Media Credibility in China and the United States*

Seth J. Hill†
Margaret E. Roberts‡

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Abstract: While it is widely understood that media sources do not deliver news with perfect objectivity, citizens' beliefs about the informative value of news media are difficult to measure. We offer a new experimental measure of the credibility attributed to different news sources that can be applied across countries. Using experiments with incentives for accuracy and a Bayesian model of learning, we measure how citizens learn about political and economic facts from the news headlines of different providers and show that knowledge of the source that produced those headlines changes how citizens learn. We implement the experimental method in the U.S. and China. Subjects attributed an average likelihood ratio of 1.3 to the information in our set of news headlines suggesting they find news coverage informative, on average. In the U.S., citizens attribute inaccuracy to Fox News and in China to the Global Times. We show that credibility attributed to news providers varies by ideological cleavages in each country.

Keywords: News media; Political information; Bayesian learning; Media bias; crossover scoring method.

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†University of California, San Diego, Department of Political Science, 9500 Gilman Drive #0521, La Jolla, CA 92093-0521; sjhill@ucsd.edu, http://www.sethjhill.com.

‡University of California, San Diego, Department of Political Science, 9500 Gilman Drive #0521, La Jolla, CA 92093-0521; meroberts@ucsd.edu, http://www.margaretroberts.net.

It is widely believed that media sources in both democratic and non-democratic regimes do not objectively deliver the news. In either form of government, news sources may slant news for commercial reasons (Gentzkow and Shapiro, 2010; Groseclose and Milyo, 2005; Hamilton, 2004; Larcinese, Puglisi, and Snyder, Jr., 2011; Puglisi and Snyder, Jr., 2011). Interference from the government may likewise lead to inaccurate delivery of information, a concern particularly prevalent in non-democratic societies (Stockmann and Gallagher, 2011; Qin, Strömberg, and Wu, 2017; King, Pan, and Roberts, 2013; Yuan, 2016; Roberts, Stewart, and Airoldi, 2016). Because citizens must depend upon the reporting of others to learn about the world beyond their own experience, bias in the media is a cause for concern to many who consider its implications for the accountability of governments to constituents. In particular, many have voiced concern about how polarization of online and televised news might lead to the spread of false information, polarization of citizens, and ultimately political conflict (Baum and Groeling, 2008; Iyengar and Hahn, 2009).

Of course, the consequences of slanted news depend upon how citizens understand and account for bias or inaccuracy in the news that they consume. Citizens may discount certain news sources and place credibility in the reporting of others, and this will have important implications for whether and how media slant impacts politics. However, measuring the ways in which citizens trust or discount news media is difficult. Current methods of simply asking a respondent whether they trust news or believe a particular fact that comes from a particular source could reflect partisan praise, cheerleading, or some other artifact of the survey setting rather than actual belief. Self-reported measures of trust also depend on respondents' self-awareness of how they process information and learn from news sources.

In this paper, we propose a new experimental measure of the credibility of news and news sources that improves on the challenges to existing measures. In experiments with incentives for accuracy, subjects learn about political and economic facts from the headlines produced by different national news sources. We elicit beliefs about each fact before and after the subject observes a news headline relevant to that fact. Change in beliefs across delivery of the news headline measures how much subjects learn from that headline. We randomize the order that headlines are delivered and whether or not subjects are informed of the news provider that produced the headline. Across subjects and facts, then, we measure how informative on average the headlines of each news provider are to the facts on which they are reported. This serves as a behavioral measure of informativeness.

Comparing learning from headlines delivered with and without the news source yields a behavioral measure of the credibility subjects attribute to that news source. When subjects update their beliefs less from a headline when informed of its source, they are discounting the news provided by that source – in other words, they attribute bias or inaccuracy to the way that news source generates headlines from facts.

Because our experimental design offers behavioral measures of informativeness and credibility on a common quantitative scale, it also allows us to compare learning from news across disparate environments, which is increasingly important as news has become more international. We fielded the experiments with samples of citizens from two large and heterogeneous nations with differing governing and media structures: the United States and China. The experimental design allows us to measure how much American and Chinese citizens learn from common national news sources and how much they discount headlines from each provider. Finally, because shirking or cheerleading may cloud elicited beliefs in surveys, (e.g., Bullock et al., 2015; Prior and Lupia, 2008), we offer incentives for subjects to get the factual responses correct. Although in the real world citizens are not compensated directly for factual knowledge when consuming news, many of our facts surround currency fluctuations and other economic indicators. Even though these facts have political relevance, they also have direct relevance to individuals' economic choices, suggesting individual economic incentives to obtain accurate knowledge about these facts. Incentives also likely mitigate priming and demand effects in responses.

We find that American and Chinese citizens learn similarly about political and economic facts from the headlines produced by their respective news providers. Applying a model of Bayesian learning to interpret the observed learning, we find that our subjects do learn from news headlines, with average likelihood ratios for each headline of about 1.3 though with more learning by American than by Chinese subjects. We also find evidence that subjects modify what they learn from news headlines when they are informed of the provider of that news. In the U.S., subjects learn more from New York Times headlines when they know the Times produced the headline than when they are not provided the source, and less when informed that Fox News produced the headline. In China, subjects learn less from Global Times headlines when they know the source than when only exposed to the headline.

The credibility attributed to news providers varies by individual ideology in both countries. In China, we find that ideological authoritarians discount news from the BBC much more than ideological democrats, who are much more likely to discount the Global Times.[1] In the U.S., we find that self-identified Democratic partisans learn relatively more than self-identified Republicans from CNN-identified headlines than those same headlines absent the source. We find that both Democrats and Republicans discount news headlines when aware they were produced by Fox News.

We offer three central contributions. First, our results provide evidence that citizens believe that different sources offer news with different slants and that the way they consume news accounts for these beliefs. Although we do not have a benchmark that allows us to characterize if the discounting citizens apply is correct – we do not have objective knowledge of the actual fidelity of these media sources to the truth – these findings give pause to concerns that biased media necessarily undermines political accountability. Second, we present and implement a new methodological approach to measuring media credibility through observed learning behavior. Rather than responses to surveys, which may not measure actual beliefs about media characteristics due to shirking, cheerleading, or lack of awareness, our technology directly measures learning with incentives for accuracy to characterize subjects' revealed beliefs about media credibility. In the concluding section, we suggest future opportunities for application of this technology. Finally, we show that our results produce different results than respondents' selection of news sources, suggesting that discounting and selection may be two fundamentally different types of processes.

[1] We use the measures created by Wu and Meng (2016) to estimate ideology in China.

Our essay proceeds as follows. We motivate the importance of media slant before presenting a theory of news consumption by consumers in a world with slanted news. We then present existing measures of media slant and our proposed behavioral measure and experimental design. We document the implementation of this design with American and Chinese samples, and then present estimation results. We finally offer concluding remarks and implications.

1 Measuring perceptions of media informativeness

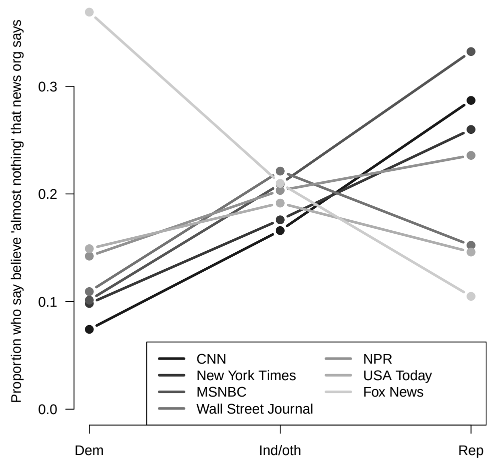
Citizens in the United States and China give survey responses that indicate they believe that news sources slant delivery of objective news. In Figure 1, for example, many American respondents to a 2012 survey by the Pew Organization expressed incredulity towards The New York Times and Fox News, with important variation by the respondent's party identification. The figure highlights that near 40 percent of self-identified Democrats claim they could believe almost nothing that Fox News says, compared to around 10 percent of self-identified Republicans. A reverse pattern obtains for MSNBC. Many Americans claim in surveys that national news providers are sufficiently biased so as to be rarely believed.

Citizens in authoritarian environments report similar skepticism toward media sources in surveys. In a Beijing survey conducted in 2002, 94% of respondents said that more commercialized newspapers were closer to their "conception of reality," and only 6% of people chose government-run or "official" papers (Stockmann, 2013, pg 165). In 2005, the Chinese Mass Media Credibility survey indicated that even though *People's Daily* was most highly trusted among citizens, local commercial papers were more trusted than local Party papers (Stockmann, 2013, pg 165). Stockmann (2013) finds higher levels of trust in the media relative to government in areas of China where there are more marketized media environments.

Yet, it may not be true that how people respond to surveys accurately measures their beliefs about media credibility. In both the U.S. and China contexts, respondents may misreport their beliefs or not be aware of the ways in which they consume news or might reflect cheerleading for their partisan team. Bullock et al. (2015) find large differences in beliefs about politically-

Figure 1: Citizens express belief of media bias in surveys

United States



Note: Data from 2012 Pew Press Believability Survey. Partisan leaners collapsed to partisans. Survey weights used to construct proportions.

relevant facts when respondents are paid for accuracy as opposed to when respondents are simply asked about the fact without incentives to get the answer correct. Without incentives for accuracy, respondents are more likely to cheerlead or praise their current political party by giving responses consistent with personal tastes.

Measuring beliefs in authoritarian contexts can be even more challenging. Citizens in authoritarian regimes may be motivated by personal safety or economic security to cheerlead the government and mis-report trust in official or non-government news sources. Reported trust in authoritarian media is noisy across surveys and experiments; for example in China, Stockmann (2013) and Stockmann and Gallagher (2011) citizen belief in news reports increases when made aware that a commercial source generated that report. Truex (2016) finds the opposite – that government-run or "official" papers are likely to be perceived as more trustworthy. Whether these divergent results are due to social desirability bias or sample variation is open to discussion (Stockmann, 2013; **?**, pg 165). There remains significant disagreement over how citizens interact with the media in China. Truex (2016) shows significant differences when respondents were asked about trust in media rather than beliefs about media bias, indicating that wording of the question influences what conclusions are drawn about citizen beliefs about media credibility in China.

