

Do People Value More Informative News?*

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Abstract

Drawing on representative samples of the U.S. population with almost 12,000 respondents in total, we measure and experimentally vary people's beliefs about the informativeness of news articles. Inconsistent with the desire for more information being the dominant motive for people's news consumption, treated respondents who think that a newspaper is less likely to suppress information reduce their demand for news from this outlet. This finding suggests that people have other motives to read news that sometimes conflict with their desire for more information. We discuss the implications of our findings for the regulation of media markets. (*JEL* D83, D91, L82)

Keywords: News Consumption, Information, Media Bias, Belief Polarization, Informativeness

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1 Introduction

What motivates people to consume economic and political news? Consistent with a core principle in standard economics—that more information is always better—Americans cite getting the facts right as their single most valued factor when choosing a specific news source (Young, 2016). While an overwhelming majority of Americans also say that the news media should be unbiased in its coverage of political issues (Mitchell, 2018), a large literature has documented that news outlets use slanted language in its reporting (Gentzkow and Shapiro, 2010).

There are two main competing explanations for why people consume slanted news. The first explanation is that people want more informative news but perceive news that are slanted to their prior beliefs as more informative (Gentzkow and Shapiro, 2006). Consistent with this explanation, both liberals and conservatives consider politically-aligned news outlets as more trustworthy (Mitchell and Weisel, 2014). The second explanation is that people have other motives to read news that sometimes conflict with expanding their knowledge, such as a preference for belief confirmation (Mullainathan and Shleifer, 2005).

The relative importance of a desire for more information versus other motives has important implications for the optimal regulation of media markets, such as the welfare effects of regulations to increase competition. Despite its relevance for optimal policy, there is no direct evidence on how people trade off the desire for more information against other motives for reading news. Previous studies on news consumption cannot identify whether the desire for more information dominates other motives because perceptions of informativeness are unobserved in observational data. To circumvent this challenge, we propose an experimental approach that allows us to measure and exogenously change perceptions about the informativeness of news.

In a series of experiments with around 12,000 Americans, we exogenously vary the perceived informativeness of news articles. We then measure news demand using real articles on economic and political news. The experiments are designed to change beliefs about informativeness without changing beliefs about the complexity or technicality of reporting. The experiments thus allow us to test whether people value more informative news in a setting where cognitive constraints are not binding. Our criterion for comparing the informativeness of news outlets is Blackwell’s (1951) ranking of information structures—the benchmark for evaluating the information content of signals. While

it is usually not possible to compare the Blackwell informativeness of different news articles, we designed the experiments such that the news articles should be perceived as strictly more Blackwell informative by treated respondents.

In our experiments, we generate exogenous variation in the perceived informativeness of news by informing treated respondents that the *New York Times* did not strategically suppress information. Specifically, we first tell our respondents that the Congressional Budget Office (CBO), Congress's official nonpartisan provider of cost and benefit estimates for legislation, published a report about the "Trump Healthcare Plan" (the American Health Care Act of 2017). Respondents are told that the CBO estimated that the plan would decrease the federal deficit by \$119 billion (contradicting claims made by Democrats) and leave 23 million more people uninsured (contradicting claims made by Republicans). To elicit beliefs about the informativeness of news, we then tell respondents that the *New York Times* wrote an article about the CBO report and ask about the subjective percent chance that it only reported the statistic on the federal deficit, only the statistic on the number of uninsured, or both statistics. This allows us to quantify beliefs about the informativeness of news articles in the *New York Times*: Reporting both statistics is strictly more informative (in the Blackwell sense) than selectively reporting only information that favors one of the parties. To generate exogenous variation in perceptions of informativeness, we then inform treated respondents that the *New York Times* reported both statistics from the CBO report. To measure how the information affects the demand for news, we offer all respondents free access to an article in the *New York Times* covering a CBO report on a different topic, namely the "Trump Tax Plan" (the Tax Cuts and Jobs Act of 2017). We also ask a series of belief questions to shed light on mechanisms.

The treatment generates a significant effect on perceptions of the informativeness of news in the *New York Times*: Treated respondents are 6.8 percentage points more likely to think that the *New York Times* will reveal both positive and negative findings from CBO evaluations of Trump policy proposals instead of selectively reporting only some of the findings. The treatment also affects more general perceptions of the *New York Times*: Treated respondents are less likely to think that it is politically biased, more likely to think that it provides high-quality news, and perceive CBO evaluations as more accurate.

Given our treatment effects on perceptions, we would thus expect a higher demand for *New York Times* articles covering CBO evaluations of Trump policy proposals if the

demand for news is driven primarily by a desire for more information. Indeed, any model where the demand for news depends primarily on the instrumental or intrinsic value of accurate information would predict a positive treatment effect. Note that this prediction does not depend on people's prior beliefs about the CBO and Trump's policy proposals, or whether they value one statistic more than the other (Blackwell, 1951, 1953). In stark contrast to this prediction, the main result of the paper is that respondents who learn that the *New York Times* does not suppress information significantly reduce their demand for news from this newspaper by 4.0 percentage points. This corresponds to a 14 percent reduction in the demand for news. This violation of the more-information-is-better principle is very robust. We replicate this result using both different sample providers (Lucid, Amazon Mechanical Turk) and different news articles from the *New York Times* in a series of robustness experiments.

What explains this violation in the more-information-is-better principle? The decrease in the demand for news suggests that some of the motives to read news directly conflict with people's desire for more information. Preferences for belief confirmation (Mullainathan and Shleifer, 2005) could lead people to seek news that confirm their beliefs ("good news") and avoid news that contradicts their beliefs and would thus create cognitive dissonance ("bad news"). Therefore, learning that the *New York Times* mentioned both the positive and negative consequences of a Trump policy proposal has two opposing effects. On the one hand, people are more likely to encounter information that confirms their beliefs, implying a gain. On the other hand, people are also more likely to encounter information that contradicts their beliefs, implying a loss. If people care more about avoiding bad news than being exposed to good news, this mechanism can explain our findings as—empirically—a large fraction of respondents believe that the *New York Times* might suppress facts that are inconsistent with their political beliefs.

Examining political heterogeneity in treatment responses, we find that both Democrats and Republicans decrease their demand for news in our experiments. This finding is consistent with the fact that a large fraction of both Republicans and Democrats initially believe that the *New York Times* might suppress facts that are inconsistent with their political beliefs. This finding is thus consistent with both Democrats and Republicans being primarily motivated to avoid news articles which contain information that potentially contradicts their beliefs, even if these articles are also more likely to contain at least some confirmatory signals. In this sense, more informative but more even-handed reporting is bad news for everyone motivated to avoid disconfirmatory signals.

We run additional mechanism experiments to rule out two alternative explanations. First, we run a placebo experiment suggesting that cognitive constraints are not binding in our setting. In this experiment, we inform respondents that the CBO highlighted two key statistics in a report on healthcare without providing any further information about the content of the report. Treated respondents are then informed that the *New York Times* reported both key statistics in its coverage of the CBO report. In this experiment, where other potentially conflicting psychological motives, such as a preference for belief confirmation, arguably play no role, we do not observe a decrease in the demand for news. Second, to address concerns about differential curiosity across treatment arms, we tell all respondents that we will inform them at the end of the experiment about which statistics the *New York Times* reported in its article. In this experiment, we find a 4.7 percentage point decrease in demand for news—an even larger effect size.

Our results contribute to the literature on media bias (DellaVigna and Ferrara, 2015; Gentzkow et al., 2018; Jo, 2019; Mullainathan and Shleifer, 2005; Perego and Yuksel, 2018; Qin et al., 2018). To measure media bias, previous studies have developed text-based measures that rank newspapers according to the similarity of their language (Gentzkow and Shapiro, 2006) or citations (Groseclose and Milyo, 2005) to that of politicians.¹ For example, more frequent use of the term “death tax” rather than “estate tax” might indicate a tendency to slant towards the right. However, it is not obvious that one term conveys more *information* than the other. Indeed, there is no generally agreed-upon method to rank the informativeness of actual newspapers. Thus, while previous studies show that consumers have a demand for slanted *language* (Garz et al., 2020; Gentzkow and Shapiro, 2010; Gentzkow et al., 2014), this does not allow for strong conclusions about how consumers would make a trade-off between the accuracy and slant of a newspaper.

The relative importance of the desire for more information compared to other motives to read news plays a major role in theoretical analyses of media markets (Baron, 2006; Bernhardt et al., 2008; Chan and Suen, 2008; Gentzkow and Shapiro, 2006; Mullainathan and Shleifer, 2005) and is of critical importance for the debate on whether policy makers should introduce regulations to increase competition in media markets (Foros et al., 2015). The main contribution of this paper is to provide the first direct evidence on whether the desire for more information dominates other motives

¹Other approaches compare the intensity of issue coverage (Larcinese et al., 2011; Puglisi and Snyder, 2011) or apply sentiment analysis (see Puglisi and Snyder, 2015, for an overview).

to read news. Our design allows us to directly vary the perceived informativeness of a news outlet in a controlled environment, which is difficult in observational studies where perceptions of informativeness are typically unobserved. Our main result—that respondents who think that a newspaper is less likely to suppress information reduce their demand for news—cannot be rationalized with standard preferences that would imply a demand for more informative news. Instead, it lends support to models where people have direct preferences over signals.

Furthermore, we also contribute to a small but growing literature on people’s demand for information and information avoidance (Charness et al., forthcoming; Falk and Zimmermann, 2017; Ganguly and Tasoff, 2016; Golman et al., 2017; Nielsen, 2020; Zimmermann, 2015).² Studying the demand for more informative news is of particular importance because of the political externalities of news consumption, including its effects on political accountability, electoral efficiency, and political polarization (Strömberg, 2015; Sunstein, 2018). Our key contribution to this literature is thus to provide clean evidence on information avoidance in the context of political news consumption. To identify information avoidance, we employ a new identification strategy by varying perceptions about the accuracy of the signal provided by a news outlet.³ In contrast to much of the previous experimental literature on information avoidance, we vary perceptions about a real-world news outlet rather than features of an artificial signal structure.

The remainder of the paper proceeds as follows. Section 2 describes the experimental design. Section 3 lays out a simple conceptual framework. We present the main results in Section 4 and discuss alternative mechanisms in Section 5. Section 6 concludes and discusses implications for the regulation of media markets. The Online Appendix provides additional theoretical and empirical results and the full set of experimental instructions.

²More broadly our evidence relates to a relatively large literature on motivated belief updating (Exley, 2015; Exley and Kessler, 2018; Schwardmann and van der Weele, 2019; Di Tella et al., 2015; Thaler, 2019).

³We thus also contribute to a literature on information provision experiments. For a review of this literature, see Haaland et al. (2020).

2 Experimental design

In this section, we describe the design of Experiments 1 and 2 as well as the samples used. Finally, we discuss how our design choices circumvent the main challenges of working with real news articles in an applied setting.

2.1 Sample

We collected the data for Experiment 1 in collaboration with *Dynata*, a leading market research company commonly used in social science research (de Quidt et al., 2018; Enke, 2020a). In Experiment 2, we collected data using *Luc.id*, a widely used online panel provider (Bursztyn et al., 2020; Haaland et al., 2020). We have a sample of approximately 7,800 respondents that is broadly representative of the U.S. population in terms of education, age, income, region, gender and political affiliation (columns 1 and 2 of Table B.1). The treatment and control group of respondents in Experiments 1 and 2 are balanced in terms of observable characteristics (Table B.2 and Table B.3).

2.2 Design of Experiment 1

This section outlines the design of Experiment 1. Figure 1 provides a summary of the structure and Section D of the Online Appendix provides the full experimental instructions.

Pre-treatment characteristics and beliefs We first measure basic demographics, namely income, age, gender, and region of residence. Furthermore, we ask for people’s political preferences and beliefs, how often they read the *New York Times*, and the three newspapers they are most likely to read. In Experiment 1, we elicit people’s beliefs about how the *New York Times* reports about the Trump Healthcare Plan. Specifically, we tell our respondents that the CBO, Congress’ official nonpartisan provider of cost and benefit estimates for legislation, published a report about the Trump Healthcare Plan (the American Health Care Act of 2017). Respondents are told that the CBO estimated that the plan would decrease the federal deficit by \$119 billion (contradicting claims made by Democrats) and leave 23 million more people uninsured (contradicting claims made by Republicans). Subsequently, we measure respondents’ beliefs about

how the *New York Times* covered the CBO report by asking our respondents to estimate the percent chance that the *New York Times* reported only the figure on the number of uninsured people, only the figure on the deficit decrease, or both figures.

We chose to focus on the *New York Times* because it is a well-known newspaper with a national coverage that is familiar to most people. Furthermore, we focused on the *New York Times*'s reporting strategy about news from the CBO for the following reasons: First, the CBO is Congress's official provider of cost and benefit estimates for legislation and is known to be nonpartisan (to stay politically neutral, it only assesses the consequences of proposed policies and does not make its own policy recommendations). Second, all major newspapers in the U.S. generally feature articles about CBO reports, which in turn are an important input to debates about policy in Congress and can determine the fate of policy proposals.

Information treatment We provide a random subset of respondents with information about the *New York Times* (treatment group).⁴ Specifically, we provide treated respondents with the following information treatment, which is framed in a neutral way to minimize experimenter demand effects:

In its article about the CBO estimates, The New York Times reported **both** that the federal budget deficit would decrease by \$119 billion **and** that the number of people without health insurance would increase by 23 million.

Respondents in the control group proceed without receiving any information.

Post-treatment outcomes To mitigate concerns about consistency bias in survey response (Falk and Zimmermann, 2012), a subset of respondents of Experiment 1 are cross-randomized to receive either (i) a question on the demand for news (2,250 respondents) or (ii) the post-treatment beliefs block (755 respondents).⁵ In all other experiments, all respondents proceed to the question on demand for news.

⁴We stratify the assignment into treatment and control group by whether respondents identify as Republicans, Democrats, or Independents.

⁵Experiment 1 was conducted in three waves. We only cross-randomized respondents into the beliefs block in the second wave. See Table 1 for more details.

Main outcome: Article demand We collect a behavioral outcome measure on people's demand for news by providing them with an opportunity to read an article from the *New York Times*. This article is unrelated to the Trump Healthcare Plan and instead covers a CBO report about a different policy: the Trump Tax Plan. However, we do not provide any additional information about the content of the article or the corresponding CBO evaluation of the Trump Tax Plan. We make this distinction salient to respondents, thus ensuring that respondents expect to receive an article containing new information not previously mentioned in the survey. Specifically, we tell respondents that the CBO analyzed the consequences of the Trump Tax Plan over the next decade and ask them whether they want to read an article about its findings in *New York Times*. We tell respondents that if they decide not to receive access to the article, they will proceed with the survey without receiving access to the article. If they decide to receive access to the article, they will receive access at the end of the survey. We thus decrease the cost of accessing the *New York Times* article both in terms of search costs and in terms of avoiding the *New York Times* paywall.⁶

There are several reasons why we choose this as our main outcome. First, the decision on whether or not to read a real news article in the *New York Times* has high external validity: the decision to read a news article is typically made after reading its headline or a one-sentence preview of its content. Second, our setting allows us to hold some beliefs about article characteristics across the treatment and control group constant. For instance, to fix perceptions of cognitive effort required to read the article across treatment arms, we directly tell respondents that the article contains about 1,100 words, which takes about three to four minutes to read. Third, by embedding the article in our online survey, we can measure not only the extensive margin, that is, whether people want to read the news article, but also the intensive margin, that is, how much time they spend reading the news article.

