chance of winning the prize are a bit complicated, but explained below if you are interested. **What is important to know is that the way your earnings are determined ensures that your chances of winning the bonus are maximized by carefully and honestly answering these questions.**

Your final score, whether you won the prize, and a list of correct answers and sources will be provided at the end of the study.

You will see a News Assessment page on the next screen.

Point system:

| Your estimate | Points earned if the source is True News | Points earned if the source is Fake News |
|---|---|---|
| 0/10 chance it's True News; 10/10 chance it's Fake News | 0 points | 100 points |
| 1/10 chance it's True News; 9/10 chance it's Fake News | 19 points | 99 points |
| 2/10 chance it's True News; 8/10 chance it's Fake News | 36 points | 96 points |
| 3/10 chance it's True News; 7/10 chance it's Fake News | 51 points | 91 points |
| 4/10 chance it's True News; 6/10 chance it's Fake News | 64 points | 84 points |
| 5/10 chance it's True News; 5/10 chance it's Fake News | 75 points | 75 points |
| 6/10 chance it's True News; 4/10 chance it's Fake News | 84 points | 64 points |
| 7/10 chance it's True News; 3/10 chance it's Fake News | 91 points | 51 points |
| 8/10 chance it's True News; 2/10 chance it's Fake News | 96 points | 36 points |
| 9/10 chance it's True News; 1/10 chance it's Fake News | 99 points | 19 points |
| 10/10 chance it's True News; 0/10 chance it's Fake News | 100 points | 0 points |

For instance, if you estimate a 7/10 chance of True News, then for that round you will earn 91 points if the source is True News and 51 points if the source is Fake News.

At the end of the study, the points you receive on all choices you make will be averaged, and this will determine the chance (out of 1000) that you win the bonus. For example, if you earn 90 points on average, you will have a 90 out of 1000 chance of winning the bonus.

News Assessment

Original question 1 of 14: Crime Under Obama

Some people believe that the Obama administration was too soft on crime and that violent crime increased during his presidency, while others believe that President Obama's pushes towards criminal justice reform and reducing incarceration did not increase violent crime.

This question asks how murder and manslaughter rates changed during the Obama administration. In 2008 (before Obama became president), the murder and manslaughter rate was 54 per million Americans.

In 2016 (at the end of Obama's presidency), what was the per-million murder and manslaughter rate?

Message:

The answer is **less than** your previous guess of **57.0**.

Do you think this information is from True News or Fake News?

- ☐ 0/10 chance it's True News; 10/10 chance it's Fake News
- ☐ 1/10 chance it's True News; 9/10 chance it's Fake News
- ☐ 2/10 chance it's True News; 8/10 chance it's Fake News
- ☐ 3/10 chance it's True News; 7/10 chance it's Fake News
- ☐ 4/10 chance it's True News; 6/10 chance it's Fake News
- ☐ 5/10 chance it's True News; 5/10 chance it's Fake News
- ☐ 6/10 chance it's True News; 4/10 chance it's Fake News
- ☐ 7/10 chance it's True News; 3/10 chance it's Fake News
- ☐ 8/10 chance it's True News; 2/10 chance it's Fake News
- ☐ 9/10 chance it's True News; 1/10 chance it's Fake News
- ☐ 10/10 chance it's True News; 0/10 chance it's Fake News

Figure 11: Crime Under Obama news assessment page.

News Assessment

Original question 1 of 14: Crime Under Obama

Some people believe that the Obama administration was too soft on crime and that violent crime increased during his presidency, while others believe that President Obama's pushes towards criminal justice reform and reducing incarceration did not increase violent crime.

This question asks how murder and manslaughter rates changed during the Obama administration. In 2008 (before Obama became president), the murder and manslaughter rate was 54 per million Americans.

In 2016 (at the end of Obama's presidency), what was the per-million murder and manslaughter rate?

Message:

The answer is **less than** your previous guess of **57.0**.

Do you think this information is from True News or Fake News?