In both democratic and authoritarian societies, scholars have tried to infer trust in sources by measuring which sources readers choose to consume. Evidence in the U.S. and China of selection into media sources could provide a measure of which news sources citizens value enough to read (Iyengar and Hahn, 2009; Levendusky, 2013). However, consumption choice does not necessarily reflect unbiasedness or informativeness – that the selected source provides the most accurate news. Instead, selection of news media could reflect personal tastes in consumption such as for entertainment (Hamilton, 2004) or for reinforcement of political tastes. Further, theoretical work shows that media slant in itself may not reflect demand by consumers for biased news. Gentzkow and Shapiro (2006) shows that firms motivated by profit may slant their news towards the prior beliefs of their customers even when customers demand unbiased factual content. An alternative model that generates slanted media even if customers demand unbiased factual reporting is Besley and Prat (2006), where bias operates through political capture. In authoritarian environments, citizens may be more likely to read certain sources simply because they are more available even if they do not believe them to be objective (Geddes and Zaller, 1989; Truex, 2016). Huang and Yeh (2017) show that even though citizens may select into foreign sources when given an option, foreign media has unexpected effects on their beliefs about the Chinese Communist Party (CCP), bolstering support for authoritarianism rather than reducing it.

1.1 Theory of citizen learning with slanted media

Given the importance of citizens' consumption of news from the media for political accountability around the world and the challenges of measuring citizen trust in the media, we sketch out a simple theory of citizen learning and discounting in the presence of slanted media. This theory provides the basis of our measurements of informativeness and credibility in the U.S. and China.

Imagine that citizens are cognizant of slant in the news media, as the game theoretic models and survey responses cited above indicate they may be. If they were to desire factual knowledge about the world, what would be a reasonable approach to learning from the news that is produced? Individuals confronted with content from a source known to be biased would account for this bias in their learning. In particular, we argue that citizens likely gain a general understanding of the informativeness of various news outlets through at least two pathways. First, repeated experience and exposure to news coverage as it evolves over time provides information about the informativeness of different providers. Second, individuals have access to alternative information about news providers through competition between providers and through their social connections. For example, in the model of Besley and Prat (2006), news providers are rewarded for getting a big scoop, and the providers who fail to get the scoop pay a reputational cost. Over time, as citizens observe scoops and corresponding coverage, they gain a sense of the slant and accuracy of various providers.

With beliefs about the informativeness of different providers, individuals can then modify their learning in response to new pieces of information from those providers. We present an interpretation of this learning strategy in the context of Bayes' Rule below, but the basic intuition is simple. If, on average, a news provider exhibits bias in a certain direction, individuals may subtract off the expected bias for any individual news story, and modify their learning from a simple reading of the content of the story. If citizens believe Fox News provides the most favorable coverage possible to Republicans, they may interpret a news story that is modestly unfavorable towards Republicans as evidence that something quite untoward is the reality. Likewise, if citizens believe the People's Daily is generally quite favorable towards the current Chinese leadership, a news article on the dramatic success the current leadership has achieved fighting corruption may be interpreted as rather uninformative about actual changes in corruption.

In sum, our arguments is that because citizens experience news coverage over many stories in a repeated fashion, even modest amounts of attention can lead to learning about the informativeness of different providers. With estimates of informativeness, citizens who desire objective knowledge about the world can account for the slant of each provider as they learn from the news produced by that provider.

This theory of individual news consumption accounting for informativeness in a world of slanted media is consistent with existing empirical findings. For example, Gerber, Karlan, and

Bergan (2009) use a field experiment to measure the effect of delivery of newspapers to Americans. Interestingly, they find similar effects of two newspapers, one widely believed liberal and the other conservative, on respondent attitudes, behaviors, and partisan vote choice. One interpretation of this result is that citizens accounted for the bias of these two sources so that in the end they learned similar information, even from providers with different slants. Similar results have been documented in Baum and Groeling (2009), who show that the identity of the person conveying a political message affects how much citizens believe the message. Our results also relate to a literature finding that the consequences of messages depend on the credibility ascribed to the source (e.g., Lupia and McCubbins, 1998; Druckman, 2001).

2 A model of Bayesian learning from news media

In this section, we present a model of how citizens learn from information they receive from news media sources. The model describes citizens who process stimuli through the canonical model of learning, Bayes' Rule. Citizens combine the information received from the news media with their prior beliefs to generate posterior beliefs. We specify a version of the model that allows citizens to account for credibility of news sources in their learning to accommodate beliefs about the news production functions of different firms. We then use the model to explain how we measure citizen learning from news headlines and how we infer the credibility citizens attribute to news sources.

Consider a statement of empirical fact about the world with political relevance. For example, the statement might be "The U.S. Economy added more than 45,000 net jobs in May, 2016."[2] This statement is factual, in that it could in principle be verified, but most citizens are not likely to possess enough personal information to know its truth with certainty. Each citizen ascribes a probability Pr(T) that the statement is true and a corresponding probability Pr(F) that the statement is false, with Pr(T) + Pr(F) = 1. Pr(T) surely varies across the population, with some citizens who are either highly informed and/or highly confident having Pr(T) near one or zero, others who are not informed or less confident having Pr(T) near 0.5, and others with varying levels of certainty.

We conceptualize information from news media (headlines, stories, pictures, etc.) as an input

[2] All of our facts are statistics published by official government sources.

to each citizen's beliefs about the statement of fact. That is, each piece of information produced by the news media that crosses the individual's attention modifies beliefs about facts through the citizen's evaluation of the content of that information. Each piece of information is a *signal* S. Citizens who receive a signal S and apply Bayes' Rule when learning from that signal generate posterior beliefs

$$\Pr(T|S) = \Pr(T)\frac{\Pr(S|T)}{\Pr(S|T)\Pr(T) + \Pr(S|F)\Pr(F)}, \tag{1}$$

where $\Pr(T|S)$ is the citizen's posterior belief that the statement is true having observed S, $\Pr(S|T)$ is the probability of observing the signal S if the statement is true and $\Pr(S|F)$ is the probability of observing the signal S if the statement is false. That is, the degree to which a citizen changes their beliefs having observed the piece of information produced by the news source depends on how the individual evaluates that information relative to the fact. If the piece of information is totally irrelevant to the statement of fact, that is $\Pr(S|T) = \Pr(S|F)$, posterior beliefs are equivalent to prior beliefs – the signal is not informative. More generally, the likelihood ratio of the piece of information $x = \Pr(S|T)/\Pr(S|F)$ summarizes how informative the citizen evaluates the news. As x increases away from 1, the citizen evaluates the news as increasingly indicative that the fact is true, and as x decreases away from 1, the citizen evaluates the news as increasingly indicative that the fact is false. The magnitude of the likelihood ratio measures how informative the signal. This ratio determines how much the individual's prior beliefs change posterior beliefs in response to the signal.

Characterizing information from the news as a likelihood ratio x is a flexible way to quantitatively measure informativeness and citizens' ascribed credibility to individual news providers. In particular, with a measure of x for each of a set of headlines relevant to the same statement of fact, we can rank the headlines from least to most informative, which might measure how effective the news providers who created each headline are in creating informative headlines. The likelihood ratio can also describe broader features of the information environment the citizen uses in their learning: a set of headlines, a full news story, exposure to an entire issue of a magazine, new knowledge about the ownership of a news provider, etc. Additionally, because the likelihood ratio has a natural metric, information of different types and quantities can be compared to each other. One can make statements such as "this television news segment is twice as informative about this fact as this newspaper article." We believe this approach characterizing the content of media stimulus as a likelihood ratio could be broadly useful in other research.

How do citizens construct the likelihood ratio x for a given news headline? Following our argument in Section 1.1 above, we suggest that citizens draw on their previous experience of news consumption and news validation to construct beliefs about what any give news headline means with respect to some statement of fact about the world. As a simple example, they might observe a headline from The Global Times and use their knowledge about how they think The Global Times generates news headlines to evaluate the likelihood ratio of that headline to the factual state of the world. In situations where they do not observe the news source, they average across potential news sources and what it would mean to observe such a headline from those sources to evaluate the likelihood.

2.1 Estimating news headline informativeness and source credibility

The likelihood ratio x characterizes how citizens evaluate information delivered from the news media as it relates to their beliefs about the world. In this section, we explain how we use the observations from our experimental technology to estimate x for headlines and for headlines with news source to measure learning and media credibility.

We use news headlines from a variety of sources to estimate informativeness and credibility. We chose news headlines because they can be read quickly and because they accord with reality – many people get their news from scanning headlines, rather than reading full sources.[3] We measure the likelihood ratio of the same news headline presented in two different conditions. In one condition, our subjects view the headline without information about what news provider produced the headline. In the other condition, subjects view the same headline but additionally view the news provider that produced that headline. For example, below we use actual headlines published by the

[3] "Americans Read Headlines and Not Much Else." *Washington Post* https://www.washingtonpost.com/news/the-fix/wp/2014/03/19/americans-read-headlines-and-not-much-else/

New York Times. In one condition, subjects only observe the headline, while in the other condition they observe the same headline and that it was published by the *New York Times*.[4] With random assignment, we can compare the headline likelihood ratios we estimate in the two conditions to infer the *credibility* subjects ascribe to that source. If our estimate of x is larger with the news source, subjects learn more when they receive the news source in addition to the headline. If our estimate of x is smaller with the news source, subjects learn less from the headline when observing the headline, discounting the headline when aware it was produced by that source.