Post-treatment belief I: Filtering To study whether our treatment intervention affected people's beliefs about informativeness, we collect a post-treatment measure of strategic information suppression, but only for the subset of respondents who were randomized not to receive the demand for news block. To do so, we provide respondents

⁶While the *New York Times* is technically behind a paywall, it offers non-subscribers free access to 10 articles per month. If our respondents were perfectly aware of this, they could thus save one of their 10 free articles if they decided to receive access through our survey rather than visiting the *New York Times* directly.

with information about cost and benefit estimates from a CBO report regarding the Trump Tax Plan. We tell respondents about the opposing predictions made by Republicans and Democrats about the plan's impact on the federal debt and job creation. To avoid consistency bias in survey responses, we employ a different way of measuring beliefs about information suppression compared to the elicitation of prior beliefs. We inform respondents that the *New York Times* reported that the Trump Tax Plan would increase the federal debt as claimed by Democrats. We then ask our respondents to estimate the percent chance that the *New York Times* also reported that the Trump Tax Plan would create 1.1 million jobs.

Post-treatment belief II: Omission Furthermore, we measure beliefs about the extensive margin of political news coverage by eliciting people's beliefs about whether the *New York Times* strategically decides not to publish articles about certain CBO reports. It allows us to test for treatment effects on beliefs about news coverage that are conceptually distinct from within-article filtering of information. Specifically, we ask respondents to estimate the percent chance that the *New York Times* wrote any article at all about a CBO report estimating that a signature policy proposed by Democrats would add \$27 billion to the federal debt. This signature policy would grant citizenship status to 1.8 million young undocumented immigrants (known as the Dreamers), and we inform respondents that Democrats claimed that it would not increase the federal debt.

Post-treatment beliefs III: Article characteristics We also measure additional beliefs about (i) the quality of news articles in the *New York Times*, (ii) whether the *New York Times* article about the Trump Tax Plan will be dry and technical, and (iii) whether the article about the Trump Tax Plan will be complex.

Additional beliefs and demographics We also separately elicit people's perception of whether the *New York Times* and the CBO are politically biased, their trust in the *New York Times* and the CBO, and general trust in the media. Furthermore, we measure beliefs about the accuracy of CBO forecasts. Finally, we ask some additional demographic questions.

2.3 Design of Experiment 2

To probe the robustness of our results, Experiment 2 relies on a very similar design as Experiment 1, but relies on different CBO articles. In Experiment 2, we measure beliefs about how the *New York Times* covered estimates from a CBO report that a bill to raise the minimum wage to \$15 per hour would lift 1.3 million people out of poverty but would decrease the number of jobs by 1.3 million. As in Experiment 1, a random subset of respondents learns that the *New York Times* reported both estimates in its article. Thereafter, we measured people’s demand for reading a *New York Times* article covering a different CBO report that analyzed the consequences of establishing a single-payer health care system. In Section 5.2 we outline in detail how Experiment 2 helps us mitigate concerns about the role of curiosity about newspaper biases in driving our results.⁷

2.4 Discussion of the design

Measuring the demand for *real* news articles and causally varying perceptions of informativeness of a real newspaper is a methodological contribution of our design. While artificial signals offer a higher level of control, the demand for political news may be driven by features that are not captured by stylized laboratory experiments. In this section, we discuss how the portable feature of our design circumvents the main challenges of working with real news articles in applied settings.

Rational benchmark The main challenge is to exogenously vary perceptions of informativeness without affecting other perceptions of how a news outlet reports the news. We lack empirical measures on the relative informativeness of news outlets that are grounded in information theory because we cannot quantify information encoded in natural language. Moreover, exposing respondents to a real news article would reveal information about how well the newspaper fits personal tastes in terms of writing or humor. To obtain a rational benchmark, we vary beliefs about the likelihood that the *New York Times* suppresses statistical information from CBO policy evaluations. Our treatment is based on a “within-article” comparisons between the actual news article that was published and the newspaper’s set of articles it could have written. In

⁷We show in Table B.4 that results from Experiment 1 and 2 are very similar.

Online Appendix A, we show that our treatment will increase the perceived Blackwell informativeness—a result that is independent of people’s preferences and prior beliefs. Moreover, we use the same source (CBO) and topic (evaluations of Trump policies) to vary beliefs and measure people’s demand for news. Thus, only beliefs about the informativeness of *New York Times* articles covering CBO reports matter for people’s decision, mitigating potential concerns related to updating about how the newspaper covers other topics.

Joint updating Another design challenge inherent to news consumption is joint updating about both the state of the world, θ , and the quality or accuracy of a newspaper article in the face of uncertainty. Gentzkow and Shapiro (2006) show that a rational agent may have a lower demand for news upon learning that a newspaper published information that is unlikely given the agent’s prior belief θ . Thus, informing respondents only about the *content* of an article without specifying the *information* available to the newspaper—which implicitly defines the newspaper’s choice set—creates an inference problem about the underlying informativeness of the source that is endogenous to people’s prior beliefs about θ (see Tappin et al., 2020, for a detailed discussion). To circumvent this issue, we inform all respondents about the information available to the *New York Times* from the CBO report, allowing subjects to make unambiguous inferences about how the newspaper reports the news.⁸ An additional benefit of this approach is that all respondents receive exactly the same information about the Trump Healthcare Plan, so beliefs about Trump’s policy agenda should not differ between treatment and control.

Varying beliefs about informativeness We took several steps to ensure that our information treatment would successfully shift beliefs about the informativeness of an outlet. First, for our manipulation to be successful, we only need the treatment to shift beliefs about how the New York Times covers CBO reports, i.e. something our respondents should hold weaker priors about than the overall bias of the New York Times. Second, we reveal information that the *New York Times* did *not* filter information which may be more persuasive than learning that it published a slanted article about

⁸Formally, one can see this as follows: Consider a newspaper that receives a signal $s \in S$ from the distribution $p : \Theta \rightarrow \Delta(S)$ (e.g. the CBO) and publishes an article $n \in N$ based on the reporting strategy $\sigma : S \rightarrow \Delta(N)$. By informing respondents about both realizations s and n , respondents’ posterior belief about σ is independent from their prior belief about θ .

the Trump Healthcare Plan.⁹ Third, respondents learn directly about the newspaper’s decision, allowing us to eliminate uncertainty about the information available from its sources.

3 Conceptual framework

We now provide a simple conceptual framework to guide the interpretation of our experimental results. There is a state space Θ with a typical element denoted by θ and an agent with prior belief $q \in \Delta(\Theta)$ about the hidden state. The newspaper provides information about θ by publishing an article $n \in \mathcal{N}$. The agent will prefer to read the article if his expected utility from reading the article exceeds the value of his outside option. In our experiment, the *New York Times* receives two signals $S = \{L, R\}$ about the consequences θ of the Trump Healthcare Plan from the CBO. This information set, which contains both a positive (R) and a negative (L) signal about the overall impact of the policy proposal, defines the set of possible articles $\mathcal{N} = \{\{L\}, \{R\}, \{L, R\}\}$.

In standard economic models, news articles are valuable only to the extent that they improve the quality of decisions, i.e., they are instrumentally valuable. We model the *informational value* v_I as

$$v_I = \mathbb{E}(u(a^*(q(n)), \theta) - u(a^*(q))) \quad (1)$$

where $a^*(q(n)) \in A$ is the agent’s optimal action given the posterior belief $q(n)$ about θ after reading the news article n and given his state-dependent payoffs over actions, $u : A \times \Theta \rightarrow \mathbb{R}$. As information can also have non-instrumental value arising from intrinsic information preferences, i.e. people wanting to learn about the truth, one can also interpret $u(a, \theta)$ as capturing these preferences.

Our information treatment is designed to exogenously increase the probability that the *New York Times* reported *both* signals in its article, i.e. $n = \{L, R\}$, while decreasing the probability that it only reports L or R . Using standard arguments, we show in Online Appendix A that this will strictly increase the perceived Blackwell (1951, 1953) informativeness of the *New York Times*, implying:

⁹Endorsements of rival candidates by partisan newspapers have been shown to be more persuasive than endorsements by like-minded outlets (Chiang and Knight, 2011).

Prediction 1 (More-information-is-better). If people read news because they care about the instrumental or non-instrumental value v_I of accurate news, treated respondents should have a higher demand for *New York Times* articles.

The primary advantage of varying the *statistical* notion of Blackwell informativeness is that it generates predictions that do not depend on people’s prior beliefs about θ and hold even if they primarily care about news that is diagnostic of a particular state. For example, our respondents are better off even if they care mostly about the budget deficit and less about the social cost of Trump’s policy proposals, making the prediction independent of people’s “informational preferences” over these statistics.

However, people’s motivation to read news might also arise from direct preferences over different *types* of news articles. For example, people might have a preference for news that confirm their prior beliefs q . News articles might also differ in their entertainment value, with one-sided stories being preferred to more balanced reports. To better understand how our information treatment might affect the direct utility from news, we assume that Republicans’ preferences over \mathcal{N} are represented by $L \preceq N \preceq R$, while Democrats’ preferences are $R \preceq N \preceq L$ where $N = \{L, R\}$. To avoid a case distinction, we use the labels $\mathcal{N} = \{G, N, B\}$ where G represents the agent’s most preferred article (“good”), N is the most informative article (“neutral”), and B is the least preferred article (“bad”). We can then define the direct utility v_D from news as

$$v_D = p_B u_B + p_N u_N + p_G u_G \quad (2)$$

where u_n is the state-independent utility from reading article $n \in \mathcal{N}$ and p_n is the agent’s belief about the likelihood of this article.¹⁰ Our information treatment is designed to exogenously increase p_N and decrease both p_B and p_G , which results in a net effect on the direct news utility of

$$\Delta v_D = \Delta p_B u_B + \Delta p_N u_N + \Delta p_G u_G = \underbrace{\Delta p_B (u_B - u_N)}_{\geq 0} + \underbrace{\Delta p_G (u_G - u_N)}_{\leq 0}. \quad (3)$$

where Δp_n is the effect of our information treatment on people’s beliefs about reporting. The sign of Δv_D is ambiguous. On the one hand, agent’s are better off because they are less likely to read their least-preferred article B . On the other hand, they expect a loss

¹⁰This nests models where $u_n = v(n, q)$ is a function of the agent’s prior belief q about θ , such as a preference for belief confirmation.

because they are less likely to encounter their most-preferred article G . Which effect dominates will depend on how people evaluate the neutral article, N . For example, our information treatment will decrease v_D if $u_N = u_B$ and increase it if $u_N = u_G$. We can thus draw the following inference from a decrease in the demand for news:

Prediction 2. Assume that people’s valuation of news articles is given by $\omega_0 v_I + \omega_1 v_d$. Then a decrease in the demand for news among treated respondents suggests that the expected loss from a lower chance of reading one’s most preferred article dominates both (1) the gain from more informative news and (2) the expected gain from a lower chance of reading one’s least-preferred article.

We would thus expect a decrease in the demand for news in our experiment if $u_N - u_B$ is small relative to $u_G - u_N$, i.e. if people care more about the absence of contradicting information than the presence of information that confirms their prior beliefs.¹¹ In Section A.2 of the Online Appendix, we discuss how this contrasts with the predictions of ideal-point models of media bias.

4 Main results

In this section, we first provide descriptive evidence on beliefs about how the *New York Times* covers CBO reports. We then study the causal effect of learning that a newspaper is less likely to suppress information on beliefs and demand for news, using data from Experiments 1 and 2.

4.1 Pre-treatment beliefs

Figure 2 shows the distribution of pre-treatment beliefs about how the *New York Times* covered the CBO report, using data from Experiments 1 and 2. Panel A shows beliefs about the percent chance that the *New York Times* would not suppress any information from CBO reports. While around 20 percent of respondents think the *New York Times* will report both statistics with certainty, most respondents expect some form of information suppression with positive probability. In Panel B and C, we focus on

¹¹For example, suppose that people receive utility $\alpha = \alpha(q)$ from a signal that confirms their prior belief q and lose utility $\beta = \beta(q)$ if a signal contradicts their beliefs. Then $u_B = -\beta$, $u_N = \alpha - \beta$, $u_G = \alpha$, implying $u_N - u_B = \alpha$ and $u_G - u_N = \beta$. If $\alpha \ll \beta$ we would expect $\Delta v_D < 0$.

the subset of respondents who expect some form of information suppression. Panel B (C) shows the percent chance that the *New York Times* would slant their article to the left (right) by suppressing the key statistic from the CBO report that would contradict claims made by Democrats (Republicans) in Congress.

The figure illustrates that beliefs about how the *New York Times* covered the CBO report are very dispersed. 42.0 percent of our respondents think that the *New York Times* is more likely to slant the news reports to the left than to the right. 33.8 percent of our respondents attach equal likelihood to the *New York Times* slanting their news reporting to the right and the left. Finally, 24.1 of our respondents think that the *New York Times* is more likely to slant news to the right. The largest fraction of respondents among both Republicans and Democrats neither assign a zero probability nor a 100 percent probability that the *New York Times* slants left. Similarly, the largest fraction of respondents among both Republicans and Democrats neither assign a zero probability nor a 100 percent probability that the *New York Times* slants right.

These findings underscore that respondents have uncertain prior beliefs about how *New York Times* covered CBO reports. While our respondents generally think the *New York Times* is more likely to slant left than to slant right, most respondents assign a positive probability to both events. Taken together, the dispersion in priors in turn motivates an experimental design which shifts beliefs through information provision to a random subset of respondents.¹²

[Insert Figure 2 here]

4.2 Empirical specification

Our main empirical specification for different outcomes, y_i , is given as follows:

$$y_i = \alpha_0 + \alpha_1 T_i + \alpha_2 \mathbf{x}_i + \varepsilon_i \quad (4)$$

where T_i is an indicator for whether subject i received the information treatment; \mathbf{x}_i is a vector of controls¹³; ε_i is an individual-specific error term. We use robust error terms

¹²Our quantitative prior beliefs about media bias are strongly correlated with people's self-reported qualitative perception of whether the *New York Times* is right-wing biased, left-wing biased or unbiased (Table B.8)

¹³We use the following pre-specified controls: gender (male indicator), age (continuous), log income (continuous), region (three indicators), race (white indicator), education (college indicator), employment

for inference. y_i is the outcome variable of interest.

4.3 Post-treatment beliefs about reporting

We provide evidence that treated respondents expect more informative news articles from the *New York Times* and hold more favorable views of the newspaper and its source. First, treated respondents positively update about the informativeness of the newspaper as they think it is 6.8 percentage points more likely that the *New York Times* does not suppress any information about the CBO report on the Trump Tax Plan ($p < 0.01$, column 1 of Table 2). Second, column 2 provides evidence that the treatment did not affect conceptually distinct beliefs about the extensive margin with which the *New York Times* covers different topics such as immigration. Treated respondents are equally likely to think that the *New York Times* wrote an article about a CBO report which contradicts claims by Democrats that granting citizenship status to undocumented immigrants would not have negative fiscal consequences. This suggests that treated respondents expect more information per article, but not a different distribution of news topics.¹⁴ Third, treated respondents are 3.7 percentage points more likely to think that the *New York Times* is not politically biased ($p < 0.01$, column 6). This provides indirect evidence that people perceive the article containing both statistics as more balanced.