- ☐ 0/10 chance it's True News; 10/10 chance it's Fake News
- ☐ 1/10 chance it's True News; 9/10 chance it's Fake News
- ☐ 2/10 chance it's True News; 8/10 chance it's Fake News
- ☐ 3/10 chance it's True News; 7/10 chance it's Fake News
- ☐ 4/10 chance it's True News; 6/10 chance it's Fake News
- ☐ 5/10 chance it's True News; 5/10 chance it's Fake News
- ☐ 6/10 chance it's True News; 4/10 chance it's Fake News
- ☐ 7/10 chance it's True News; 3/10 chance it's Fake News
- ☐ 8/10 chance it's True News; 2/10 chance it's Fake News
- ☐ 9/10 chance it's True News; 1/10 chance it's Fake News
- ☐ 10/10 chance it's True News; 0/10 chance it's Fake News

After seeing this message and assessing its truthfulness, what is your guess of the answer to the original question?

Figure 12: Crime Under Obama news assessment page: Second Guess question.

News Valuation

On the previous News Assessment pages you were given messages that said that the correct answer was either "greater than" or "less than" your guess, and you were then asked to guess how likely it was that this message came from a True News versus Fake News source.

This section is designed to assess how useful you think those messages are. On this page you will decide whether to see the message or whether to receive additional points and see a screen with a black bar as in the following example:

Original question 12: Gender and Math Grades

In the United States, men are more likely to enter into mathematics and math-related fields. Some people attribute this to gender differences in interest in or ability in math, while others attribute it to other factors like gender discrimination.

This question asks whether high school boys and girls differ substantially in how well they do in math classes. A major testing service analyzed data on high school seniors and compared the average GPA for male and female students in various subjects.

Male students averaged a 3.04 GPA (out of 4.00) in math classes. What GPA did female students average in math classes?

(Please guess between 0.00 and 4.00.)

Message:

The answer is your previous guess of **3.1**.

Do you think this information is from True News or Fake News?

- ☐ 0/10 chance it's True News; 10/10 chance it's Fake News
- ☐ 1/10 chance it's True News; 9/10 chance it's Fake News
- ☐ 2/10 chance it's True News; 8/10 chance it's Fake News
- ☐ 3/10 chance it's True News; 7/10 chance it's Fake News
- ☐ 4/10 chance it's True News; 6/10 chance it's Fake News
- ☐ 5/10 chance it's True News; 5/10 chance it's Fake News
- ☐ 6/10 chance it's True News; 4/10 chance it's Fake News
- ☐ 7/10 chance it's True News; 3/10 chance it's Fake News
- ☐ 8/10 chance it's True News; 2/10 chance it's Fake News
- ☐ 9/10 chance it's True News; 1/10 chance it's Fake News
- ☐ 10/10 chance it's True News; 0/10 chance it's Fake News

To determine whether you receive the message or the black bar, you will write down a "valuation" at the bottom of this page. The more that you think the message helps you, the higher your valuation should be.

(If you would prefer to see the message instead of the black bar, you should submit a valuation between 0 and 25 points, where a larger valuation indicates a stronger preference for the message.)

(If you would prefer to see the black bar instead of the message, you should submit a valuation between -25 and 0 points, where a more negative valuation indicates a stronger preference for the black bar.)

The details of the procedure to determine whether you receive the message or the black bar is a bit complicated, but explained below. **What is important to know is that the way your earnings are determined ensures that your chances of winning the bonus are maximized by honestly answering this question.**

Valuation of message (in points):

Point and message procedure given your valuation:

A computer will randomly select a number between -25 and 25 with all numbers being equally likely.

If this number is greater than your valuation in points, this number will be added to the points you earn on the next News Assessment page, but you will receive the black bar instead of the message (as above).

If this number is less than your valuation in points, you will earn the standard amount of points on the next News Assessment page, and you will receive either the "greater than" or the "less than" message (as in previous pages).

News Assessment

Original question 12 of 14: Gender and Math Grades

In the United States, men are more likely to enter into mathematics and math-related fields. Some people attribute this to gender differences in interest in or ability in math, while others attribute it to other factors like gender discrimination.

This question asks whether high school boys and girls differ substantially in how well they do in math classes. A major testing service analyzed data on high school seniors and compared the average GPA for male and female students in various subjects.

Male students averaged a 3.04 GPA (out of 4.00) in math classes. What GPA did female students average in math classes?

(Please guess between 0.00 and 4.00.)

Message:

The answer is your previous guess of **3.1**.

Do you think this information is from True News or Fake News?