Our strategy to estimate headline likelihood ratios x is to measure subject beliefs about statements of fact before and after they observe a news headline (with or without source). That is, we design an experiment that measures prior beliefs Pr(T) and posterior beliefs Pr(T|S) for a set of subjects across a variety of political and economic statements of fact. Consider a single news headline, S_k, with a corresponding likelihood ratio $x_k = \Pr(S_k|T)/\Pr(S_k|F)$. We can average observed movement from prior to posterior beliefs across subjects who observe headline S_k to estimate x_k. Consider the log-odds specification of Bayes' Rule,

$$\text{logit}[\Pr(T|S_k)] = \text{logit}[\Pr(T)] + \log[x_k], \tag{2}$$

where $\log[x_k]$ is the log likelihood ratio.[5] With observed data across individuals $\Pr_i(T|S_k)$ and $\Pr_i(T)$ for subject i, a sample estimator for $\log[x_k]$ is the differences in means

$$\widehat{\log[x_k]} = \frac{1}{n}\sum_i \left(\text{logit}[\Pr_i(T|S_k)] - \text{logit}[\Pr_i(T)]\right). \tag{3}$$

Eq. 3 assumes subjects learn with perfect application of Bayes' Rule in our experiment. Hill (2017) presents evidence that Americans do not learn about political facts as perfect Bayesians,

[4] We do not cross-randomize headlines with sources for simplicity and to avoid deception.

[5] See Appendix Section A for the derivation of eq. 2.

and presents a statistical model allowing for departures from Bayesian learning

$$\text{logit}[\text{Pr}_i(\text{T}|\text{S}_k)] = \delta \, \text{logit}[\text{Pr}_i(\text{T})] + \beta \log[\text{x}_k] + \varepsilon_i, \tag{4}$$

where β and δ are parameters to be estimated and ε is an unmeasured error term meeting the usual assumptions for OLS. Eq. 4 is a regression model where subject learning can be estimated to depart from perfect application when β or δ are not equal to one. When $\beta = \delta = 1$, we have Bayesian learning with random noise – and if $\text{Var}[\varepsilon] = 0$ perfect Bayesian learning. As β and δ move away from one, subject learning on average departs from perfect Bayes.[6]

Readers will notice that β and $\log[\text{x}_k]$ are not separately identified in the regression model when we don't know the likelihood ratio x_k for each headline. We designed our experiment to provide an estimate for β separately from $\log[\text{x}_k]$ to estimate the x_k for the news headlines if citizens are learning with caution. In one contest of the experiment, subjects were presented simple true/false signals from the computer rather than headlines. We inform subjects of the likelihood ratio of these signals relative to the statement of fact. Because they are informed of the value of x_k, we can observe their learning in response to $\log[\text{x}_k]$ to estimate the β they apply within this experiment.[7] We present details of the experiment below. In practice, we present the unadjusted estimates from the headline experiments in the main body of the text.

Our experiment allows us to estimate the signal likelihood ratio implied by each headline given the observed learning of subjects. The experiment has two conditions, one where subjects observe the news headlines without being presented the news source that produced them, and one where subjects observe the same news headlines with the source that actually produced them. This design allows us to estimate three quantities of interest. First, *headline informativeness* is the average likelihood of the headlines produced by each source from the without-source condition. This measures how much subjects learn on average from the text and prose of the headlines by each

[6] Hill (2017) finds that Americans learn about political facts with β and δ of 0.73 and 0.61, but that the Bayesian model in (4) reasonably describes subject learning.

[7] Specifically, we deliver random signals t and f that each reveal the truth with probability 0.75. Given this feature of signals, the likelihood ratios of each are $\text{Pr}(\text{S} = \text{t}|\text{T})/\text{Pr}(\text{S} = \text{t}|\text{F}) = (3/4)/(1/4) = 3$ for a true signal and $\text{Pr}(\text{S} = \text{f}|\text{T})/\text{Pr}(\text{S} = \text{f}|\text{F}) = (1/4)/(3/4) = 1/3$ for false.

source when they don't know what news organization produced it. Second, *total informativeness* is the average likelihood of the headlines produced by each source from the with-source condition. This measures how much subjects learn on average from each source from the combination of the text and prose of the headlines and with knowledge about what news organization produced it – and whatever additional inferences they make from the two together. Third, *source credibiliity* is how much more or less they learn with knowledge of the source than without.

To estimate the headline and total informativeness of each source, we run the regression

$$\mathrm{logit}[\mathrm{Pr_{it}(T|S_{ikt})}] = \delta\ \mathrm{logit}[\mathrm{Pr_{it-1}(T)}] + \gamma_{\mathrm{j(k)}} + \varepsilon_{\mathrm{it}}, \tag{5}$$

with γ_{j} a fixed effect for each news source j, $\mathrm{S_{ikt}}$ the headline k observed by subject i in round t, the function $\mathrm{j}(\cdot)$ returns the news source that produced its argument, and $\mathrm{Pr_{it}(T)}$ the elicited beliefs from subject i in round t. With this specification, γ_{j} is the product of β and the average signal log likelihoods of the headlines by news provider j. As noted above, for clarity of presentation we assume $\beta = 1$ in the main body of the essay.

Running eq. (5) on the without-source condition yields estimates of the headline informativeness of each source, and estimating on the with-source condition yields estimates of the total informativeness of each source. When subjects are not provided the source of the news headline, they make an inference about what that headline means about the truth of the statement of fact. We average observed learning across individuals and across headlines for each source to estimate the average meaning – likelihood – of the headlines produced by each source. When subjects are provided with the source, we can average across individual learning to see the average likelihood they attribute to the combination of the text and prose of the headline and the information from the news source.

To estimate the *source credibility* of each news provider, we run the regression

$$\mathrm{logit}[\mathrm{Pr_{it}(T|S_{ikt})}] = \delta\ \mathrm{logit}[\mathrm{Pr_{it-1}(T)}] + \tau_{\mathrm{k}} + \gamma_{\mathrm{j(k)}}\mathrm{z_{it}} + \varepsilon_{\mathrm{it}}, \tag{6}$$

with each parameter as in (5) with the addition a fixed effect for each headline τ_k, and the experimental condition indicator z_{it} taking the value of one for the with-source condition and the value of zero for the without-source condition. Estimating Eq. (6) on the combined sample of both with- and without-source conditions, the headline fixed effects τ_k estimate the log likelihood of each headline in the without-source condition and the γ_j estimate the average offset for each source in the with-source condition. Thus, the γ_j are the source credibility that subjects attribute to news source j when they observe the provider who produced the headline relative to the without-source condition where their learning only follows from observing that headline.

In sum, this section presents the details of a model and experimental technology to measure informativeness of news headlines and credibility of news sources. We use beliefs about a statement of fact elicited before and after exposure to a news headline to estimate these three theoretical quantities of interest. We provide statistical regression specifications to capture how subjects learn in response to computer signals, how they learn in response to headlines with and without source provided, and how to derive from these observations the informativeness and credibility they attribute to news sources. We next turn to the experimental design and implementation in the U.S. and China before presenting the results.

3 Experimental design and eliciting beliefs

The dependent variable of our experiments is the probabilistic beliefs subjects assign to the truth of political and economic statements of fact. We elicit these beliefs across multiple rounds for each of multiple statements of fact. For each fact, we first elicit beliefs without providing additional information in order to retrieve a baseline prior belief. Each subsequent elicitation follows the delivery of a signal of some kind, either a true/false signal from the computer, a news headline without information as to its source, or a news headline with information about its source. Changes in elicited beliefs measure learning, and we measure magnitude of learning through the change in the probability reported.[8] With facts and headlines delivered in randomized order, we can use the average change in probability across subjects to estimate our three quantities of interest. Details of

[8] The experimental design follows that of Hill (2017).

the U.S. and China implementations follow the next paragraph, which documents the technology we use to elicit probabilistic beliefs with incentives in both samples.

Subject beliefs are elicited using monetary incentives with the crossover scoring method (proposed by Allen, 1987; Karni, 2009; Möbius et al., 2011). The crossover method asks participants for what probability p they would be indifferent between receiving a payment with probability p and receiving a payment if their answer is correct. With these incentives, the subject maximizes their probability of payment by accurately reporting their subjective belief about the factual statement.[9] Subjects in each round provide this probability p, which serves to measure their probabilistic beliefs. Holt and Smith (2016) show that this method outperforms the Quadratic Scoring Rule in an experimental comparison. Full presentation of the elicitation is available in the experimental protocols presented in the Appendix.

3.1 Implementation: U.S.

For the U.S. sample, we recruited 794 subjects aged 18 and older and U.S. citizens from Amazon.com's Mechanical Turk (MTurk) worker platform between September 8 and 12, 2016. Participants were paid a $0.60 flat fee and offered the opportunity to earn bonuses of up to $4.00 depending upon their performance in the experiment, which was advertised to and did take about 15 minutes. The study did not deceive, which was advertised prominently on the consent screen. Respondents were 53 percent female and had an average age of 35, and 48 percent had a four year college degree or more. The sample wasn't overly political – 65 percent reported voting in the 2012 presidential election – but tilted Democratic and liberal, with 54 percent Democrat (including leaners) and 28 percent Republican, and only 19 percent conservative or very conservative.[10]

Upon consenting to participate, subjects first took an IQ-like quiz. They had two minutes to answer up to 15 logic and reasoning questions. They were paid $0.10 for each point of their total score on the quiz, which was the number answered correctly less the number answered incorrectly,

[9] In the experiment, we presented the details of the mechanism in simple terms and highlighted at multiple points that participants would maximize payment conditional on beliefs by accurately reporting their beliefs.