Fourth, our design allows respondents to draw direct inferences about the reporting strategy by keeping the source of the information constant across articles and knowledge of the information available to the newspaper constant across respondents, as discussed in Section 2.4. While this rules out a Bayesian mechanism based on negative updating about quality (Gentzkow and Shapiro, 2006), the treatment may still affect people's evaluation of the *New York Times* along the quality dimension. However, the perceived quality of *New York Times* articles is 10.3 percent of a standard deviation higher among treated respondents ($p < 0.10$, column 3). Treated respondents also display identical

status (indicator for full-time work), frequency of reading the *New York Times* (continuous, elicited pre-treatment), beliefs about the consequences of the Trump Tax Plan and the Trump Healthcare Plan (both continuous and elicited pre-treatment), pre-treatment beliefs about the probability that the *New York Times* would report both statistics, and experiment fixed effects. We also have a few respondents in the sample who did not complete all demographic questions; we include indicators for missing values for these respondents.

¹⁴This simplifies the interpretation of our treatment as it is not possible to rank different topic distribution according to Blackwell's criterion. However, as we measure demand for an article with a *known* topic, beliefs about the likelihood that the *New York Times* covers a particular topic should not have a differential effect on the demand for news between treatment and control.

levels of trust in the *New York Times* (columns 7). Finally, there are no obvious reasons why our treatment should affect beliefs about the CBO. In line with this, we find no treatment effect on respondents' perceptions of the political bias of the CBO (column 9) or their level of trust in the CBO (column 10). Rather, respondents do update positively about the accuracy of the CBO ($p < 0.05$, column 11).

Taken together, treated respondents think that the *New York Times* provides more information, is less politically biased, writes higher quality articles and uses more accurate sources. Any of these changes in beliefs should imply a subsequent increase in demand for news in rational models of information demand. Moreover, we do not identify a single dimension on which respondents hold less favorable views of the newspaper, its articles, or its source.

[Insert Table 2 here]

4.4 Treatment effects on demand for news

Our main object of interest is people's demand for news, which takes value one if our respondents want free access to a second news article in the *New York Times* covering a different CBO report, and zero otherwise. The main finding of this paper is that respondents who learn that the *New York Times* is more informative than they thought reduce their demand for news. Column 1 of Table 3 highlights that treated respondents on average significantly reduce their demand for news by 4.0 percentage points. This corresponds to a reduction in the demand for news of approximately 14 percent, i.e. one third of the control group difference in demand for reading the article between Republicans and Democrats.¹⁵ A comparison of the treatment effect with the magnitude of the first-stage—i.e., the 6.8 percentage point increase in the perceived likelihood that the *New York Times* does not suppress information—suggests that people's demand for news is relatively elastic to changes in perceptions of informativeness.

The median time spent reading the article about the Trump Tax Plan is 56 seconds, suggesting that a substantial fraction of our respondents read at least some parts of the article.¹⁶ The time spent reading the article does not vary significantly across treatment

¹⁵The baseline demand for news of 27.7 percent in the control group reflects people's opportunity cost of reading the article and is in itself not indicative of a violation of the more information is better principle.

¹⁶Reading the full article takes between three and four minutes.

arms, indicating that the treatment did not affect how carefully people read the article.

[Insert Table 3 here]

4.5 Preference for belief confirmation

The negative treatment effect on people's demand for news is inconsistent with people reading news because they want to be better informed: Any model where news articles are instrumentally or intrinsically valuable would predict a positive treatment effect. This includes models where people derive pleasure from knowledge or gain social status from being well-informed about current affairs. We can thus conclude that people must have other motives to read news that sometimes dominate their desire to be better informed. One mechanism that could explain our results is that people have direct preferences over different types of news articles, implying that people sometimes face a trade-off between the informational value and their preferences over news. In particular, people might receive disutility from reading news articles that contain information that contradicts their beliefs (Mullainathan and Shleifer, 2005). In our experiment, we use news articles about the consequences of different Trump policy proposals. A mechanism based on a preference for belief confirmation and dissonance avoidance would thus assume that a Republican (Democrat) who supports (opposes) Trump prefers an article that mentions only positive (negative) signals to an article that mentions both positive and negative signals, which in turn is preferred to reading only negative (positive) signals.

As discussed in Section 3, our information treatment has two opposing effects: First, respondents should be less likely to expect an article that only covers information that contradicts their belief, implying a gain (see Equation (3)). Second, they will also be less likely to expect an article that will only mention information that confirms their beliefs, implying a loss. We would then expect a negative treatment effect if these losses loom larger than the gains.

Columns 2 and 3 of Table 3 show treatment effects by political affiliation. We see that treated Democrats (who disapprove of Trump) have a 4.5 percentage points lower demand for news (column 2, $p < 0.01$).¹⁷ We also see a negative treatment effect

¹⁷Since people might receive disutility from reading news inconsistent with their own beliefs as well as news inconsistent with claims made by their political party, it is not clear what we should predict

among Republicans (who approve of Trump) (column 3, $p < 0.01$). Given that a large fraction of respondents believe that the *New York Times* might suppress facts that are inconsistent with their political beliefs, these patterns are consistent with Democrats and Republicans being primarily motivated to avoid any news articles that may contain information that contradicts their beliefs, which includes balanced articles that cover both positive and negative consequences of Trump policy proposals.

While one could hypothesize that this trade-off should only operate for Democrats because the *New York Times* is generally perceived as a liberal-leaning outlet—and thus unlikely to suppress information in favor of Democrats—Figure 2 shows that our respondents have very dispersed beliefs about how the *New York Times* covers CBO reports about Trump policy proposals. Indeed, 60.8 (63.8) percent of Republicans assign a positive probability to the state that the *New York Times* chose to only disclose the positive signal about the Trump Healthcare Plan (the Democrats’ \$15 Minimum Wage Bill), suggesting that a large fraction of Republicans expected less belief utility from reading a balanced article.

Finally, we turn to heterogeneity by pre-treatment beliefs. It is worth noting that there are some challenges to study heterogeneity in treatment effects by pre-treatment beliefs about reporting. First, the discussion at the end of Section 3 illustrates that the predictions of models of belief confirmation are ambiguous unless we know the utility consequences of different types of news articles. Indeed, the interaction between the information treatment and the belief that the *New York Times* only reports the negative (positive) signals about the Trump Healthcare Plan could be either positive or negative for Republicans (Democrats). Second, there may be measurement error in the probabilistic belief elicitation, which makes the identification of interaction effects challenging. Third, pre-treatment beliefs are not exogenously assigned, implying that we are not causally identifying the interaction between our treatment and people’s prior beliefs about reporting. Table B.5 in the Online Appendix reports the results on heterogeneity by prior beliefs and underscores that there is little significant heterogeneity by prior beliefs.

when people hold divergent beliefs from claims made by their own political party. We, therefore, exclude Democrats who think that the plan has overall positive consequences and Republicans who think it has overall negative consequences from the regressions.

5 Alternative mechanisms and robustness

In this section, we discuss alternative mechanisms and assess the robustness of our results. We argue that explanations based on cognitive constraints, curiosity or experimenter demand effects are unlikely to drive our results. In Section C.2 of the Online Appendix, we rule out additional explanations such as delegation and diversification motives.

5.1 Cognitive constraints

The more-information-is-better principle might not hold in our setting if the marginal cognitive cost of processing one additional statistic from a CBO report exceeds the expected informational value from the additional statistic. Our main finding could then be driven by treated respondents who expect the article about the Trump Tax Plan to contain too much statistical information to justify the cognitive cost of reading the article.

To assess whether cognitive constraints are likely to drive our main result, we conduct a placebo experiment in collaboration with Dynata (Experiment 3, $n = 930$; see Table 1). As in Experiment 1, we inform respondents that the CBO analyzed the impact of the Trump Healthcare Plan.¹⁸ We then inform respondents that the CBO highlighted two key statistics in its report and that the *New York Times* subsequently wrote an article about the report. However, in contrast to Experiment 1, we do not tell respondents what the statistics are about. We then ask our respondents to state the percent chance they assign to the *New York Times* citing zero, one, or two of these two key statistics from the report. To exogenously vary beliefs about how many statistics the *New York Times* is likely to mention from CBO reports, we inform a random subset of respondents that the *New York Times* reported both key statistics in its coverage of the Trump Healthcare Plan. We then measure demand for news exactly as in Experiment 1 by asking respondents whether they want access to an article in the *New York Times* about the Trump Tax Plan. In this neutral setting, people do not reduce their demand for news when learning that the *New York Times* provides more informative news. If anything, we see an statistically insignificant increases of 1.5 percentage points in people’s demand for news (column 1 of Table B.6)—the opposite of the prediction of

¹⁸In this experiment, we used the term “GOP Health Bill” instead of “Trump Healthcare Plan.”

the cognitive constraints account.

Explanations based on cognitive constraints are also inconsistent with several patterns in the data. First, if we use educational attainment as a proxy for cognitive constraints, we do not find any statistically significant differences in treatment effects for people with low or high cognitive costs (column 2 of Table C.2). Second, for respondents who were cross-randomized into not being offered free access to the article, we collected a series of post-treatment measures related to perceived cognitive costs of reading the article about the Trump Tax Plan. Respondents in the treatment group think the article about the Trump Tax Plan would be equally complex, dry and technical as respondents in the control group (columns 4 and 5 of Table 2).

5.2 Curiosity

In Experiment 1, we elicit pre-treatment beliefs about the suppression of information in the *New York Times* and only inform treated respondents about whether the newspaper actually suppressed information. This might create two potential curiosity motives that could differ between the treatment and control group. First, treated respondents might be curious about whether the information we provided was accurate and perceive the article about the Trump Tax Plan as a chance to validate the information, thereby increasing demand relative to the control group. Second, control group respondents might be curious to learn whether or not the *New York Times* tends to suppress information from CBO reports and view the article about the Trump Tax Plan as an opportunity to learn about this, thereby increasing demand relative to the treatment group. However, it is worth emphasizing that learning about whether the *New York Times* suppressed information from the Trump Tax Plan is not straightforward as it would require both reading the published article in the *New York Times* as well as retrieving and reading the original CBO report about the Trump Tax Plan.¹⁹ The net directional effect of the two curiosity motives is difficult to predict since they work in opposite directions, but curiosity could potentially explain our negative main effect if the motive is present and stronger in the control group.

To address concerns about curiosity, in Experiment 2 we tell all respondents that we will ask them a question about how the *New York Times* covered the findings from a

¹⁹Our respondents do not receive any information about the CBO report about the Trump Tax Plan.

CBO report and highlight the following text in bold: “We will tell you how The New York Times covered these findings at some later point in the survey” (Section D.2.2 in the Online Appendix provides a screenshot). If control respondents were curious to find out whether the *New York Times* tends to suppress information from CBO reports, they would no longer have an extra incentive to read the article to find out.²⁰ As column 2 of Table B.4 illustrates, we find a quantitatively similar effect size in this experiment—suggesting a limited role for curiosity in driving the treatment effects.²¹

Several patterns in the data from the other experiments are also inconsistent with a strong curiosity motive driving the negative treatment effect on demand for news. First, in Experiment 1, we collected a post-treatment measure on how interested people were in learning whether the *New York Times* “reports unbiasedly about political issues.” Column 8 of Table 2 shows that treated respondents are not more curious to learn about this. The effect is close to zero and relatively precisely estimated. Second, curiosity motives might also be present in the placebo experiment (Experiment 3; see Table 1) in which we measure people’s beliefs about whether the *New York Times* suppressed any key statistics from a CBO report without giving respondents any information about what the statistics were. Instead of being curious about bias in reporting, respondents in the control group might be curious to learn how much statistical information the *New York Times* tends to report. However, we find, if anything, that the treatment increases people’s demand for news—inconsistent with the predictions of the curiosity motive (column 1 of Table B.6).

5.3 Experimenter demand effects

It is possible that treated respondents form different beliefs about the experimenter’s expectations compared to control group respondents. However, we do not believe that experimenter demand is a major concern in our setting: First, it seems more likely that learning that a newspaper provides more informative news should create the expectation that demand for news should be increased—the opposite of what we find. Additionally, the treatment was framed in a neutral way specifically to avoid

²⁰Expected learning about biases in reporting is thus constant across the treatment and control group, and learning about any possible bias in the second article would again require respondents to read both the article and the underlying CBO report.

²¹As we discuss in Section C.1 on robustness of design choices, this experiment also used different articles from Experiment 1 to elicit beliefs and article demand.

concerns about experimenter demand effects. Second, we do not observe a decline in the demand for news in the placebo experiment (see p. 20 for a description) where we also inform people that the *New York Times* provides more information. Third, recent evidence suggests that experimental subjects respond only moderately to explicit signals about the experimenter’s expectations, indicating a limited quantitative importance of experimenter demand effects (de Quidt et al., 2018; Mummolo and Peterson, 2018).

5.4 Robustness

The negative treatment effect on the demand for news is robust and replicates across experiments (see Table B.4). We show that our findings are robust to choosing different news articles from the *New York Times* and incentivizing pre-treatment beliefs about reporting. We also show that our results replicate using samples from different providers (Mturk, Lucid, Dynata). Finally, we validate our measure of people’s demand for news by showing that it predicts people’s incentivized willingness-to-pay for a three months subscription to the *New York Times*. In Section C.1 of the Online Appendix, we discuss these robustness experiments in more detail.

6 Conclusion

Our paper provides direct causal evidence on whether the desire for more information is people’s dominant motive for reading economic and political news in a context where cognitive constraints are not binding. Our main finding is that respondents who learn that a news outlet does not strategically suppress information, and thus expect to receive more information, reduce their demand for articles from this outlet. This finding is inconsistent with the theoretical benchmark prediction of the more-information-is-better principle and suggests that people hold other motives for consuming news that sometimes dominate their desire for more information.

Understanding how both demand and supply side factors shape media content is of high relevance due to the media’s influence on public discourse (King et al., 2017) and political outcomes (DellaVigna and Kaplan, 2007). Our findings suggest an important role for demand-side explanations of media bias. The distinction between demand and supply side factors has important policy implications as competition generally

reinforces the incentives to deliver the product consumers want. If people’s dominant motive for reading news is to obtain more information, market regulations designed to increase competition—such as limiting ownership concentration—should reduce bias in reporting and improve information aggregation. However, our finding that people do not respond to variation in informativeness in the way predicted by the more-information-is-better principle suggests that the effects of regulation are more nuanced. The distinction between demand and supply side factors also has implications for demand-side policy interventions that aim to correct consumers’ misperceptions of the informativeness of news, such as transparency initiatives to inform consumers about the extent of media bias in markets and efforts of fact-checking organizations to debunk false claims. Under supply-driven media bias, increasing consumer knowledge about factual correctness leads to welfare improvements by steering consumers toward more informative news. Under demand-driven media bias, by contrast, such interventions might backfire and actually increase political belief polarization by shifting people toward more biased sources. Our findings thus demonstrate the complexity of optimal regulation and policy.