- ☐ 0/10 chance it's True News; 10/10 chance it's Fake News
- ☐ 1/10 chance it's True News; 9/10 chance it's Fake News
- ☐ 2/10 chance it's True News; 8/10 chance it's Fake News
- ☐ 3/10 chance it's True News; 7/10 chance it's Fake News
- ☐ 4/10 chance it's True News; 6/10 chance it's Fake News
- ☐ 5/10 chance it's True News; 5/10 chance it's Fake News
- ☐ 6/10 chance it's True News; 4/10 chance it's Fake News
- ☐ 7/10 chance it's True News; 3/10 chance it's Fake News
- ☐ 8/10 chance it's True News; 2/10 chance it's Fake News
- ☐ 9/10 chance it's True News; 1/10 chance it's Fake News
- ☐ 10/10 chance it's True News; 0/10 chance it's Fake News

Next

Feedback

This is the last page before you see your results. Your feedback is not required, but it is very helpful for designing future studies.

Your earnings and bonus are not affected by your answers to these questions.

What did you think of the study? What did you like or dislike about it?

What was your thought process when you received a message and were deciding whether it was True News or Fake News?

Next

Results: Click the Finish button at the bottom of this page to complete the HIT

Sorry, you did not win the bonus. Your additional bonus was \$0.00.

You earned 80.32 points on average across all questions in this study. For questions, solutions, points and whether information was from True News or Fake News, see the tables below.

| Question | Correct answer | Your initial guess | Message said | Was the News Real or Fake | Your likelihood of this being True News | Points you earned for your likelihood |
|---|----------------|--------------------|--|---------------------------|---|---------------------------------------|
| In a study, researchers sent fictitious resumes to respond to thousands of help-wanted ads in newspapers. The resumes sent had identical skills and education, but the researchers gave half of the (fake) applicants stereotypically White names such as Emily Walsh and Greg Baker, and gave the other half of the applicants stereotypically Black names such as Lakisha Washington and Jamal Jones. 9.65 percent of the applicants with White-sounding names received a call back. What percent of the applicants with Black-sounding names received a call back? (Please guess between 0 and 100.) | 6.45 | 3.0 | The answer is less than your previous guess. | Fake News | 9/10 | 19.0 |
| What is the year right now? This is not a trick question and the first sentence is irrelevant; this is a comprehension check to make sure you are paying attention. For this question, your lower and upper bounds should be equal to your guess if you know what year it currently is. | 2018.0 | 2018.0 | The answer is equal to your previous guess. | True News | 10/10 | 100.0 |
| How many degrees West is this geographic center? (Please guess between 0 and 180. The continental U.S. lies in the Western Hemisphere, which ranges from 0 degrees West to 180 degrees West.) | 98.583 | 90.0 | The answer is less than your previous guess. | Fake News | 5/10 | 75.0 |

| Question | Correct answer | Your guess | Your lower bound | Your upper bound | Points you earned for your guess and bounds | Source |
|---|----------------|------------|------------------|------------------|---|---|
| In a study, researchers sent fictitious resumes to respond to thousands of help-wanted ads in newspapers. The resumes sent had identical skills and education, but the researchers gave half of the (fake) applicants stereotypically White names such as Emily Walsh and Greg Baker, and gave the other half of the applicants stereotypically Black names such as Lakisha Washington and Jamal Jones. 9.65 percent of the applicants with White-sounding names received a call back. What percent of the applicants with Black-sounding names received a call back? (Please guess between 0 and 100.) | 6.45 | 3.0 | 3.0 | 3.0 | 94.25 | http://bit.ly/labor-market-discrimination |
| What is the year right now? This is not a trick question and the first sentence is irrelevant; this is a comprehension check to make sure you are paying attention. For this question, your lower and upper bounds should be equal to your guess if you know what year it currently is. | 2018.0 | 2018.0 | 2018.0 | 2018.0 | 100.0 | http://bit.ly/what-year-is-it |
| How many degrees West is this geographic center? (Please guess between 0 and 180. The continental U.S. lies in the Western Hemisphere, which ranges from 0 degrees West to 180 degrees West.) | 98.583 | 90.0 | 80.0 | 100.0 | 90.47 | http://bit.ly/center-of-the-us |