[10] Some readers have concerns about the MTurk subject populations. Recent work shows that MTurk samples yield experimental treatment effects highly similar to other samples (Berinsky, Huber, and Lenz, 2012; Mullinix et al., 2015).

skipped questions not counted. The average quiz score was 2.1, with a minimum of -11 and a maximum of 11.[11] After the IQ-like quiz, subjects were taught about the main section of the experiment. They were told that they would participate in a contest consisting of 25 rounds. For each round won, they would be paid a $0.10 bonus, $0.00 otherwise. In each round, they would be asked to evaluate a difficult factual statement with a number from 0 to 100 that described how likely they believed the statement to be true.[12] The instructions presented the response as a probability in terms designed to be accessible to those not trained in statistics. The instructions then explained how participants would win each round, which was a function of their probabilistic belief through the crossover design. The experiment presented the crossover design in simple terms and highlighted at multiple points that the subject's chances of winning would be highest if they accurately reported their probabilistic belief.

After presenting the overview of the contest and the mechanism of payment, subjects were instructed that they would evaluate the same factual statement in multiple rounds, and that in some rounds they would receive a signal from the computer about whether or not the statement was true. They were told that the signal from the computer would indicate that the correct answer was true or false, and that this signal would be correct three out of four times on average. They were also told that in other rounds, they may receive a news headline related to the statement of fact. They were told that they might want to change their beliefs in response to signals or headlines.

After the instructions for the contest, the subjects played three practice rounds evaluating the factual statement "It rained (more than 0.00 inches of precipitation) in Santa Fe, New Mexico on July 7, 2004." Mimicking the contest they would play, in the first round they evaluated the statement without any signal from the computer. In the second round they received signals from the computer and again evaluated the statement. In the third round, they received a headline from a newspaper related to the fact and again evaluated the statement. After the third round, the instruc-

[11] Subjects were told that money would not be deducted from the show-up fee for scores less than zero.

[12] The prompt in each round was "Please tell us how likely you believe this statement is true: [Statement presented]. How likely you believe that the statement is true (for example, 1 if you believe it almost certainly false, 99 if you believe it almost certainly true, 50 if totally unsure): [textbox entry]." Full instructions as presented are in Appendix Section D.

tions explained how they would be paid as a function of their response.[13]

Once the practice contest was complete, participants then proceeded to the main contest for which they would be paid based upon their performance. For each of five statements of fact, beliefs were elicited for five rounds. Beliefs were elicited in the first round for each statement prior to the delivery of any signal or headline, measuring the subject's initial belief. In each round subsequent to the first, their previous response was presented for their reference.[14] We present overviews of the order of contests in each experiment in Table 1.

The first and fifth contest were contests where subjects received signals from the computer as to the truth of the statement. In rounds two through five of these two contests, they received one new (independent) signal in each round from the computer about the statement and reported their (potentially-updated) belief. In each round with a signal, the subject was reminded that the signal would be correct three out of four times. With this design, we observe how subjective beliefs about the statement change over time in response to the noisy signals received.

In the second, third, and fourth contests, subjects received news headlines published on the day of or shortly after the statistic related to the statement of fact in rounds two, three, four, and five. That is, for each statement of fact we collected four news headlines, and these four headlines were delivered in random order to each subject. In the second contest, the four headlines were delivered without information about the news source that produced the headline. This allows us to observe learning about each headline when subjects are not yet aware that we might deliver the source of headlines in subsequent rounds. In the third and fourth contests, headlines were presented along with the news source that published it. We thus observe how subjects change their beliefs about the truth of the statement in response to each headline and in response to the same headline along with the news source that published it, with randomized order across subjects.

All subjects had beliefs elicited about five different statements of fact for five rounds each. All subjects evaluated one statement of fact about an abstract, non-economic, non-political topic, the

[13] See Appendix Section D for the feedback and instructions.

[14] In all rounds, subjects had 20 seconds to evaluate the statement, to limit the option of searching for the truth on the web. After 20 seconds, responses were recorded and they were automatically forwarded to the next round.

Table 1: Summary of order of contests in each experiment

Experiment	Contest	Type
U.S.	1	Computer signals
	2	Headlines only
	3	Headlines with source
	4	Headlines with source
	5	Computer signals
China	1	Computer signals
	2	Headlines only
	3	Headlines only
	4	Headlines with source
	5	Headlines with source
	6	Select source for single headline

length of the day in Doha, Qatar on January 8, 2012. Subjects only evaluated this fact in one of the two computer signal contests (the first or fifth contest, at random) as we did not have headlines related to this fact. This fact serves as a benchmark of learning about non-economic, non-political facts. Subjects additionally evaluated four other facts. Half of the sample evaluated one fact not presented in this essay for use in a separate research project. This half evaluated three of the four facts for this project in addition to the Doha fact. The other half of the sample evaluated all four of the facts for this project in addition to the Doha fact. Which facts were delivered with computer signals versus headlines versus headlines with news sources were all randomized at the subject level.[15]

We selected four statements of fact about economic statistics released from official sources that the news media deemed sufficiently salient to mention in a news story headline. In Appendix Section B we document how we selected facts and news sources for the U.S. study. Our goal was to select facts that were difficult but similar to economic judgments the public would have to make, particularly in evaluating the economic outcomes under incumbent governments. We sought four facts related to economic releases with an objective value (government-produced statistics or

[15] Finally, we randomized for each statement whether the subjects evaluated a true or a false version of the statement to protect against any global bias toward evaluating statements as true or false. We find little difference on this dimension, and so recode all signals and response in the direction of true.

equity market values) that each had headlines relevant to the fact from the same four news sources. We also wanted economic statistics relevant to political knowledge and judgments. After extensive searching over multiple topics and multiple years, we identified the facts (see Table 2 below) with such headlines for four U.S. news sources: the New York Times, USA Today, CNN, and Fox News. While these are not an exact representative sample from the full set of headlines, our belief having read hundreds of headlines related to economic and political news is that these are roughly representative of how these news sources covered such events during this time period.

Finally, after completing the five contests, participants answered a series of survey questions about their demographics, political attitudes, and political behaviors. This includes standard demographics and political questions such as partisanship and ideology. On the final screen, a code was presented to the subjects for them to submit on Mechanical Turk in order to collect any bonuses from the IQ-like quiz responses and the five contests.

3.2 Implementation: China

For the China sample, we recruited 1,014 survey respondents 18 and older using the online survey platform Qualtrics between February 3 and April 21, 2017. Participants were paid through Qualtrics, with the opportunity to make an additional eight yuan depending on their performance.[16] The sample was about 56% male, 44% female, with a mean age of 40.[17] Respondents are not overly critical of the government, they rated central government and local government satisfaction at means of 76 and 63 on a scale of 1 to 100, which is consistent with high levels of government trust in other surveys of in China.

Like the U.S. sample, respondents were first asked to take an IQ-like quiz, with two minutes to answer 15 questions.[18] The average score on the quiz was 2.4, with a minimum of -11 and a maximum of 12. Similar to the U.S. survey, they were then told the instructions of the contest.

[16] Payments based on the Economist's Big Mac index, which as of July 2016, was $2.79 in China and $5.04 in the U.S. such that participants in China should receive about half the U.S. compensation after accounting for the exchange rate.

[17] The survey was quota sampled on age and education in order to reflect the urban population in China; however, the quotas were not met by the survey firm. We plan to provide results weighted to the urban population of China in the Appendix.

[18] IQ questions were almost identical to the U.S. quiz, excepting a few modifications for Chinese translation.

All other aspects of the survey were the same as the U.S. case, except that we conducted three (rather than five) rounds in a total of six contests.[19] Also departing from the U.S. design, in the sixth contest participants were asked to select a source to receive news from to see what source individuals would choose to consume knowing they would be compensated for learning. In this contest, only two rounds of beliefs were elicited – their prior beliefs before seeing the source and their beliefs after choosing and observing the source.

We selected six statements of fact about economics and politics released from official sources. Like the U.S. case, we selected facts that were informative about domestic and international politics. We were interested in using a mix of official, commercial, and international sources and also wanted to select one overlapping fact with the U.S. sample. We used the facts in Table 2 with headlines from four sources: BBC, Xinhua, Global Times, and Nanfang Dushibao. BBC is a Western source, Xinhua is one of the two main official sources of the Chinese Communist Party, Global Times is a official paper that is known to have a nationalistic and anti-Western slant, and Nanfang Dushibao is a commercial Chinese paper in the South and known to be more independent of the government.

Unlike the U.S. sample, where the political cleavage can be approximated using respondent-reported partisan affiliation, China is ruled by one political party. Recent scholarship (Pan and Xu, Forthcoming; Wu and Meng, 2016) suggests, however, that political ideology does differentiate citizens in China despite one-party rule. We follow Wu and Meng (2016) and included with our survey 12 questions to scale ideology. Our scalings largely accord with theirs, resulting in two dimensions of ideology. The first is the economic, "left-right" scale where "left" indicates preferences for a socialist or communist economic system where the government provides large-scale public goods and reduces inequality and the "right" indicates preferences for a market economy. The second is "democratic-authoritarian" dimension where "democratic" indicates preferences for individual rights and democracy and "authoritarian" indicates preferences for the current system of government without political competition. We use these two dimensions to measure how source

[19] We found that in the U.S. sample learning decreased in rounds 4 and 5 and we were hoping to save time and resources by targeting rounds of greatest learning.

Table 2: Facts in each experiment

U.S.	1	In the third quarter of 2014, gross domestic product (GDP) of the United States grew at the fastest quarterly rate since [2003/1998].
	2	The U.S. Economy added [fewer/more] than 45,000 net jobs in May, 2016.
	3	In August 2015, the Chinese currency, the Yuan, was worth [less/more] against the U.S. dollar than it had been in the time period from September 2012 to July 2015.
	4	On January 8, 2012, the length of the day from sunrise to sunset in the city of Doha, Qatar was [less/more] than 11 hours.
China	1	GDP growth in 2015 was [above/below] 6.5%.
	2	Defense spending increased by [more/less] than 10% in 2015.
	3	The renminbi entered the IMF SDR currency basket at a rate [greater/less] than 10%.
	4	In August 2015, the Chinese currency, the Yuan, was worth [less/more] against the U.S. dollar than it had been in the time period from September 2012 to July 2015.
	5	In 2015, the National Development and Reform Commission of China fines Qualcomm for monopoly behavior with a fine [more/less] than 4 billion yuan.
	6	China's GDP growth rate in 2016 was [higher/lower] than the GDP growth rate in 2015.