One important caveat for the interpretation of our results is that the value of information might vary across decision-making contexts. We believe that future research should explore whether people also violate the more-information-is-better principle in news domains in which people have potentially stronger instrumental motives to acquire informative news. However, whether people value more informative political news is of particular interest nonetheless because it is a key input for the functioning of democracies (Strömberg, 2004).

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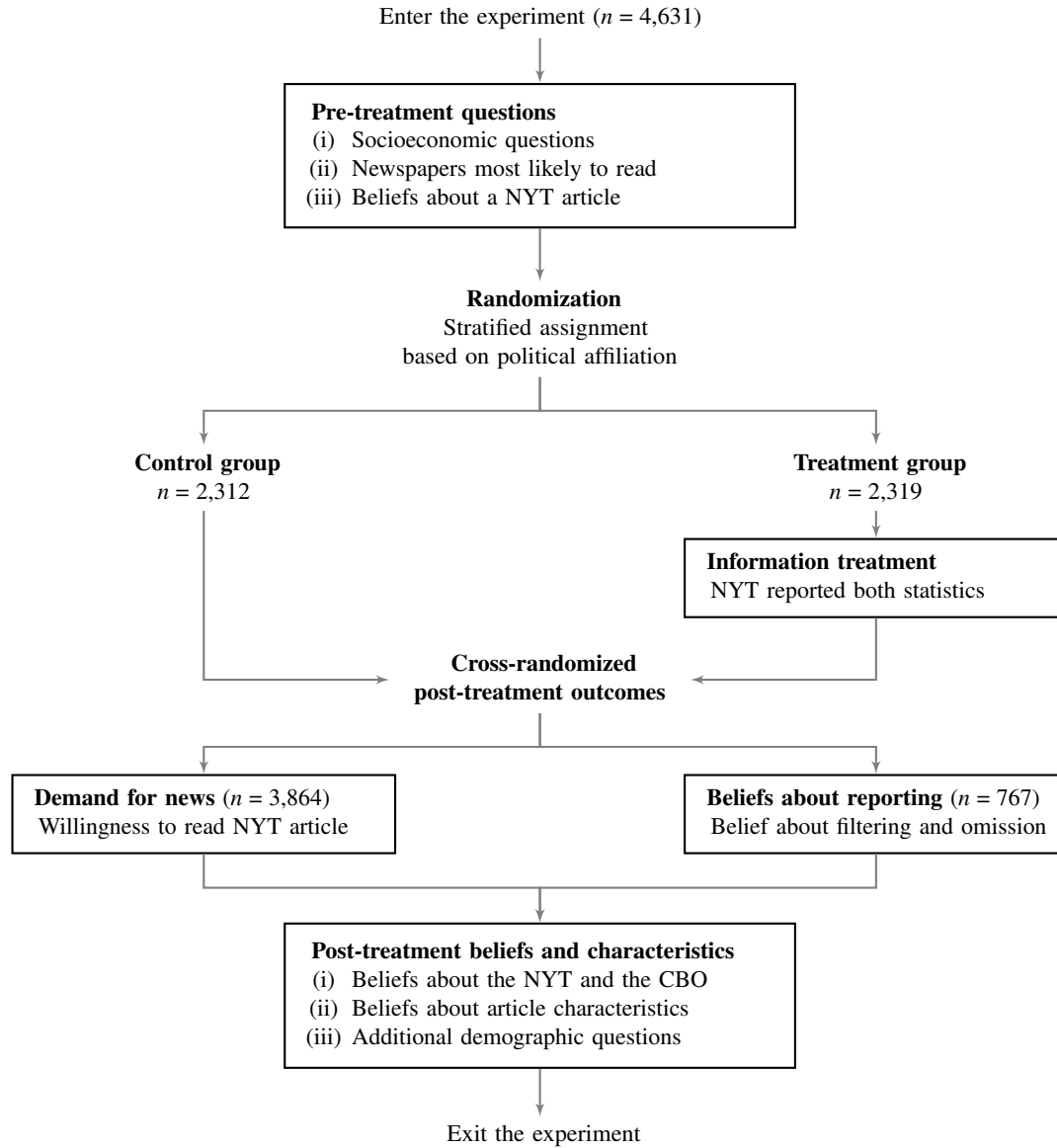
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Appendix

Figure 1: Overview of Experiment 1



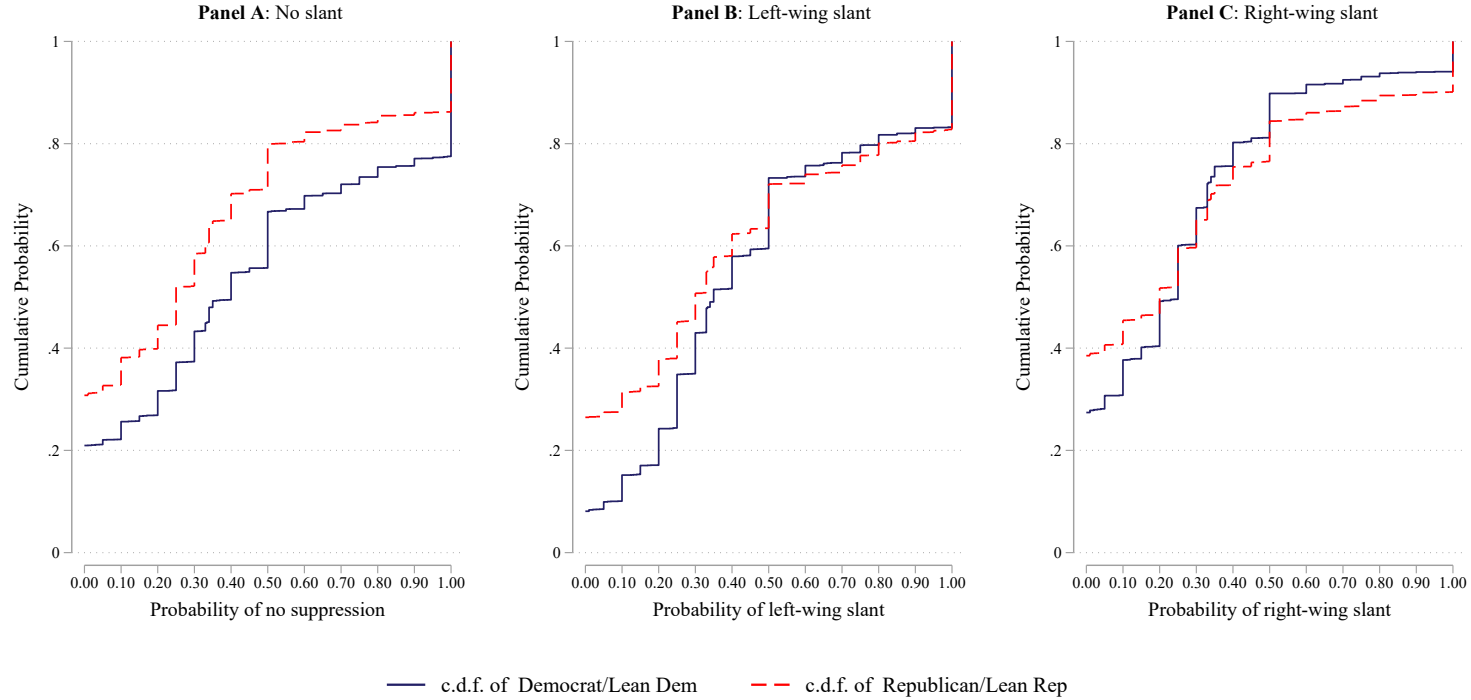
Note: This figure shows the features and order of blocks in our experiment conducted with Dynata (Experiment 1). Our other experiments have a similar structure but do not cross-randomize post-treatment outcomes (Experiments 2, 3, 6, and 7; see Table 1).

Table 1: Overview of experiments

Experiment	Sample	Treatments Arms	Main Outcomes
Experiment 1 <i>Dynata</i> Wave 1: Jan 2019 Wave 2: Feb 2019 Wave 3: Feb 2019	Dynata: representative sample (region, income, gender, education, and age); $n = 4,631$	Treatment: Information about how the NYT covered the CBO report on the Health Bill Control: No information	Demand for reading a NYT article about the Tax bill; Post-treatment beliefs about reporting
Experiment 2 <i>Curiosity</i> September 2019	Lucid: representative sample (region, income, gender, education, and age); $n = 3,387$	Treatment: Information about how the NYT covered the CBO report on the Minimum Wage Bill Control: No information	Demand for reading a NYT article about a single-payer health care system
Experiment 3 <i>Cognitive constraints placebo</i> April 2019	Dynata: representative sample (region, income, gender, and age); $n = 930$	Treatment: Information about how many statistics from the CBO report on the Health Bill the NYT reported Control: No information	Demand for reading a NYT article about the Tax Bill
Experiment 4 <i>Information demand</i> May 2019	Lucid: representative sample (region, income, gender, education, and age); $n = 703$	None	Demand for information about CBO estimates for the Tax Bill and the Health Bill
Experiment 5 <i>External validity</i> April 2019	MTurk: $n = 199$	None	Demand for reading a NYT article about the Tax Bill; Incentivized WTP for a digital NYT subscription
Experiment 6 <i>Incentives and reversed article order</i> September 2018	MTurk: Democrats and Democrat-leaning respondents; $n = 723$	Treatment: Information about how the NYT covered the CBO report on the Tax Bill Control: No information	Demand for reading a NYT article about the Health Bill
Experiment 7 <i>Platform robustness</i> January 2019	MTurk: $n = 1,332$	Treatment: Information about how the NYT covered the CBO report on the Health Bill Control: No information	Demand for reading a NYT article about the Tax Bill

Note: This table provides an overview of all experiments. Waves 2 and 3 of Experiment 1 ($n = 4,025$) were registered in the AEA RCT Registry as trial 3855.

Figure 2: Distribution of pre-treatment beliefs about reporting by political views



Note: This figure uses data from Experiment 1 and Experiment 2 (see Table 1). It shows pre-treatment beliefs about information suppression in the *New York Times* separately for Democrats (including Independents leaning toward the Democratic Party) and Republicans (including Independents leaning toward the Republican Party). Panel A shows data on the belief about the percent chance that the *New York Times* would not suppress any information from a CBO report. Panel B and C focus on the subsample of respondents who expect *some* form of slant with positive probability. Panel B shows beliefs about the percent chance that the *New York Times* would slant to the left (by suppressing the statistic that contradicts claims made by Democrats). Panel C shows beliefs about the percent chance that the *New York Times* would slant to the right (by suppressing the statistic that contradicts claims made by Republicans).

Table 2: Post-treatment beliefs

	Beliefs: Less suppression		Article characteristics			The New York Times			Congressional Budget Office		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Filtering	Omission	Quality	Dryness	Complex	No bias	Trust	Curious	No bias	Trust	Accuracy
Treatment	0.068*** (0.020)	0.033 (0.020)	0.103* (0.060)	-0.004 (0.074)	0.048 (0.074)	0.037*** (0.011)	-0.019 (0.027)	-0.007 (0.028)	-0.007 (0.011)	0.019 (0.029)	0.064** (0.029)
N	749	742	737	737	737	7720	4547	4547	7680	4523	4523
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Z-scored	No	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Control group mean	0.479	0.528	0	0	0	0.400	0	0	0.523	0	0

32

Note: This table displays main treatment effects on a series of post-treatment beliefs using data from Experiment 1 and Experiment 2 (see Table 1). Columns 1 to 5 use respondents who were cross-randomized into not receiving the option to read an article in the *New York Times*, while columns 6 to 11 use all respondents. “Filtering” refers to the percent chance that the *New York Times* reported that the Trump Tax Plan would create 1.1 million jobs. “Omission” refers to the percent chance that the *New York Times* wrote an article about the CBO’s analysis of granting citizenship to the Dreamers. “Quality” refers to people’s perception of the quality of articles in the *New York Times*. “Dryness” captures people’s perception of whether reporting of the *New York Times* is dry and technical. “Complex” measures people’s perception of whether reporting of the *New York Times* is complex. “No bias” is a dummy variable taking value one if our respondents think that the *New York Times* is not politically biased (column 6), and is defined similarly for the CBO (column 9). “Trust” measures people’s trust in the *New York Times* (column 7) and the CBO (column 10). “Curious” measures people’s interest in learning whether the *New York Times* is biased. “Accuracy” measures people’s perception of the accuracy of the forecasts of the CBO. The outcomes in columns 3, 4, 5, 7, 8, 10, and 11 are measured on five-point Likert scales and then z-scored. Regressions include the following controls: gender, age, income, region, race, education, employment status, frequency of reading the *New York Times*, pre-treatment beliefs about the probability that the *New York Times* would report both statistics, beliefs about the consequences of the policy bills, and experiment fixed effects.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

Table 3: Treatment effects on the demand for news

	(1) All	(2) Democrats	(3) Republicans
Treatment	-0.040*** (0.010)	-0.045*** (0.016)	-0.043*** (0.015)
N	7,047	3,033	2,555
Controls	Yes	Yes	Yes
Control group mean	0.277	0.327	0.234

Note: This table shows OLS regressions where the dependent variable is an indicator that takes the value one for respondents who wanted to read an article in the *New York Times* about a CBO report, using respondents from Experiments 1 and 2 (see Table 1). “Treatment” is an indicator that takes the value one for respondents who received information that the *New York Times* did not suppress any key facts from the CBO report. Democrats are respondents who either identify with the Democratic Party or identify as Independents leaning toward the Democratic Party and excluding respondents who approve of Trump. Republicans are respondents who identify with the Republican Party or identify as Independents leaning toward the Republican Party and excluding respondents who disapprove of Trump. Columns 1 uses all respondents, column 2 and 3 use only Democrats and Republicans, respectively. All regressions include the set of controls from Table 2.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

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Do People Value More Informative News?

Felix Chopra, Ingar Haaland, and Christopher Roth

Summary of the Online Appendix

Section A contains proofs and discussions related to Section 3.

Section B contains additional tables. Table B.1 provides the summary statistics. Table B.2 and Table B.3 examine the integrity of randomization for Experiment 1 and Experiment 2. Table B.4 shows treatment effects by experiment. Table B.5 explores heterogeneity in treatment effects by interacting the treatment with the continuous pre-treatment beliefs about reporting. Table B.6 shows the main treatment effects in the placebo experiment (Experiment 3). Table B.7 explores heterogeneity by political affiliation in Experiment 1.

Section C provides results from additional robustness experiments. It also discusses additional explanations and mechanisms that we think are unlikely to drive our results.

Section D contains screenshots of the experimental instructions. Table D.1 provides an overview of variables collected by experiment. Section D.1 shows the full set of experimental instructions for Experiments 1 and 7. In Section D.2, we provide the instructions for Experiment 2. In Section D.3, we show the instructions for Experiment 3. Section D.4 provides instructions for Experiment 4. Section D.5 shows the instructions for Experiment 5 and Section D.6 those for Experiment 6.

A Model appendix

A.1 Rational benchmark

We present a simple framework that formalizes the implications of strategic information suppression of news outlets for the Blackwell informativeness of news in our empirical design. This provides us with a theoretical benchmark for how learning that a newspaper is less likely to strategically suppress information should affect the demand for news according to the more-information-is-better principle.