Note: We asked about a fifth fact of the U.S. sample on monthly changes in retail sales in June, 2015. We believe the statement itself was ambiguous to participants, as on average subjects learned from all four headlines in the wrong (away from truth) direction. We exclude this statement from analysis below.

credibility varies by ideology in China.

4 Results

We begin by comparing the observed learning of our subjects from the computer signals to the observed learning from the headlines. In Figure 2, we present our estimate of informativeness (the log likelihood ratio) for computer signals versus news headlines on each statement of fact in each sample. Figure 2 shows that subjects updated their beliefs more in response to computer signals than to news headlines in all cases but for Americans learning about the Yuan devaluation, where the headlines and computer signals led to the same amount of learning, on average. If we assume caution in learning is similar when evaluating computer signals and news headlines, we can measure how informative subjects found the news headlines relative to the computer signal benchmark.[20] The computer signals have a likelihood ratio of three (Pr(S = T|T) = .75/Pr(S = T|F) = .25), with log(3) = 1.09.

On average, subjects were cautious interpreting the computer signals as most of the informativeness (logged likelihood ratio) measures are less than 1. The informativeness of the news headlines was lower than that attributed to signals in each case but for the Yuan devaluation in the U.S. In seven of nine cases, the subjects found the news headlines informative towards the truth. On two facts in China, subjects learned in the wrong direction from headlines, on average: military spending and GDP difference.

Figure 2 also suggests the Chinese sample learned less from news headlines than the American sample. However, because facts and headlines varied across the two experiments undermining comparison.

4.1 Regression estimates

We present our regression estimates of informativeness and credibility in Tables 3, **??**, 5, and 6. Table 3 presents our estimates of headline informativeness (columns one through four) and total informativeness (columns five through eight) corresponding to eq. 5 for all subjects and then separately by party identification from the U.S. sample. The first column presents how subjects learn on average from only the text and prose of the headlines produced by each provider. Subjects appear to learn similarly from the text from three news providers, but notably less from the headlines produced by CNN.[21] Exponentiating each of these point estimates returns the implied likelihood of these headlines, which varies from 1.8 (exp[.6]) for the Fox News headlines to 1.2 for the CNN headlines. Subjects learn as if these headlines are more likely to be generated if the statements of fact are true than if false, but the Fox News headlines, when not presented with their source, are on average more informative about the truth.[22]

Informing subjects of the news provider who produced the headlines leads to changes in how subjects learn from those headlines. Column five shows that total informativeness is larger for CNN

[20] We estimate caution parameters (β) of 0.83 and 0.93 in the two samples.
[21] See Appendix Table C for the full set of headlines from each source.
[22] Columns two through four indicate little heterogeneity by partisanship in headline informativeness.

Figure 2: China and U.S. Sample Learn More from Computer Signal and Learn Similarly

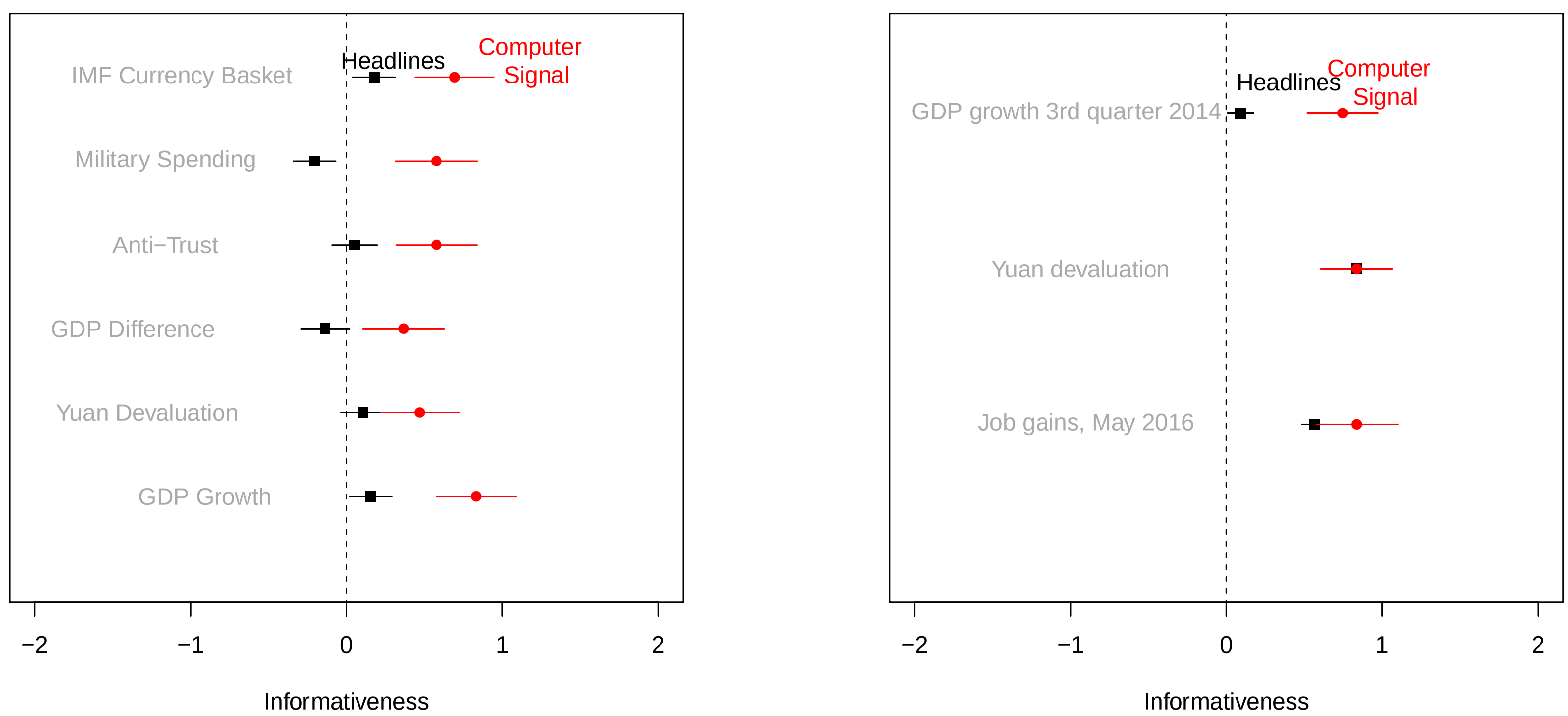


Table 3: Estimates of headline and total informativeness, U.S. experiment

	Headline informativeness	Dems	Reps	Inds	Total informativeness	Dems	Reps	Inds
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prior	0.64***	0.63***	0.65***	0.67***	0.66***	0.66***	0.67***	0.63***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.02)	(0.02)	(0.03)
New York Times	0.58***	0.57***	0.52***	0.70***	0.60***	0.57***	0.58***	0.73***
	(0.09)	(0.12)	(0.18)	(0.19)	(0.06)	(0.08)	(0.12)	(0.14)
USA Today	0.55***	0.52***	0.59***	0.65***	0.52***	0.41***	0.76***	0.49***
	(0.09)	(0.12)	(0.18)	(0.19)	(0.06)	(0.08)	(0.12)	(0.14)
CNN	0.22**	0.20*	0.24	0.26	0.34***	0.41***	0.35***	0.15
	(0.09)	(0.12)	(0.18)	(0.19)	(0.06)	(0.08)	(0.12)	(0.14)
Fox	0.60***	0.58***	0.50***	0.81***	0.46***	0.46***	0.45***	0.49***
	(0.09)	(0.12)	(0.18)	(0.19)	(0.06)	(0.08)	(0.12)	(0.14)
Observations	2,444	1,344	640	456	4,750	2,524	1,342	872
R^2	0.45	0.44	0.45	0.52	0.47	0.46	0.50	0.45
Adjusted R^2	0.45	0.44	0.44	0.51	0.47	0.46	0.49	0.44
Residual Std. Error	2.17	2.20	2.21	2.02	2.08	2.07	2.11	2.06

Note: *p<0.1; **p<0.05; ***p<0.01
Dependent variable is logit posterior beliefs after receiving headline.
First four columns from without-source condition only, second four from with-source condition only.

headlines and smaller for Fox News headlines when subjects are informed of the source. The CNN headlines move from an average likelihood ratio of 1.2 to an average 1.4, an increase in information of one sixth, while Fox headlines move from 1.8 to 1.6, a decrease of one eighth. Although the differences are not statistically significant, there is heterogeneity in changes in learning by partisanship. Independents appear to modify their learning most with the source cue, learning less from the USA Today, CNN, and Fox News headlines when aware of the source (yet learning the same from New York Times headlines). Democrats learn less from USA Today and Fox News headlines when aware of the source, but more from the CNN headlines. Republicans learn more from CNN and much more from USA Today. Interestingly, Republicans discount Fox News with the source to an almost identical likelihood ratio as Democrats, about 1.6.

The differences of learning apparent comparing columns one through four with columns five through eight in Table 3 are our definition of source credibility. We estimate source credibility formally in Table **??** with the specification of eq. 6. Table **??** confirms the qualitative comparisons of Table 3. Subjects change their learning in response to the source cue, but not to a dramatic degree. Column one for all subjects indicates very little change in learning for headlines from the New York Times or USA Today, but larger magnitude shifts of more learning for CNN and less for Fox News. Democrats change their learning most in response to the CNN cue (more learning) followed by learning less from Fox News and USA Today. Republicans change their learning most in response to the USA Today (more) and CNN (more) cues. Independents appear to be skeptical of news providers, learning less when aware of the source for headlines from USA Today, CNN, and Fox News, the latter being the largest magnitude change in learning observed across the sample.

Table 5 presents the headline informativeness and total informativeness for the China sample. In comparison to the U.S. sample, subjects in China learned less in both conditions. In the first column of Table 5, only the Global Times headlines (without source) were subtantively informative. However, with source in the fourth column the respondents learned much differently, learning most form Nanfang Dushibao and least from Global Times. The difference between these two quantities measures credibility, which we present in Table 6. Across all ideologies, we see that

Table 4: Estimates of credibility, U.S. experiment

	Credibility, All	Credibility, Dems	Credibility, Reps	Credibility, Inds
	(1)	(2)	(3)	(4)
Prior	0.64***	0.63***	0.65***	0.64***
	(0.01)	(0.01)	(0.02)	(0.02)
New York Times	0.02	–0.01	0.08	0.01
	(0.10)	(0.14)	(0.20)	(0.23)
USA Today	–0.02	–0.12	0.19	–0.17
	(0.10)	(0.14)	(0.20)	(0.23)
CNN	0.13	0.21	0.12	–0.13
	(0.10)	(0.14)	(0.20)	(0.23)
Fox	–0.14	–0.13	–0.03	–0.33
	(0.10)	(0.14)	(0.20)	(0.23)
Observations	7,194	3,868	1,982	1,328
R^2	0.42	0.42	0.43	0.42
Adjusted R^2	0.42	0.42	0.43	0.41
Residual Std. Error	2.09	2.09	2.12	2.03

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Dependent variable is logit posterior beliefs after receiving headline.
All models include headline fixed effects (suppressed).

Nanfang Dushibao is perceived as most credible. On average across the ideological spectrum, respondents discount the Global Times headline more when they see the source than when they do not see the source. However, these findings are less pronounced with ideological authoritarians whose credibility estimate for the Global Times source is small and cannot be distinguished from zero. Interestingly, those on the economic Left and Right discount the Global Times similarly, indicating that the two dimensional nature of ideology is useful in assessing the interactions between news and belief in China.

As a graphical summary of the strategic consumption of news headlines in both countries, we present Figures 3, 4, and 5. Both American and Chinese respondents consume news strategically as shown in Figure 3. While Fox News is similarly informative to the New York Times before the inclusion of the source cue, with the inclusion of the source cue, it becomes less informative than both New York Times and USA Today. Strikingly, in the Chinese case, the Global Times is the most informative source without the source cue, but becomes the least informative when the source cue is included.

Interestingly, in neither the case do we find that ideology is such an important determinant of source credibility that providers are trusted with completely different patterns among ideological groups. In the U.S., subjects discount Fox News across the board, even though Republicans discount it slightly less than Democrats. Similarly, in China the Global Times is less trusted by all ideological groups, even though the discounting is less for ideological authoritarians than other groups.

5 Comparison: Selection Into News Sources

In this section, we compare the estimates of credibility from the first four headline contests in the China experiment with the news source choices of respondents in the final contest. Do citizens account for their beliefs about informativeness and credibility that they exhibit behaviorally when selecting a news source for information? Interestingly, we find that choices of source do not align with their behavioral attribution of credibility. This suggests that the process of news source selec-

Table 5: Estimates of headline and total informativeness, China experiment

	Headline Info	Left	Right	Auth	Dem	Total Info	Left	Right	Auth	Dem
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Prior	0.58***	0.60***	0.72***	0.62***	0.56***	0.63***	0.65***	0.76***	0.70***	0.71***
	(0.01)	(0.04)	(0.03)	(0.03)	(0.04)	(0.01)	(0.04)	(0.03)	(0.03)	(0.04)
Xinhua	–0.02	–0.04	0.07	–0.22	0.12	0.08	0.28	0.16	–0.08	0.51**
	(0.08)	(0.19)	(0.20)	(0.21)	(0.22)	(0.08)	(0.19)	(0.20)	(0.19)	(0.22)
NFDSB	–0.002	–0.003	–0.04	–0.01	–0.05	0.17*	0.20	0.32	–0.08	0.01
	(0.09)	(0.21)	(0.23)	(0.23)	(0.26)	(0.09)	(0.21)	(0.20)	(0.21)	(0.23)
BBC	–0.08	–0.14	–0.03	0.18	–0.23	0.02	–0.07	0.17	–0.07	0.02
	(0.08)	(0.19)	(0.19)	(0.21)	(0.22)	(0.08)	(0.19)	(0.20)	(0.20)	(0.21)
Global Times	0.17**	0.47**	0.21	0.25	0.28	–0.07	–0.12	–0.29	0.06	–0.51**
	(0.08)	(0.20)	(0.20)	(0.21)	(0.24)	(0.08)	(0.18)	(0.18)	(0.20)	(0.20)
Observations	3,478	543	510	575	479	3,460	547	502	577	471
R^2	0.33	0.34	0.50	0.38	0.33	0.39	0.39	0.56	0.47	0.48
Adjusted R^2	0.33	0.33	0.49	0.37	0.32	0.38	0.38	0.55	0.46	0.47
Residual Std. Error	2.49	2.31	2.27	2.55	2.57	2.41	2.24	2.17	2.41	2.31

Note: *p<0.1; **p<0.05; ***p<0.01
Dependent variable is logit posterior beliefs after receiving headline.
First four columns from without-source condition only, second four from with-source condition only.

Table 6: Estimates of bias, China experiment

	Bias All	Bias, Left	Bias, Right	Bias, Auth	Bias, Dem
	(1)	(2)	(3)	(4)	(5)
Prior	0.60***	0.62***	0.73***	0.66***	0.63***
	(0.01)	(0.03)	(0.02)	(0.02)	(0.03)
Xinhua	0.10	0.32	0.05	0.22	0.40
	(0.12)	(0.28)	(0.28)	(0.28)	(0.32)
NFDSB	0.18	0.22	0.42	–0.12	0.09
	(0.13)	(0.30)	(0.30)	(0.31)	(0.35)
BBC	0.13	0.15	0.19	–0.21	0.33
	(0.11)	(0.27)	(0.27)	(0.28)	(0.31)
Global Times	–0.24**	–0.69**	–0.51*	–0.13	–0.70**
	(0.11)	(0.27)	(0.27)	(0.29)	(0.32)
Observations	6,938	1,090	1,012	1,152	950
R^2	0.37	0.38	0.54	0.45	0.41
Adjusted R^2	0.36	0.36	0.53	0.44	0.39
Residual Std. Error	2.43	2.26	2.21	2.43	2.46

Note: *p<0.1; **p<0.05; ***p<0.01
Dependent variable is logit posterior beliefs after receiving headline.
All models include headline fixed effects (suppressed).