There is a binary state space $\Theta = \{L, R\}$ with a typical element denoted by θ and an agent with prior belief $q \in \Delta(\Theta)$ about the hidden state. The agent has the option to acquire information from a newspaper. The newspaper provides information about θ by publishing an article $n \in N$ whose content is revealed only upon acquiring it. To introduce scope for information suppression, we assume that the newspaper receives a set of private signals $s = \{s_1, \dots, s_K\} \in S$ from its information source. The set consists of K binary bits of information $s_i \in \Theta$ about the state of the world θ , where K is randomly drawn and independent of θ . The individual bits, s_i , are drawn from a state-dependent distribution, F_θ . We assume that F_L places higher weight on L compared to F_R , implying that s_i is informative about θ . The source signal can thus be represented as an information structure (S, π) with state-dependent likelihood $\pi : \Theta \rightarrow \Delta(S)$. In our main empirical design, the CBO is the newspaper's source, providing two conflicting bits $s = \{L, R\}$ about the desirability, θ , of the Trump Healthcare Plan.

The newspaper can disclose any subset of s in its article n , i.e. $n \subseteq s$, implying that it cannot distort individual bits. Information suppression occurs whenever $n \neq s$. We are agnostic about the newspaper's incentives to suppress information, subsuming them in the reader's belief $\rho : S \rightarrow \Delta(N)$ about how the newspaper reports conditional on s .

From the agent's perspective, the informativeness of an article n should be an invariant of the state-dependent distribution over news articles, $\sigma : \Theta \rightarrow \Delta(N)$, induced by the agent's belief about the quality of the newspaper's source, π , and the belief about how the newspaper reports, ρ . Specifically, consider two articles n and n' with distributions $\sigma, \sigma' : \Theta \rightarrow \Delta(N)$. We use Blackwell's (1951) notion of informativeness and say that n is (*Blackwell*) *more informative* than n' if (n, σ) is *sufficient* for (n', σ') , that is: there is a stochastic transformation τ such that n' and $\tau(n)$ are identically distributed. Intuitively, we obtain n' by adding noise to n . This is the benchmark for

evaluating the informativeness of an information structure: any agent with access to an article n that is more informative than n' can attain an expected payoff at least as large as the maximal expected payoff attainable with n' , regardless of the prior q and the decision problem $a \in A$ with payoffs $u(a, \theta)$ (Blackwell, 1953). This provides the prediction that the demand for news should be strictly increasing in the perceived informativeness of the news.

How does strategic suppression affect the informativeness of news? Suppose the newspaper received the signals $s = \{s_1, \dots, s_K\}$ and let $\sigma(s' | s)$ denote the agents' belief that the newspaper would report $s' \subseteq s$ after receiving s . Intuitively, the informativeness of the article n should be increasing in the probability of fully conveying the signal. Indeed, the Blackwell informativeness of an article strictly increases if we decrease the probability $\sigma(s' | s)$ of reporting a filtered signal $s' \subsetneq s$ and instead increase the probability of full information transmission, $\sigma(s | s)$. To summarize:

Proposition 3 (Benchmark). Fix $s = \{s_1, \dots, s_K\} \in S$ and two reporting strategies $\rho, \rho' : S \rightarrow \Delta(N)$. Let $\sigma, \sigma' : \Theta \rightarrow \Delta(N)$ be the information structures induced by combining the source signal $\pi : \Theta \rightarrow \Delta(S)$ with the reporting strategies, respectively. Suppose that (i) $\rho(t | s) \leq \rho'(t | s)$ for all $t \subsetneq s$, (ii) $\rho(s | s) > \rho'(s | s)$, and that (iii) $\rho(\cdot | s') = \rho'(\cdot | s')$ for all $s' \neq s$. Then the information structure σ is Blackwell more informative than σ' .

Proof. It suffices to show that the conclusion obtains if we strengthen the assumption by additionally assuming that $\rho(t | s) < \rho'(t | s)$ for some $t \subsetneq s$ and that for all other $t' \subsetneq s$ with $t' \neq t$, we have $\rho(t' | s) = \rho'(t' | s)$. The general case then follows by applying the result to the sequence $\rho = \rho_1, \dots, \rho_L = \rho'$ where ρ_k and ρ_{k+1} differ at most on the set $\{s, s'\}$ for some $s' \subseteq s$ and $L = |\mathcal{P}(s)|$. Suppose that $n \in N$ is a random variable with state-dependent distribution σ . To show that σ is Blackwell more informative than σ' , it suffices to construct an n -measurable random variable $n' \in N$ with state-dependent distribution σ' , thereby establishing statistical sufficiency. We construct n' as follows: let $n' = n$ whenever $n \neq s$ and set $\beta = \rho'(s | s) / \rho(s | s)$. If $n = s$, then n' takes value s with probability β and value t with probability $1 - \beta$. One can then verify that conditional on the state $\theta \in \Theta$, the distribution of n' is $\sigma'(\cdot | \theta)$. This concludes the proof. \square

This provides us with an empirical test of the more-information-is-better principle. Specifically, we leverage an information treatment that decreases respondents'

expectation that the *New York Times* strategically filters information from CBO reports and increases their expectation that the *New York Times* reveals all information from the report. By the previous discussion, treated respondents should perceive articles from the *New York Times* as more informative, especially for articles covering reports from the CBO. If the desire for more information is the dominant motive for economic and political news consumption, the theoretical benchmark prediction is that treated respondents should strictly increase their demand for news.

A.2 Ideal-point models of media bias

There is an intuition that decreasing the left-wing bias of a news outlet should lead to an *increase* in the demand for news from this outlet among Republicans. Yet, the discussion at the end of Section 3 shows that Republicans might *decrease* their demand depending on how they evaluate neutral articles. We argue that the former intuition is based on a representation of the direct news utility similar to

$$\mathbb{E}(u(n)) = -\phi(|b - b^*|) \quad (5)$$

where ϕ is an increasing function of the distance between the news outlet's bias $b \in [-1, 1]$ and the agent's preferred, or *ideal*, bias b^* .¹ Then moving the news outlet's bias $b < 0$ by some ε towards 0 will increase the utility for agents with $b + \varepsilon \leq b^*$ and decrease the direct news utility for agents with $b^* \leq b$. Decreasing the left-wing bias of the *New York Times* should then lead to an increase in the demand for news among Republicans and to a decrease among Democrats. To apply these models in practice, we need to clarify: What is b ? Real news articles are not constrained to binary messages, which means that the utility evaluations of news articles are a potential confound to definitions of b based only on the reporting strategy of the newspaper.² For example, suppose a newspaper changes its reporting from $p_L = 1/2$ and $p_N = p_R = 1/4$ to $p_N = 1$. A Republican with preferences $L \preccurlyeq N \preccurlyeq R$ represented by $u_L = 0 \leq u_N \leq u_R = 1$ will be worse off if $u_N \leq 1/3$. This example illustrates why intuitions based on Equation (5) might fail in real-world settings with non-binary news articles. While experimental

¹In the case of filtering bias, one possibility is to assume that the news outlet receives a continuous signal $s \in \mathbb{R}$ and can only report a binary message, $n \in \{L, R\}$. If a right-wing biased news outlet reports R whenever $s \geq \tau$ for some $\tau < 0$, we can set $b = P(n = R \mid s < 0)$ (see Gentzkow et al., 2015).

²Both a newspaper that reports N with certainty and a newspaper that reports G and B in equal proportions seem to be equally “biased”, but people will not be indifferent unless $u_N = (u_G + u_B)/2$.

designs with binary news articles would allow for clear notions of bias, they have the drawback that Blackwell informativeness now depends on the likelihood of making false claims, which is much more difficult to vary experimentally than beliefs about information suppression in applied settings.

B Additional tables

Table B.1: Summary statistics

	(1) Exp. 1	(2) Exp. 2	(3) Exp. 3	(4) Exp. 6 and 7
Male	0.442	0.459	0.463	0.508
Age (midpoint)	48.546	42.712	44.774	36.063
White	0.871	0.779	0.846	0.797
Log income	3.355	3.099	3.499	3.349
College education	0.450	0.301	0.556	0.675
Full-time work	0.392	0.477	0.490	0.782
Northeast	0.195	0.161	0.218	0.217
Midwest	0.245	0.232	0.218	0.225
West	0.192	0.169	0.208	0.147
South	0.369	0.438	0.356	0.411
Republican	0.325	0.300	0.320	0.163
Democrat	0.340	0.355	0.343	0.553
Observations	4,625	3,189	930	2,169

Note: This table displays the mean value of basic covariates in our information treatment experiments (see Table 1 for an overview). “Male” is a binary variable with value one for male respondents. “Age” is coded as the continuous midpoint of the age bracket (18 to 24, 25 to 34, 35 to 44, 45 to 54, 55 to 64, 65 or older). “White” is a binary variable with value one if the respondent selected “Caucasian/White”. “Log income” is coded continuously as the logarithm of the income bracket’s midpoint (Less than \$15,000, \$15,000 to \$24,999, \$25,000 to \$49,999, \$50,000 to \$74,999, \$75,000 to \$99,999, \$100,000 to \$149,999, \$150,000 to \$200,000, \$200,000 or more). “College education” is a binary dummy variable taking value one if the respondent selected “Some college, no degree”, “Associates degree”, “Bachelor’s degree”, or “Post-graduate degree”. “Full-time work” is a binary dummy variable taking value one if the respondent is working full-time. “Northeast”, “Midwest”, “West” and “South” are binary dummy variables with value one if the respondent lives in the respective region. “Republican” and “Democrat” are binary dummy variables with value one if the respondent identifies as Republican or Democrat.

Table B.2: Test of balance: Experiment 1

	Treatment (T)	Control (C)	P-value(T - C)	Observations
Gender	0.45	0.44	0.703	4631
Age	48.30	48.78	0.314	4631
Log income	10.91	10.88	0.248	4025
South	0.36	0.37	0.473	4631
West	0.20	0.18	0.196	4631
Northeast	0.19	0.20	0.216	4631
Republicans	0.33	0.32	0.907	4631
Democrats	0.34	0.34	0.916	4631
White	0.87	0.87	0.963	4458
College education	0.45	0.45	0.563	4488

Note: This table provides a balance test for Experiment 1 (see Table 1). The p -value of a joint F-test regressing the treatment indicator on a series of observables is given by $p = 0.62$. “Gender” is a binary variable with value one for male respondents. “Age” is coded as the continuous midpoint of the age bracket (18 to 24, 25 to 34, 35 to 44, 45 to 54, 55 to 64, 65 or older). “Log income” is coded continuously as the logarithm of the income bracket’s midpoint (Less than \$15,000, \$15,000 to \$24,999, \$25,000 to \$49,999, \$50,000 to \$74,999, \$75,000 to \$99,999, \$100,000 to \$149,999, \$150,000 to \$200,000, \$200,000 or more). “South”, “West”, and “Northeast” are binary dummy variables with value one if the respondent lives in the respective region. “Republican” and “Democrat” are binary dummy variables with value one if the respondent identifies as Republican or Democrat. “White” is a binary variable with value one if the respondent selected “Caucasian/White”. “College education” is a binary dummy variable taking value one if the respondent selected “Some college, no degree”, “Associates degree”, “Bachelor’s degree”, or “Post-graduate degree”.

Table B.3: Test of balance: Experiment 2

	Treatment (T)	Control (C)	P-value(T - C)	Observations
Gender	0.45	0.46	0.685	3205
Age	42.80	42.64	0.754	3205
Log income	10.71	10.66	0.169	3192
South	0.44	0.44	0.871	3205
West	0.18	0.16	0.175	3205
Northeast	0.15	0.18	0.024	3205
Republicans	0.31	0.29	0.361	3205
Democrats	0.35	0.36	0.409	3205
White	0.78	0.78	0.773	3205
College education	0.30	0.31	0.505	3205

Note: This table provides a balance test for Experiment 2 (see Table 1). The p -value of a joint F-test regressing the treatment indicator on a series of observables is given by $p = 0.38$. “Gender” is a binary variable with value one for male respondents. “Age” is coded as the continuous midpoint of the age bracket (18 to 24, 25 to 34, 35 to 44, 45 to 54, 55 to 64, 65 or older). “Log income” is coded continuously as the logarithm of the income bracket’s midpoint (Less than \$15,000, \$15,000 to \$24,999, \$25,000 to \$49,999, \$50,000 to \$74,999, \$75,000 to \$99,999, \$100,000 to \$149,999, \$150,000 to \$200,000, \$200,000 or more). “South”, “West”, and “Northeast” are binary dummy variables with value one if the respondent lives in the respective region. “Republican” and “Democrat” are binary dummy variables with value one if the respondent identifies as Republican or Democrat. “White” is a binary variable with value one if the respondent selected “Caucasian/White”. “College education” is a binary dummy variable taking value one if the respondent selected “Some college, no degree”, “Associates degree”, “Bachelor’s degree”, or “Post-graduate degree”.

Table B.4: Treatment effects on demand for news by experiment

	(1) Exp. 1	(2) Exp. 2	(3) Exp. 6 and 7	(4) Pooled
Treatment	-0.035** (0.014)	-0.047*** (0.015)	-0.053*** (0.019)	-0.043*** (0.009)
N	3858	3189	2169	9216
Controls	Yes	Yes	Yes	Yes
Control group mean	0.274	0.280	0.325	0.288

Note: This table shows OLS regressions where the dependent variable is an indicator that takes the value one for respondents who wanted to read an article in the *New York Times* about a CBO report. Column 1 includes respondents from Experiment 1 (conducted with Dynata; see Table 1). Column 2 includes respondents from Experiment 2 designed to alleviate concerns about curiosity as a mechanism (conducted with Lucid; see Table 1). Column 3 includes respondents from additional robustness experiments conducted on Amazon Mechanical Turk (Experiments 6 and 7; see Table 1). Column 4 pools all respondents from Columns 1 to 3. “Treatment” is an indicator that takes the value one for respondents who received information that the *New York Times* did not suppress any key facts from the CBO report. All regressions include the set of controls from Table 2.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

Table B.5: Heterogeneity in treatment effects by prior beliefs about reporting

	Experiment 1		Experiment 2		Pooled	
	(1) Democrats	(2) Republicans	(3) Democrats	(4) Republicans	(5) Democrats	(6) Republicans
Treatment	-0.025 (0.037)	0.038 (0.046)	-0.090* (0.051)	-0.040 (0.055)	-0.042 (0.030)	0.006 (0.035)
Treatment x Prior right	-0.079 (0.086)	-0.139** (0.067)	0.157 (0.109)	-0.014 (0.090)	0.006 (0.067)	-0.087 (0.054)
Treatment x Prior left	-0.021 (0.064)	-0.081 (0.065)	0.030 (0.082)	-0.031 (0.078)	-0.011 (0.050)	-0.061 (0.050)
N	1,783	1,536	1,250	1,019	3,033	2,555
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Control group mean	0.333	0.218	0.319	0.259	0.327	0.234