Figure 3: Both China and U.S. Sample Strategically Consume Information

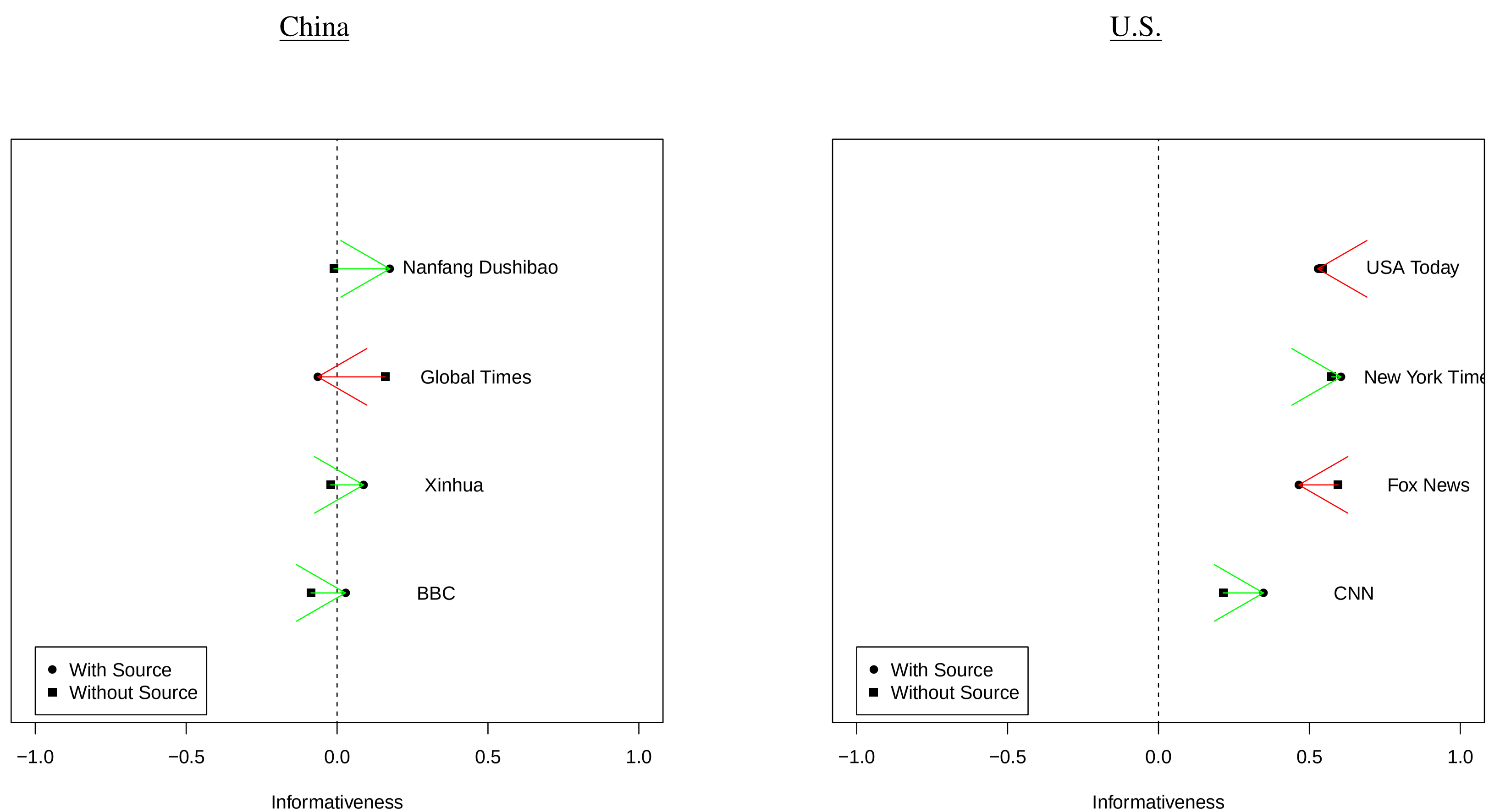


Figure 4: U.S. Partisanship Moderates Learning, But Does Not Flip it

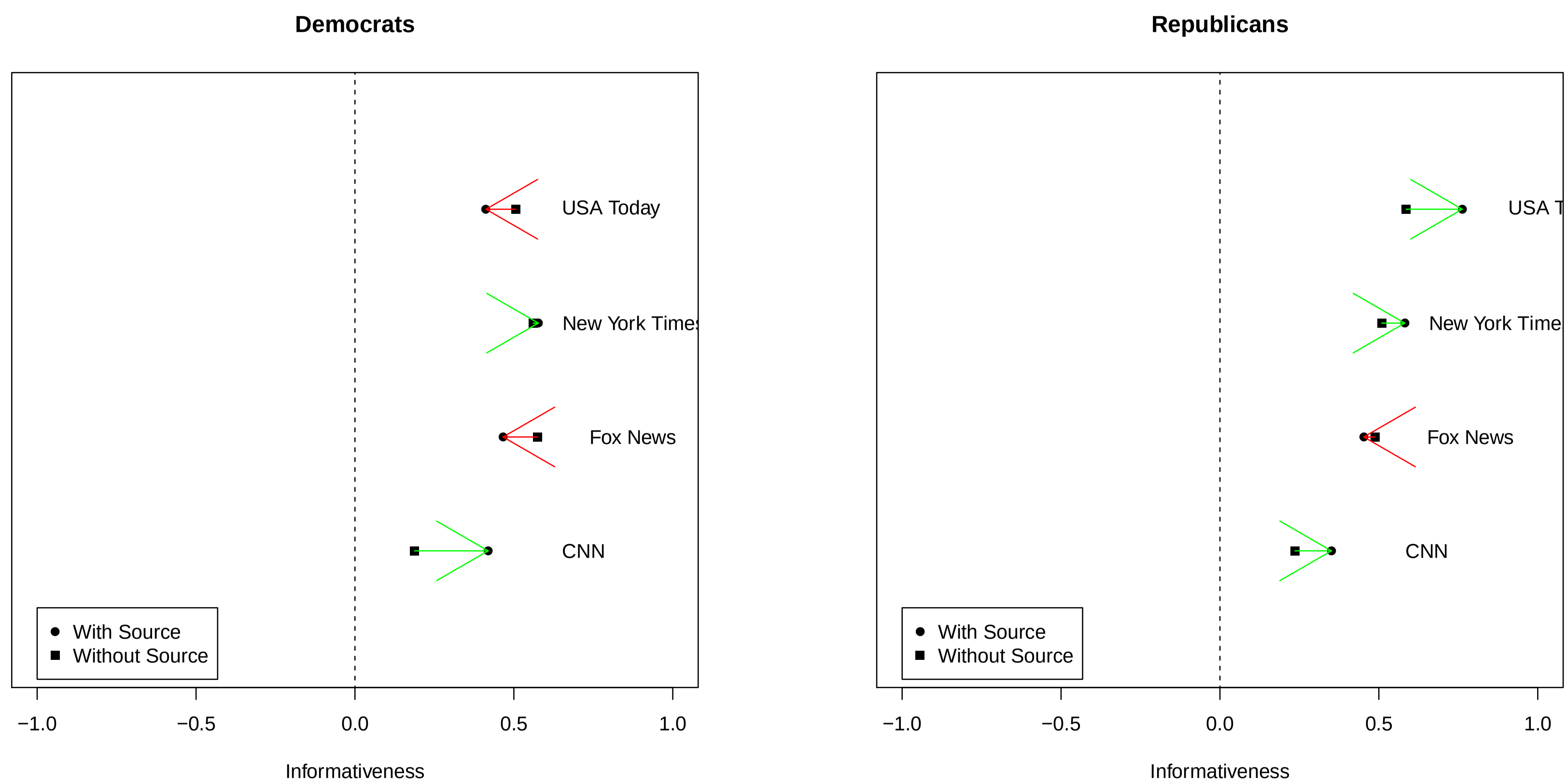
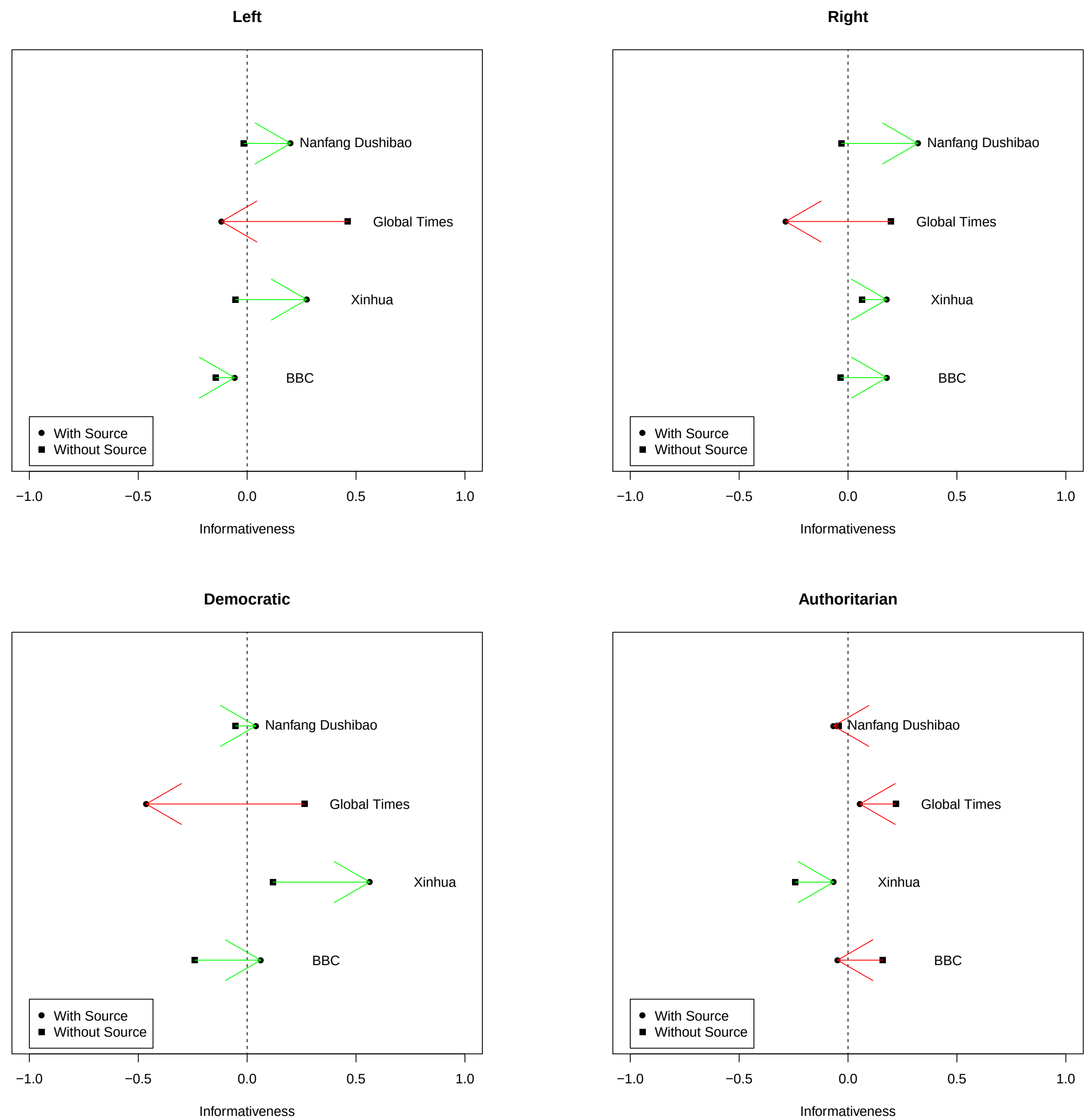


Figure 5: China Ideology Moderates Learning, But Does Not Flip it



tion is separate from the behavioral attribution of credibility. Interestingly, this holds even with the same incentives for accuracy on the statement of fact. This implies that self-reported evaluations of trust or source selection are not accurate measures of the way citizens ascribe credibility and informativeness when actually learning from the news.

We compare the estimates of credibility in the previous section with two measures of source selection.[23] First, respondents were asked how frequently they read each of the four news sources. Respondents reported reading Xinhua the most (15% of respondents reported that they had read Xinhua yesterday), Global Times second (11%), Nanfang Dushibao third (10%), and BBC least (7%). These are inconsistent with the evaluations of credibility retrieved from the experiment, as the headlines from Global Times generated significantly less learning than headlines from the other sources.

Second, respondents were asked to select which news source they would like to have presented to them in the last round of the final contest. They had played multiple rounds of the contest and knew that their compensation depended on learning as much as possible about the statement of fact. Thus, they should select the news source they evaluate most informative. Interestingly, participants' selections were largely in line with their self-reported reading habits: 42% of respondents chose Xinhua, 26% Global Times, 21% Nanfang Dushibao, and 11% BBC.