Note: This table shows OLS regressions where the dependent variable is an indicator that takes the value one for respondents who wanted to read an article in the *New York Times* about a CBO report. Democrats are respondents who either identify with the Democratic Party or identify as Independents leaning toward the Democratic Party and excluding respondents who approve of Trump. Republicans are respondents who identify with the Republican Party or identify as Independents leaning toward the Republican Party and excluding respondents who disapprove of Trump. “Treatment” is an indicator that takes the value one for respondents who received information that the *New York Times* did not suppress any key facts from the CBO report. “Prior left” (“Prior right”) is the percent chance, from 0 to 1, that the *New York Times* only mentioned negative (positive) signals from a CBO report about a Trump policy proposal. Columns 1 and 2 only include respondents from Experiment 1 (see Table 1), column 3 and 4 only include respondents from Experiment 2, and columns 5 and 6 pool respondents from both experiments. All regressions include the set of controls from Table 2 as well as platform fixed effects.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

Table B.6: Treatment effects in the placebo experiment

	(1) Article demand	(2) Quality	(3) No bias
Treatment	0.015 (0.029)	0.099* (0.054)	0.019 (0.030)
N	930	928	928
Controls	Yes	Yes	Yes
Z-scored	No	Yes	No
Control group mean	0.265	0	0.384

Note: This table shows OLS regressions using data from the “Placebo experiment” conducted with Dynata (Experiment 3; see Table 1). “Treatment” is an indicator taking the value one for respondents who were informed that the *New York Times* reported two out of two statistics from the CBO report. “Article demand” is a binary variable with value one if the respondent wanted to read the *New York Times* article about the Trump Tax Plan. “Quality” refers to perceptions of quality in the *New York Times* and is measured on a 5-point Likert scale and then z-scored by the mean and standard deviation of control group respondents. “No bias” is a binary variable with value one if the respondent thinks that the *New York Times* is not politically biased. Regressions include the following controls: gender, age, income, region, race, education, employment status, and prior beliefs that the *New York Times* would report both statistics.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

Table B.7: Political heterogeneity in treatment responses

	Beliefs: Less suppression		Article characteristics			The New York Times			Congressional Budget Office			NYT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Filtering	Omission	Quality	Dryness	Complex	No bias	Trust	Curious	No bias	Trust	Accuracy	Demand
Treatment	0.027 (0.028)	0.048* (0.026)	0.122* (0.072)	0.033 (0.091)	0.074 (0.096)	0.056*** (0.016)	-0.011 (0.036)	-0.012 (0.037)	0.017 (0.016)	0.042 (0.043)	0.109*** (0.042)	-0.033** (0.015)
Treatment \times Rep.	0.083** (0.040)	-0.033 (0.040)	-0.067 (0.115)	-0.080 (0.147)	-0.050 (0.147)	-0.025 (0.022)	-0.017 (0.054)	0.008 (0.055)	-0.039* (0.023)	-0.049 (0.057)	-0.095 (0.058)	-0.011 (0.021)
N	749	742	737	737	737	7104	4547	4547	7064	4523	4523	6423
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Z-scored	No	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Control group mean	0.479	0.528	0	0	0	0.400	0	0	0.523	0	0	0.277

Note: This table displays heterogeneous treatment effects by political affiliation on a series of post-treatment beliefs in addition to article demand using data from Experiment 1 and Experiment 2 (see Table 1). “Rep.” is an indicator that takes the value one for self-identified Republicans and Independents who lean toward the Republican Party. Columns 1 to 5 use respondents who were cross-randomized into not receiving the option to read an article in the *New York Times*, while column 6 to 11 use all respondents. “Filtering” refers to the percent chance that the *New York Times* reported that the Trump Tax Plan would create 1.1 million jobs. “Omission” refers to the percent chance that the *New York Times* wrote an article about the CBO’s analysis of granting citizenship to the dreamers. “Quality” refers to people’s perception of the quality of articles in the *New York Times*. “Dryness” captures people’s perception of whether reporting of the *New York Times* is dry and technical. “Complex” measures people’s perception of whether reporting of the *New York Times* is complex. “No bias” (column 6) is a dummy variable taking value one if our respondents think that the *New York Times* is not politically biased. “Trust” (column 7) measures people’s trust in the *New York Times*. “Curious” measures people’s interest in learning whether the *New York Times* is biased. “Accuracy” measures people’s perception of the accuracy of the forecasts of the CBO. “No bias” (column 9) measures people’s perception of whether the CBO is biased. “Trust” (column 10) measures people’s trust in the CBO. “Demand” is a dummy variable taking value one if our respondents wanted to read an article in the *New York Times* about the Trump Tax Plan. The outcomes in columns 3, 4, 5, 7, 8, 10, and 11 are measured on five-point Likert scales and then z-scored. All regressions include the set of controls from Table 2.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

Table B.8: Correlation between quantitative and qualitative measures of media bias

	Quantitative priors		
	(1) Prior: left	(2) Prior: right	(3) Prior: both
Left-wing bias	0.091*** (0.012)		
Right-wing bias		0.112*** (0.012)	
No bias			0.084*** (0.012)
N	3857	3857	3857
Control group mean	0.367	0.239	0.393

Note: This table shows correlations between the quantitative pre-treatment beliefs about how the *New York Times* covered CBO reports and the post-treatment ratings of the media bias of the *New York Times* (5-point Likert scale). We use respondents from the control group in Experiment 1 and 2 (see Table 1). “Left-wing bias” is a binary variable taking value 1 if respondents said the *New York Times* is somewhat or very left-wing biased. “No bias” is a binary variable taking value 1 if respondents said the *New York Times* is not politically biased. “Right-wing bias” is a binary variable taking value 1 if respondents said the *New York Times* is somewhat or very right-wing biased. “Prior: left” is the percent chance (from 0 to 1) that the *New York Times* suppressed a statistic from a CBO report that contradicts claims made by Democrats. “Prior: right” is the percent chance (from 0 to 1) that the *New York Times* suppressed a statistic from a CBO report that contradicts claims made by Republicans.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

C Additional experiments and mechanisms

In this section, we first provide results from additional experiments that complement our results. We first assess the robustness of our results to (i) choosing different articles, (ii) financially incentivizing pre-treatment belief about reporting, (iii) using different sample providers, and we (iv) validate our measure of people’s demand for news. We then discuss additional, alternative mechanisms and why we think that they are unlikely to explain our results.

C.1 Robustness experiments

We conducted additional experiments using samples from Lucid (Experiment 2) and Amazon Mechanical Turk (Experiment 5, 6, and 7) to assess the robustness of our results (Table 1 provides an overview of all experiments).

Article choice and monetary incentives We first assess the robustness of our main result to a different choice of articles. In Experiment 2 with Lucid ($n = 3,189$; see Table 1) we use two new CBO reports to elicit beliefs about information suppression and measure article demand. In this experiment, we also address concerns about curiosity as discussed on page 21. To elicit beliefs about information suppression, we rely on a CBO report about the consequences of “Democrats’ \$15 Minimum Wage Bill” (the Raise the Wage Act, a Democratic bill to raise the federal minimum wage to \$15). Respondents are told that the CBO estimated that the bill would lift 1.3 million people out of poverty (contradicting claims made by Republicans) and decrease the number of jobs by 1.3 million (contradicting claims made by Democrats). To measure article demand after an information treatment in which respondents are informed that the *New York Times* reported both statistics, we offer all respondents free access to an article in the *New York Times* covering a CBO report about the consequences of establishing a single-payer health care system. As shown in column 2 of Table B.4, demand for news declines by 4.7 percentage points in this experiment ($p < 0.01$), confirming that our main result is robust to using different articles.

In an experiment on Amazon Mechanical Turk (Experiment 6, $n = 723$), conducted with Democrats and Democrat-leaning Independents, we reverse the order of articles used in Experiment 1. Furthermore, in this experiment, we elicit pre-treatment beliefs

about how the *New York Times* covered the findings from the CBO report about the Trump Tax Plan using monetary incentives and a quadratic scoring rule. We randomly selected one in ten respondents to be paid up to \$1 according to their guess. We subsequently measure people’s demand for the article about the CBO evaluation of the Trump Healthcare Plan. The patterns of beliefs and treatment effects are very similar to those in Experiment 1 (column 1 of Table C.1), suggesting that monetary incentives and reversed article order do not substantially affect our results. The point estimate of -0.04 is very close to the change in the demand for news in Experiment 1 of -0.035, but would require larger samples to be statistically significant.

Platform Across the experiments, we recruit respondents from three different platforms: Dynata, Lucid, and Amazon Mechanical Turk. These platforms are extensively used in social science research.³ Table B.4 shows that the main treatment effect on demand for news is very stable across platforms, which includes an experiment on Amazon Mechanical Turk with an identical design as in Experiment 1 (Experiment 7; $n = 1,332$). If anything, the estimated treatment effects are larger in our experiment using a representative sample from Lucid (column 2) and in our experiments on Amazon Mechanical Turk (column 3).

External validity We conducted an additional experiment on Amazon Mechanical Turk (Experiment 5; $n = 199$) in which we assess the external validity of our behavioral measure of article demand. Specifically, we measure in randomized order both people’s demand for news and (incentivized) willingness to pay for a 3-month subscription to the *New York Times* using a multiple price list.⁴ We find that our measure of article demand is significantly correlated with people’s willingness to pay ($\rho = 0.298$, $p < 0.01$). Despite being a binary variable, article demand has greater explanatory power for people’s willingness to pay compared to a saturated regression controlling for political affiliation, gender, income, and people’s beliefs about how the *New York Times* covered a CBO report.

³Coppock and McClellan (2019) find that samples from Lucid score similarly to the American National Election Study’s on the Big-5 personality inventory and show similar levels of political knowledge. Horton et al. (2011) find that experiments on MTurk closely replicate traditional lab experiments.

⁴Respondents decide between varying amounts of U.S. dollars and a subscription to the *New York Times*. We informed respondents that one out of ten randomly chosen participants would get one of their choices implemented. We used the following monetary amounts: 50 cents, \$1, \$2, \$3, \$4, \$5, \$10. Screenshots of the willingness to pay elicitation are provided in Section D.5.

Table C.1: Treatment effects in the robustness experiments

	(1) Experiment 6 Incentives and reverse order	(2) Experiment 7 Platform robustness
Treatment	-0.040 (0.036)	-0.063*** (0.023)
N	752	1,417
Controls	Yes	Yes
Control group mean	.392	.289

Note: This table shows OLS regressions where the dependent variable is an indicator that takes the value one for respondents who wanted to read an article in the *New York Times* (see Table 1). Regressions include the following controls: gender, age, income, region, race, education, employment status, frequency of reading the *New York Times*, pre-treatment beliefs about the probability that the *New York Times* would report both statistics, and beliefs about the consequences of the policy bills.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

C.2 Alternative mechanisms

Diversification Another potential explanation is based on the idea that people might consume a diverse set of news articles to extract a more informative signal by combining the different pieces of information (Mullainathan and Shleifer, 2005).⁵ Accordingly, a newspaper is particularly valuable if it provides information that is complementary to the information contained in the consumer’s news portfolio. Our treatment might then reduce the value of the *New York Times* in balancing out right-leaning news sources because it is perceived as more even-handed. We asked people pre-treatment to list up to three newspapers they are likely to read from a list of 20 popular newspapers across the political spectrum. For 46 percent of our respondents, the diversification motive is not present as they selected only left-leaning or right-leaning newspapers. Moreover, treatment effects are similar for respondents that only consume newspapers on one side of the political spectrum compared to those who read both at least one left-wing newspaper and one right-wing newspaper (column 1 of Table C.2).

Delegation Consumers delegate costly information acquisition to newspapers. If demand-side or supply-side constraints limit newspapers’ ability to communicate all the information available to them, Suen (2004) and Chan and Suen (2008) show that it can be rational for consumers to have a demand for articles that primarily contain information that confirms their prior beliefs. Delegation incentives are psychologically different from a behavioral preference for belief confirmation, but can make similar predictions. The key assumption behind this mechanism is that there is a need to filter information. Without such a constraint, it is optimal to disclose all facts.

We think that delegation incentives do not drive our treatment effects. First, supply-side constraints in the form of article word limits are unlikely given that all major newspapers reported both findings. We verified that all top 15 newspapers by circulation (as of June 2019) reported both findings, including the right-leaning news outlets such as Fox News. Moreover, all respondents were informed that the *New York Times*’s article contains 1,100 words, which is sufficient to discuss the two headline statistics from the CBO report. Second, our placebo experiment provides evidence against demand-side constraints based on cognitive constraints (see p. 20 for the discussion).

⁵This portfolio motive hinges on people’s perceived ability to debias themselves. However, empirical evidence suggests that it may be difficult for people to fully debias themselves (Enke, 2020b).

Third, one implication of delegation is that people from different political groups may have differential demand for different pieces of information. In Experiment 4 (see Table 1), we test empirically whether Democrats and Republicans exhibit such patterns of differential demand with data from a representative online panel in which we measure people’s demand for learning about the CBO estimates about the Trump Healthcare Plan and the Trump Tax Plan. In the first block, we tell respondents that the CBO analyzed the consequences of the Trump Healthcare Plan and separately elicit their demand for learning how the plan would affect the federal debt and the number of jobs. However, we do not tell them the value of these estimates. Thus, respondents do not know whether the estimates will be positive or negative, i.e., whether they confirm or contradict claims made by the political party they identify with. In the second block, we proceed similarly with the Trump Tax Plan. The order of blocks and the order of statistics within block was randomized. We find no differential demand for different pieces of information within each political group (as shown in Figure C.1). Indeed, both groups are equally interested in both of the two statistics, suggesting that our results are not driven by people having a demand for selective reporting about either the social consequences (Jobs, Uninsured) or the fiscal consequences (Debt, Deficit) of Trump policies.

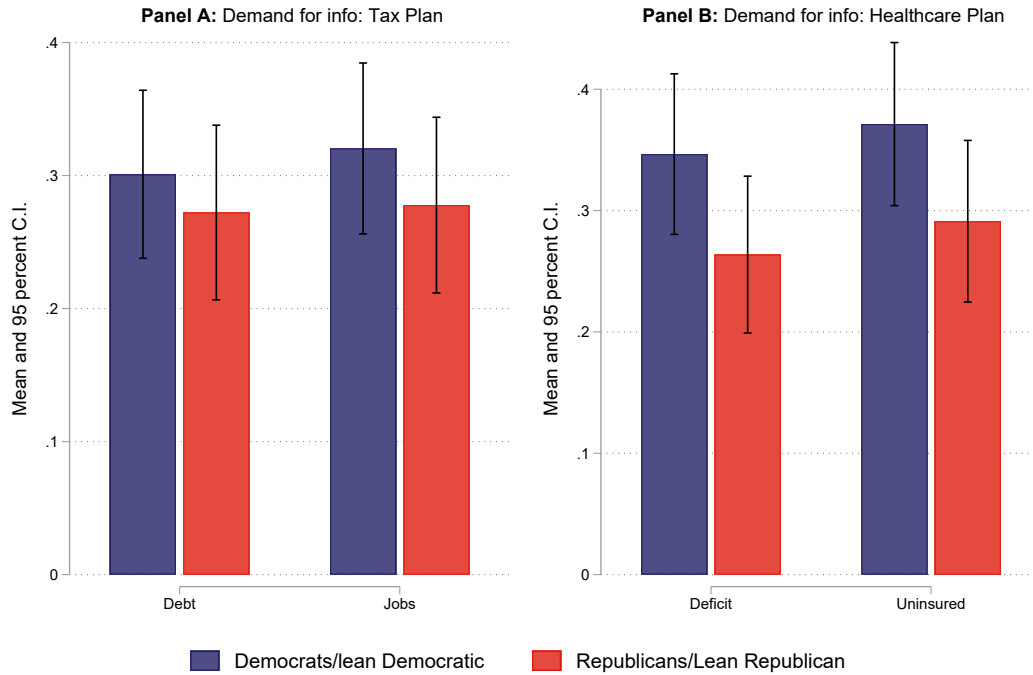
Table C.2: Heterogeneity in treatment effects by news consumption and education

	(1)	(2)
Treatment	-0.027 (0.018)	-0.041** (0.017)
Interactant	0.015 (0.020)	0.042* (0.022)
Treatment \times Interactant	-0.018 (0.028)	0.015 (0.028)
Interactant	Portfolio	College
N	3858	3858
Controls	Yes	Yes

Note: This table displays heterogeneous treatment effects on people’s demand for reading an article in the *New York Times* (Experiment 1; see Table 1). “Portfolio” takes value one for respondents who read both at least one left-wing newspaper and one right-wing newspaper. “College” takes value 1 for respondents who received at least some college education. All regressions include the set of controls from Table 2.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

Figure C.1: Demand for information about CBO statistics



Note: This figure uses data from an experiment with Lucid (Experiment 4, see Table 1). The figure shows, separately for Democrats/Democrat-leaners and Republicans/Republican-leaners, the fraction of respondents who wanted information about different statistics from the CBO reports. Specifically, respondents were either asked about their demand for information about the Trump Tax Plan (see Panel A) or about their demand for information about the Trump Healthcare Plan (see Panel B). Respondents were then asked separately and in randomized order for each of the two headline statistics from the respective CBO report, whether they want to receive the CBO's point estimate or not. However, respondents do not know anything about the value of the statistics prior to making the decision. If they selected "Yes", we provided them with the information at the end of the survey. "Debt" is the share of respondents who want to learn how the Trump Tax Plan will affect the federal debt. "Jobs" is the share of respondents who want to learn how the Trump Tax Plan will affect the number of jobs. "Deficit" is the share of respondents who want to learn how the Trump Healthcare Plan will affect the federal deficit. "Uninsured" is the share of respondents who want to learn how the Trump Healthcare Plan will affect the number of people with health coverage.

D Instructions

This section contains screenshots from all experiments. Table D.1 provides an overview of measures collected for each experiment. We provide screenshots of the full experimental instructions for Experiment 1 (see Table 1). For all other experiments, we always provide screenshots of the instructions used to measure pre-treatment beliefs about reporting, the information treatment, and the measure of article demand used in the experiment. We also provide screenshots of elements that differ from Experiment 1. For example, the robustness curiosity experiment (Experiment 2; see Table 1) informs all respondents pre-treatment that they will learn about how the *New York Times* reported about a CBO report at the end of the survey. To avoid repetition, we do not include screenshots of demographic variables and post-treatment measures for other experiments if they are measured as in Experiment 1.

Table D.1: Overview of measures collected by experiment

Experiment:	1	2	3	4	5	6	7
Attention check	Yes	Yes	Yes	Yes	Yes		
Gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes		
State						Yes	Yes
Household size						Yes	Yes
Household income	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethnicity	Yes			Yes		Yes	Yes
Race	Yes	Yes	Yes	Yes		Yes	Yes
Employment status	Yes	Yes	Yes	Yes		Yes	Yes
Education	Yes	Yes	Yes	Yes		Yes	Yes
Subscription to the NYT						Yes	Yes
Frequency of reading the NYT	Yes	Yes		Yes	Yes		Yes
3 newspapers most likely to read	Yes					Yes	Yes
Political affiliation (3-point scale)	Yes		Yes	Yes	Yes	Yes	Yes
Political affiliation (5-point scale)		Yes					
Political leaning (for Independents)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Voting: 2012 and 2016		Yes	Yes				
Approval: Trump's policy agenda	Yes	Yes					Yes
Pre-treatment beliefs: Tax	Yes		Yes		Yes	Yes	Yes
Pre-treatment beliefs: Health	Yes		Yes		Yes	Yes	Yes
Pre-treatment beliefs: Dreamers							Yes
Beliefs about reporting	H	MW	H		H	T	H
Article demand	T	SP	T		T	H	T
Posterior: Filtering (cont.)	Yes						Yes
Posterior: Omission (cont.)	Yes						Yes
Posterior: Quality (5-point)	Yes	Yes	Yes		Yes		Yes
Posterior: Dry and technical (5-point)	Yes	Yes					Yes
Posterior: Complex (5-point)	Yes						Yes
Political bias (5-point)	Yes	Yes	Yes		Yes		Yes
Trust (5-point)	Yes				Yes		
Curiosity about NYT's bias (4-point)	Yes						
CBO: Trust (5-point)	Yes						Yes
CBO: Accuracy (5-point)	Yes						Yes
CBO: Political bias (5-point)	Yes	Yes					Yes
Top three reasons for reading news	Yes						
Section: Most interesting	Yes						
Platform to read news	Yes						
Willingness to pay					Yes		

Note: This table provides an overview of collected variables by experiment (see Table 1). Rows above “Beliefs about reporting” list measures collected pre-treatment. “Beliefs about reporting” refers to the pre-treatment belief elicitation about how a news outlet reported underlying facts. “Article demand” is the main outcome of interest, and rows below it describe measures collected post-treatment. “H” refers to the *New York Times* article about the CBO evaluation of the Trump Healthcare Plan. “T” refers to an article about the CBO evaluation of the Trump Tax Plan. “MW” refers to an article about the CBO evaluation of raising the minimum wage to \$15. “SP” refers to an article about the CBO evaluation a single-payer health care system.

D.1 Experiment 1 and 7

D.1.1 Attention Check (Experiment 1)



The next question is about the following problem. In questionnaires like ours, sometimes there are participants who do not carefully read the questions and just quickly click through the survey. This means that there are a lot of random answers which compromise the results of research studies. To show that you read our questions carefully, please choose **both** "Extremely interested" and "Not at all interested" on the question below.

Given the text above, how interested are you in sports?

Extremely interested

Very interested

A little bit interested

Very little interested

Not at all interested

>>

D.1.2 Pre-treatment beliefs and characteristics (Experiment 1 and 7)



Please indicate your gender.

Male

Female

What is your age?

18–24

25–34

35–44

45–54

55–64

65 or older

What is your region of residence?

Northeast (CT, ME, MA, NH, RI, VT, NJ, NY,PA),

Midwest (IL, IN, MI, OH, WI, IA, KS, MN, MO, NE, ND, SD)

South (DE, DC, FL, GA,MD, NC, SC, VA, WV, AL, KY, MS, TN, AR, LA, OK, TX)

West (AZ, CO, ID, NM, MT, UT,NV, WY, AK, CA, HI, OR, WA)

What was your family's gross household income in 2017 in US dollars?

Less than \$15,000

\$15,000 to \$24,999

\$25,000 to \$49,999

\$50,000 to \$74,999

\$75,000 to \$99,999

\$100,000 to \$149,999

\$150,000 to \$200,000

More than \$200,000

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

Republican

Democrat

Independent

>>

NHH



In politics, as of today, do you lean towards the Republican Party or lean towards the Democratic Party?

The Republican Party

The Democratic Party

>>

NHH



How often do you read The New York Times (in print or digital)?

Daily

4-6 times a week

2-3 times a week

Once a week

Monthly

Once a year

Never

>>

NHH



Please rank the three newspapers that you are most likely to read from the list below (where 1 is the one you are most likely to read), and drag them to the appropriate position.

Items

Breitbart
BuzzFeed News
Chicago Sun-Times
Daily Mail
Drudge Report
InfoWars
Los Angeles Times
New Republic
New York Daily News
New York Post
Palmer Report
The Denver Post
The Huffington Post
The Mercury News
The New York Times
The Wall Street Journal
The Washington Post
The Washington Times
USA Today

3 newspapers most likely to read

>>

NHH



Do you approve or disapprove of Donald Trump's policy agenda?

Strongly approve

Approve

Disapprove

Strongly disapprove

>>

NHH



President Trump and Republicans in Congress have suggested two major legislative reforms:

- The **Trump Tax Plan** (to cut corporate taxes by \$1.5 trillion)
- The **Trump Healthcare Plan** (to repeal and replace Obamacare)

On balance, do you think that the **Trump Tax Plan** will have positive or negative consequences?

Very positive consequences

Somewhat positive consequences

Neither positive nor negative consequences

Somewhat negative consequences

Very negative consequences

On balance, do you think that the **Trump Healthcare Plan** would have positive or negative consequences?

Very positive consequences

Somewhat positive consequences

Neither positive nor negative consequences

Somewhat negative consequences

Very negative consequences

>>

D.1.3 Prior: Filtering (Experiment 1 and 7)

NHH

The Congressional Budget Office (CBO) is Congress's nonpartisan provider of cost and benefit estimates for legislation. In 2017, the CBO analyzed the consequences of the Trump Healthcare Plan.

When debating the Trump Healthcare Plan, Republicans claimed that the plan would decrease the federal deficit, but would not increase the number of people without health coverage. The Democrats, by contrast, claimed that the plan would fail to decrease the deficit and massively increase the number of people without health coverage.

In its published report, the CBO estimated that the Trump Healthcare Plan would **decrease the deficit by \$119 billion** and leave **23 million more people uninsured**.

What do you think?

After the CBO published its report, **The New York Times** wrote an article about its findings.

What would you say is the percent chance that **The New York Times** reported...
(Please note: The numbers need to add up to 100%)

that the deficit would decrease by \$119 billion **but not** that the number of uninsured people would increase by 23 million.

0 %

that the number of uninsured people would increase by 23 million **but not** that the deficit would decrease by \$119 billion.

0 %

that the deficit would decrease by \$119 billion **and** that the number of uninsured people would increase by 23 million.

0 %

Total

0 %

>>

D.1.4 Treatment (Experiment 1 and 7)

NHH

In its article about the CBO estimates, The New York Times reported **both** that the federal budget deficit would decrease by \$119 billion **and** that the number of people without health insurance would increase by 23 million.

>>

D.1.5 Main outcome (Experiment 1 and 7)

NHH

Last year, the Congressional Budget Office analyzed the consequences of the **Trump Tax Plan** over the next decade.

Do you want to read an article about its findings in **The New York Times**?

Yes

No

If you click "Yes" we will provide you with free access to the article (1100 words) at the end of the survey. If you click "No" you will proceed with the survey without receiving access to the article.

>>

D.1.6 Posterior beliefs (Wave 2 of Experiment 1 only)

NHH

When debating the Trump Tax Plan, Republicans claimed that the plan would create new jobs without increasing the federal debt. By contrast, Democrats claimed that the plan would fail to create more jobs and massively increase the federal debt.

In its report, the Congressional Budget Office estimated that the Trump Tax Plan would add **\$1.6 trillion to the federal debt** and **create 1.1 million jobs**.

What do you think?

After the CBO published its report, **The New York Times** wrote an article about its findings.

In its article, The New York Times reported that the Trump Tax Plan would add \$1.6 trillion to the federal debt.

What would you say is the percent chance that The New York Times **also reported** that the Trump Tax Plan would create 1.1 million jobs?

Extremely unlikely

Somewhat unlikely

Neither likely nor unlikely

Somewhat likely

Extremely likely

0

10

20

30

40

50

60

70

80

90

100

Percent

>>

NHH



Democrats have urged President Trump to grant citizenship status for up to 1.8 million young undocumented immigrants, known as the Dreamers. Democrats have claimed that this would decrease the federal debt, whereas Republicans have claimed that it would increase the federal debt.

The CBO recently also analyzed the impact of granting citizenship status for the Dreamers. In its report, the CBO estimated that this would **add \$27 billion to the federal debt**.

What do you think?

What would you say is the percent chance that **The New York Times** did **not** write an article about the findings from this CBO report?



>>

NHH



In general, how do you rate the **quality of news articles** in The New York Times?

Very low

Low

Medium

High

Very high

When thinking about its coverage of the CBO report about the Trump Tax Plan, how **dry** and **technical** do you expect the article to be?

Not at all dry and technical

Not dry and technical

Somewhat dry and technical

Very dry and technical

Extremely dry and technical

When thinking about The New York Times' coverage of the CBO report about the Trump Tax Plan, do you expect a **very simple message** or a **very complex message**?

Very simple

Simple

Neither simple nor complex

Complex

Very complex

>>

D.1.7 Perceptions: NYT and CBO (Experiment 1)



In general, do you think **The New York Times** is politically biased?

Very right-wing biased

Somewhat right-wing biased

Not biased

Somewhat left-wing biased

Very left-wing biased

>>

NHH



How much do you trust The New York Times?

Strongly trust

Trust

Somewhat trust

Do not trust

Do not trust at all

How much do you trust the media in general?

Strongly trust

Trust

Somewhat trust

Do not trust

Do not trust at all

How interested would you be in learning about statistics on whether The New York Times reports unbiasedly about political issues?

Very interested

Interested

Not interested

Not interested at all

>>

NHH



How much do you trust the forecasts of the Congressional Budget Office?

Strongly trust

Trust

Somewhat trust

Do not trust

Do not trust at all

In your opinion, how accurate are the forecasts of the Congressional Budget Office?

Very accurate

Accurate

Somewhat accurate

Inaccurate

Very inaccurate

Do you think the Congressional Budget Office is politically biased?

Very right-wing biased

Somewhat right-wing biased

Not biased

Somewhat left-wing biased

Very left-wing biased

>>

D.1.8 Post-treatment beliefs and characteristics (Experiment 1)

NHH

Why do you usually read political news? Please rank the three most important reasons (where 1 is the the most important one for you)

Items	Main 3 reasons
To improve my knowledge about political issues	
To be able to follow the national conversation	
To expose myself to different points of view	
For the entertainment value	
To make more informed voting choices	
Because it is important for my job	

>>

NHH



In newspapers, which section are you most interested in?

Entertainment

Advice columns

Editorial & opinion pages

Lifestyle

Political news

Which of these platforms are you most likely to use as news sources?

Radio

Social media

Print newspapers

News websites

Television

>>

NHH



Which of the following best describes your race or ethnicity?

African American/Black

Asian/Asian American

Caucasian/White

Native American, Inuit or Aleut

Native Hawaiian/Pacific Islander

Other

Are you of Hispanic, Latino, or Spanish origin?

Yes

No

Which category best describes the highest level of education you have completed?

Eighth grade or less

Some high school

High school degree/GED

Some college

2-year college degree

4-year college degree

Master's degree

Doctoral degree

Professional degree (JD, MD, MBA)

What is your current employment status?

Full-time employee

Part-time employee

Self-employed or small business owner

Unemployed and looking for work

Student

Not in labor force (for example: retired or full-time parent)

>>

D.1.9 End of Survey

NHH



Please see below to find your free access to The New York Times article covering the CBO estimates of the Trump Tax Plan.

The New York Times

Federal Budget Deficit Projected to Soar to Over \$1 Trillion in 2020

By Thomas H. Kneitel

April 9, 2018

WASHINGTON — The federal government's annual budget deficit is set to widen significantly in the next few years, and is expected to top \$1 trillion in 2020 despite healthy economic growth, according to new projections from the nonpartisan Congressional Budget Office released Monday.

The national debt, which has exceeded \$21 trillion, will soar to more than \$33 trillion in 2028, according to the budget office. By then, debt held by the public will almost match the size of the nation's economy, reaching 96 percent of gross domestic product, a higher level than any point since just after World War II and well past the level that economists say could court a crisis.

The fear among some economists is that rising deficits will drive up interest rates, raise borrowing costs for the private sector, tank stock prices and slow the economy, which would only drive the deficit higher.

"Such high and rising debt would have serious negative consequences for the budget and the nation," said Keith Hall, the director of the budget office. "In particular, the likelihood of a fiscal crisis in the United States would increase."

The budget office forecast is the first since President Trump signed a sweeping tax overhaul, then signed legislation to significantly increase military and domestic spending over the next two years. The figures are sobering, even in a political climate where deficit concerns appear to be receding.

The tax overhaul, which includes permanent tax cuts for corporations and temporary ones for individuals, will increase the size of the economy by an average of 0.7 percent from 2018 to 2028, according to the budget office.

But that added economic growth does not come close to paying for the tax overhaul, which the budget office said would add more than \$1.8 trillion to deficits over that period, from lost tax revenue and higher interest payments.

D.2 Experiment 2 – Robustness curiosity

D.2.1 Pre-treatment beliefs and characteristics

Which of these describes you more accurately?

Male
Female

What is your age?

18–24
25–34
35–44
45–54
55–64
65 or older

What is your region of residence?

Northeast (CT, ME, MA, NH, RI, VT, NJ, NY,PA)
Midwest (IL, IN, MI, OH, WI, IA, KS, MN, MO, NE, ND, SD)
South (DE, DC, FL, GA,MD, NC, SC, VA, WV, AL, KY, MS, TN, AR, LA, OK, TX)
West (AZ, CO, ID, NM, MT, UT,NV, WY, AK, CA, HI, OR, WA)

What was your family's gross household income in 2018 in US dollars?

Less than \$15,000

\$15,000 to \$24,999

\$25,000 to \$49,999

\$50,000 to \$74,999

\$75,000 to \$99,999

\$100,000 to \$149,999

\$150,000 to \$200,000

More than \$200,000

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

Republican

Democrat

Independent

>>

Do you approve or disapprove of Donald Trump's policy agenda?

Strongly approve

Approve

Disapprove

Strongly disapprove

Who did you vote for in the 2016 Presidential election?

Donald Trump

Hillary Clinton

Other

I did not vote

Who did you vote for in the 2012 Presidential election?

Barack Obama

Mitt Romney

Other

I did not vote

>>

Which of the following best describes your race or ethnicity?

White	Asian
Black or African American	Native Hawaiian or Pacific Islander
American Indian or Alaska Native	Other

Which category best describes the highest level of education you have completed?

12th grade or less

Graduated high school or equivalent

Some college, no degree

Associate degree

Bachelor's degree

Post-graduate degree

Which of these describes your current situation most accurately?

Employed full-time

Employed part-time

Self-employed

Unemployed and looking for a job

Unemployed but not looking for a job

Retired

Student

Other



How often do you read **The New York Times** (in print or digital)?

Daily

4-6 times a week

2-3 times a week

Once a week

Monthly

Once a year

Never

>>

D.2.2 Belief elicitation

Information

The Congressional Budget Office (CBO) is Congress's nonpartisan provider of cost and benefit estimates for legislation.

We will now ask you a question about how The New York Times covered the findings from a recent major policy report from the CBO.

We will tell you how The New York Times covered these findings at some later point in the survey.

>>

Democrats' \$15 Minimum Wage Bill

In July, the CBO analyzed the consequences of a bill to increase the federal minimum wage to \$15 an hour.

When debating the bill, **Democrats** claimed that the bill would lift more people out of poverty without reducing the number of jobs.

Republicans, by contrast, claimed that the bill would fail to lift people out of poverty and massively reduce the number of jobs.

In its report, the CBO estimated that the bill would **lift 1.3 million people out of poverty** and that the bill would **decrease the number of jobs by 1.3 million**.

What do you think?

After the CBO published its report, The New York Times wrote an article about its findings.

What would you say is the percent chance that **The New York Times** reported that...
(Please note: The numbers need to add up to 100%)

1.3 million people would be lifted out of poverty **but not** that the number of jobs would decrease by 1.3 million. %

the number of jobs would decrease by 1.3 million **but not** that 1.3 million people would be lifted out of poverty. %

1.3 million people would be lifted out of poverty **and** that the number of jobs would decrease by 1.3 million. %

Total %

D.2.3 Treatment

Information

In its article about the CBO estimates, The New York Times reported **both** that 1.3 million people would be lifted out of poverty **and** that the number of jobs would decrease by 1.3 million.

D.2.4 Main outcome

The Congressional Budget Office recently also analyzed the consequences of establishing a **single-payer health care system** (to achieve universal health insurance coverage).

Do you want to read an article about its findings in **The New York Times**?

Yes

No

If you click "Yes" we will provide you with free access to the article (1100 words) at the end of the survey. If you click "No" you will proceed with the survey without receiving access to the article.

D.3 Experiment 3 – Cognitive constraints placebo

Figure D.1: Belief elicitation

The Congressional Budget Office (C.B.O.) is Congress's nonpartisan provider of cost and benefit estimates for legislation.

In 2017, the C.B.O. analyzed the consequences of the G.O.P. Health Bill.

When the C.B.O. published its report about the G.O.P. Health Bill, the **C.B.O. highlighted two key statistics** from the report.

After the C.B.O. published its report, **The New York Times** wrote an article about the report.

What do you think?

What would you say is the percent chance that the **The New York Times** cited zero, one, or two of the two key statistics from the C.B.O. report?

(Please note: The numbers must total 100%)

The New York Times cited 0 of the 2 key statistics.	<input type="text" value="0"/>	%
The New York Times cited 1 of the 2 key statistics.	<input type="text" value="0"/>	%
The New York Times cited 2 of the 2 key statistics.	<input type="text" value="0"/>	%
Total	<input type="text" value="0"/>	%

Next >>

Figure D.2: Treatment screen

In its article, **The New York Times** cited **2 of the 2 key statistics** from the C.B.O. report.

Next >>

Figure D.3: Willingsness to read about GOP Tax Bill in the NYT

Last year, the C.B.O. analyzed the consequences of the **G.O.P. Tax Bill** over the next decade.

Do you want to read an article about its findings in **The New York Times**?

☐ Yes

☐ No

If you click "Yes" we will provide you with free access to the article (1100 words) at the end of the survey. If you click "No" you will proceed with the survey without receiving access to the article.

Next >>

D.4 Experiment 4 – Information demand

For this experiment, we provide the instructions for the measurement of people's demand for information about the CBO estimates about the consequences of the (i) Trump Tax Plan and (ii) the Trump Healthcare Plan. The order of these two blocks was randomized.

Figure D.4: Demand for information: Tax Bill

The Congressional Budget Office (CBO) is Congress's nonpartisan provider of cost and benefit estimates for legislation. In 2018, the CBO analyzed the economic consequences of the Trump **Tax** Plan (to cut corporate taxes by \$1.5 trillion).

Would you like to receive the estimate from the CBO about how the Trump Tax Plan would affect the **federal debt** over the next decade?

If you click "Yes" you will receive the estimate at the end of the survey.

Yes

No

Would you like to receive the estimate from the CBO about how the Trump Tax Plan would affect the **number of jobs** over the next decade?

If you click "Yes" you will receive the estimate at the end of the survey.

Yes

No

>>

Figure D.5: Demand for information: Health Bill

The Congressional Budget Office (CBO) is Congress's nonpartisan provider of cost and benefit estimates for legislation. In 2018, the CBO analyzed the economic consequences of the Trump **Healthcare** Plan (to repeal and replace Obamacare).

Would you like to receive the estimate from the CBO about how the Trump Healthcare Plan would affect the **federal budget deficit** over the next decade?

If you click "Yes" you will receive the estimate at the end of the survey.

Yes

No

Would you like to receive the estimate from the CBO about how the Trump Tax Plan would affect the **number of people without health insurance** over the next decade?

If you click "Yes" you will receive the estimate at the end of the survey.

Yes

No

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D.5 Experiment 5 – External validity

We provide the instructions for the measurement of people's willingness to pay for a digital subscription to the *New York Times*. The demand for news was measured as in Experiment 1 (see Table 1).

NHH



You will now make multiple decisions that can have **real financial consequences for you**. Please consider each decision carefully.

In each decision, we will ask you to choose one of two options:

- Option A: 3-month digital subscription to **The New York Times**.
- Option B: Varying amounts of money.

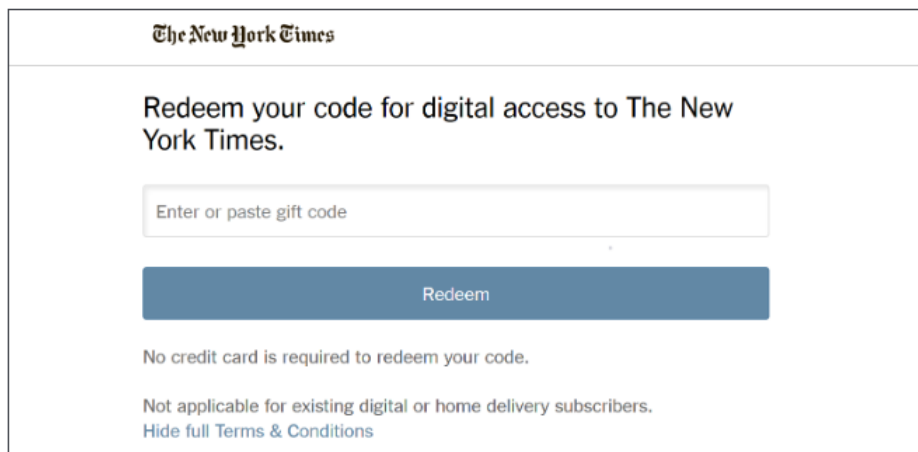
We will randomly select **1 out of 10** participants of this study. If we select you, we will randomly choose one of your decisions and implement the option you chose. Each decision has the same chance of being implemented.

If we implement Option A, you will receive a unique gift code for a 3-month subscription. If we implement Option B, you will receive an amount of money (paid out as a bonus to your MTurk account).

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How would you receive your digital subscription to The New York Times?

1. We will send you a **unique gift code**. It looks like this: `4432a7af8c83b5da72gb`
2. We provide you with a **link to a website** where you can redeem it. It looks like this:

A screenshot of a web page for redeeming a gift code. At the top, the "The New York Times" logo is displayed. Below the logo, the text "Redeem your code for digital access to The New York Times." is shown. Underneath this text is a text input field with the placeholder "Enter or paste gift code". Below the input field is a blue button labeled "Redeem". At the bottom of the page, there is a line of text: "No credit card is required to redeem your code." followed by "Not applicable for existing digital or home delivery subscribers." and a link "Hide full Terms & Conditions".

The New York Times

Redeem your code for digital access to The New York Times.

Enter or paste gift code

Redeem

No credit card is required to redeem your code.

Not applicable for existing digital or home delivery subscribers.

[Hide full Terms & Conditions](#)

3. Enter the code and **create an account**. You only need an email address for this.
4. **That's all!**

No credit card information is required to create an account. The subscription will automatically be canceled after the 3 month period. You can also cancel the subscription at any time if you want.

The code is completely anonymous and cannot be used to identify your email or any other of your personal characteristics.

We will now give you the opportunity to decide between two options:

- **Option A:** 3-month digital subscription to **The New York Times (NYT)**.
- **Option B:** Varying amounts of money.

Which option do you prefer?

Option A	Option B
NYT subscription	50 cents
NYT subscription	\$1
NYT subscription	\$2
NYT subscription	\$3
NYT subscription	\$4
NYT subscription	\$5
NYT subscription	\$10

D.6 Experiment 6

We provide the instructions for the (i) financially incentivized pre-treatment belief elicitation, (ii) the information treatment, and (iii) the demand for news.

Figure D.6: Explanations of probability

In some of the following questions, we will ask you to think about the percent chance of something happening in the future. Your answers can range from 0 to 100, where 0 means there is absolutely no chance, and 100 means that it is absolutely certain.

For example, numbers like:

- 2 or 5 percent may indicate “almost no chance.”
- 18 percent or so may mean “not much chance.”
- 47 or 52 percent chance may be a “pretty even chance.”
- 83 percent or so may mean a “very good chance.”
- 95 or 98 percent chance may be “almost certain.”

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Figure D.7: Explanations of incentive payment

In what follows, we will ask you to make some estimates on factual statements which are either true or false. One out of ten participants can earn additional money based on their estimates. For those participants, we will randomly pick one of the questions in which they can earn money, and pay them according to their estimate. They can earn up to an additional \$1.

We will ask you to think about the percent chance that of different statements being true. The below formula explains in detail how the payout is determined. While this formula may appear to be complicated, the important take-away message from the formula is that participants will earn more money the closer they are to the truth. If the statement is true then participants will receive a higher payoff the higher their estimate. If the statement is false then they will receive a higher payoff the lower their estimate. Moreover, they can never make a loss by giving an estimate.

Your payment depends on your estimate in the following way:

$$\text{Payment (in US dollars)} = 1 - 1 \times (\text{estimate} / 100 - \text{truth})^2$$

where **truth** takes the value 1 if the statement is true, and zero otherwise.

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Figure D.8: Beliefs about reporting I

The Congressional Budget Office (CBO), Congress's nonpartisan provider of cost and benefit estimates for legislation, recently analyzed the impact of the GOP Tax Bill on the economy.

When debating the GOP Tax Bill, Republicans claimed that the Tax Bill would create new jobs without increasing the federal debt. By contrast, Democrats claimed that the GOP Tax Bill would fail to create more jobs and massively increase the federal debt.

In April 2018, CBO published its report about the impact of the GOP Tax Bill on the economy. The CBO estimated that the GOP Tax Bill would add **\$1.6 trillion to federal debt** and **create 1.1 million jobs** over the next decade.

What do you think?

After the Congressional Budget Office published its report in April 2018, **The New York Times** wrote an article about its findings.

What would you say is the percent chance that **The New York Times** reported...
(Please note: The numbers need to add up to 100 percent)

that jobs would increase by 1.1 millions but not that the federal debt would increase by \$1.6 trillion	<input type="text" value="0"/> %
that the federal debt would increase by \$1.6 trillion but not that jobs would increase by 1.1 millions	<input type="text" value="0"/> %
that the federal debt would increase by \$1.6 trillion and that jobs would increase by 1.1 millions	<input type="text" value="0"/> %
Total	<input type="text" value="0"/> %

Figure D.9: Treatment screen

In its coverage of the CBO estimates, The New York Times reported both that the federal debt would increase by \$1.6 trillion **and** that jobs would increase by 1.1 millions.

Figure D.10: Article demand

The Congressional Budget Office also analyzed the economic impact of the **GOP Health Care Bill**. Do you want to read a story about its findings in **The New York Times**?

If you click “Yes” we will provide you with free access to the article. If you click “No” you will proceed with the survey without receiving access to the article.

Yes

No

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