Further, both self-reported readership and selection of sources during the last round of the contest exhibit more ideological disparity than differences in learning from the experiment. Selection into news sources is highly ideological among the Chinese respondents even though discounting of particular sources is similar across ideologies. Table 7 shows the results of a multinomial logit on selection of sources in the last round. Respondents who select into Xinhua and Global Times are much more likely to be authoritarian and left, respondents who select into Nanfang Dushibao are on average more economically left than Global Times and Xinhua but likely to be democratic, and respondents who select into BBC are likely to be democratic and economically right.

In total, these results suggest that the two common ways to evaluate media credibility do not

[23] The source selection contest was not included on the U.S. instrument.

Table 7: Ideological Selection of News Sources, China Survey

	Dependent variable:		
	BBC	Xinhua	Global Times
	(1)	(2)	(3)
Left-Right	0.389***	0.176***	0.162***
	(0.045)	(0.031)	(0.034)
Authoritarian-Democrat	0.401***	–0.251***	–0.172***
	(0.045)	(0.033)	(0.035)
Constant	–0.750***	0.715***	0.260***
	(0.047)	(0.031)	(0.034)
Akaike Inf. Crit.	19,357.670	19,357.670	19,357.670
Note:			*p<0.1; **p<0.05; ***p<0.01

line up very well with the way citizens actually learn from their news. First, selection into consumption and self-reported consumption are more polarized than learning from the news. This also suggests that the responses participants give to survey questions asking their opinion of media credibility are not necessarily consistent with the way they behave.

6 Discussion

Citizens in both the U.S. and China learn about political and economic facts differently from news headlines when provided information about the news provider that produced them. They do so in a behavioral experiment with incentives to learn factual information from these headlines. This suggests that citizens believe that different news providers vary in their informativeness and credibility *and* that they change their learning to account for these beliefs when exposed to the product of these providers. Our findings suggest a new way of thinking about media bias beyond the two current modes of study: documenting attitudes of individuals towards media or measuring the output of media. Effort should be made not only to measure bias, but to understand its consequences for knowledge and political accountability. Our results indicate that establishing that the media has slant is not sufficient to establish negative consequences for knowledge and accountability. We need to know if citizens are able to learn enough to attain accountability from the combination of the news produced and how they learn from that news given their beliefs about the slant of its producers.

We present a methodological innovation to help measure the degree to which citizens modify their learning due to their beliefs about news producers. The technology pushes beyond the survey query on attitudes towards the news media. Instead, the technology allows observation of behavioral responses to experimentally-randomized delivery of information about those providers. We believe this technology can be used in other settings to further understanding of how citizens and consumers learn about the political, social, and economic world. For example, our experiments could be extended to other types of information, from full news articles to TV programs, pictures, or commentary. Overall, this approach could be used to measure the informational content delivered through many different mediums.

An important choice in our design was to truthfully deliver the news source that produced each headline. That is, we did not tell subjects that the New York Times produced a Fox News headline. We did this not only to avoid deception but also to promote external validity. In our view, the treatment effect of a New York Times headline outside of the lab is exactly the combination of the way the organization crafts its headlines and the reputation and information consumers attribute to the organization's brand. Our experiment estimates the actual likelihood subjects attribute to the headlines produced by each provider. That said, we see as an advantage of our measurement technology its flexibility. There is no reason it could not be applied to factorial or conjoint designs, which may be valuable to future research.

Our substantive findings speak to literatures on media slant and political information. We find a surprising degree of ideological uniformity in the source credibility attributed to different news providers. While it is true that Democrats and Republicans attribute different amounts of credibility in the U.S. and democrats and authoritarians attribute different amounts of credibility in China, in general these differences are small. When citizens aim to learn facts, rather than whatever other motives might generate survey responses without incentives, they seem to generally agree on how to do so. This finding is inconsistent with theories suggesting extensive motivated reasoning (e.g., Bartels, 2002) or the Hostile Media Effect in political learning (Vallone, Ross, and Lepper, 1985). We believe our results add to work suggesting revision to the strong version of these theories (e.g., Bullock et al., 2015; Gerber and Green, 1999; Hill, 2017), but stipulate that degree of revision will depend on how readers interpret the external validity of our experiments and on the outcome of future replications and extensions.

Our results indicate that the Chinese sample learned less from news headlines than the American sample. There are many differences that make it difficult to interpret the estimated differences in learning. The instruments were fielded in different languages, the headlines, news providers, and media environment vary, mathematical training and educational attainment are different in the two nations, headline production processes may vary between providers in the two settings, and the sample recruitment procedures also differ. We are reluctant to make too much of the differences, but one interesting interpretation is that the media environment may be more segmented in China. In particular, citizens in China may go to different providers for economic news than for political news or for entertainment. While the American news sources we use tend to aim to provide broad coverage on many subjects, the Chinese sources are more focused. Perhaps Chinese citizens are used to seeking specific providers for specific topics of news, and thus feel that they learn less from the subject-inconsistent providers. These seem interesting questions for future research.

Interestingly, despite similar behavioral choices in how subjects learn from providers, when these same subjects turn to choosing which news source to consume, we observe much greater divergence by ideology. The subjects in our Chinese sample exhibited more divergence by ideology in selecting a news source than in learning. An important question for future research follows this finding: If citizens select to consume like-minded news, but if citizens apply similar behavioral learning rules and attribute similar bias to news sources – even the news sources they select to consume – what are the consequences for aggregate learning of political and economic facts? We suspect that aggregate learning may not suffer considerably in such a system of biased selection but consistent learning, but look forward to research on this question. We suspect formal theoretical work could be useful here.

We see as a final contribution of this work the comparison of citizens from two important yet distinct nations. We apply the same research design towards understanding the same research question in these two settings. We believe the comparison highlights the similarity with which citizens in the U.S. and China approach learning from news headlines. In our view, this similarity in decidedly different contexts adds considerable weight to the evidence and arguments we have presented here. It appears that citizens in both countries have strategies, perhaps subconsciously developed through lived experience, to learn from the slanted products of their news providers. Citizens in the U.S. and China behave in ways that suggest they believe their media are biased, but seem nonetheless able to learn from these slanted products.

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Appendix

A Derivation of logit specification of Bayesian learning

We show here how Bayes' Rule from Equation 1 can be transformed to the logit version in Equation 2.[24] Consider a statement of fact with a probabilistic prior belief that it is true Pr(T) [and corresponding prior belief the statement is false 1 – Pr(T) = Pr(F)] and a probabilistic posterior

[24] This section follows closely that in Hill (2017).

belief $\Pr(T|S = s)$ after receiving a signal s (potentially) relevant to the statement of fact. The logit specification of the posterior beliefs, $\log[\Pr(T|S = s)/\Pr(F|S = s)]$ can be derived by letting

$$\Pr(S = s) = \Pr(S = s|T)\Pr(T) + \Pr(S = s|F)\Pr(F)$$

be the probability of the data, and the two Bayes' Rule specifications of posterior beliefs be

$$\begin{aligned}\Pr(T|S = s) &= \Pr(T)\frac{\Pr(S = s|T)}{\Pr(S = s)}\\ \Pr(F|S = s) &= \Pr(F)\frac{\Pr(S = s|F)}{\Pr(S = s)}.\end{aligned}$$

Then, dividing the first by the second, the posterior odds are

$$\begin{aligned}\frac{\Pr(T|S = s)}{\Pr(F|S = s)} &= \frac{\Pr(T)\Pr(S = s|T)/\Pr(S = s)}{\Pr(F)\Pr(S = s|F)/\Pr(S = s)}\\ &= \frac{\Pr(T)}{\Pr(F)} \times \frac{\Pr(S = s|T)}{\Pr(S = s|F)}.\end{aligned}$$

Taking logs of both sides, and noting that $\text{logit}(p) = \log(\frac{p}{1-p})$,

$$\text{logit}[\Pr(T|S = s)] = \text{logit}[\Pr(T)] + \log[\Pr(S = s|T)/\Pr(S = s|F)].$$

B Selection of facts, headlines, and news sources

We started our headline search by selecting six major U.S. news outlets: Fox News, MSNBC, CNN, the New York Times, National Public Radio (NPR), and USA Today. We selected these sources because they all have written articles that readers can access online and extensive previous research has explored their potential bias (e.g., Budak, Goel, and Rao, 2016; Groseclose and Milyo, 2005; Gentzkow and Shapiro, 2010). USA Today and CNN are generally considered moderate news outlets without political slant, while Fox News is more conservative and the New York Times is more liberal (Budak, Goel, and Rao, 2016). After selecting the news outlets, we deliberately excluded opinion or editorial sections as we started our search for news headlines.

Next, we created a list of objective economic facts with political implications about which to find news headlines. We searched for facts that would be (1) relevant to voter decision-making, especially if Americans make decisions based on the state of the economy, and (2) could be verified in an objective data report. We thus focused primarily on economic indicators such as GDP growth, manufacturing data, retail sales, the unemployment rate, and Consumer Price Index (CPI). We then sought topics that were specifically focused on U.S.-China relations to allow for meaningful comparisons across the countries. We focused on trade deficits between the countries, currency exchange rates, and the U.S.-China cap-and-trade deal.

After brainstorming this list of topics, we located the data release dates. For example, the Bureau of Labor Statistics releases a monthly report called "The Employment Situation" that contains information on the unemployment rate, the number of jobs added to the economy, and other eco-

Table A1: Topics considered and search terms used to identify facts and headlines

Topic	Search Terms
GDP Annualized Quarter-over-Quarter	GDP, gross domestic product, economic growth, growth rate, growth, annualized
China devalues the yuan	Yuan, China, currency, devalue
US-China cap and trade	US, China, cap and trade, emissions, carbon, CO2
Nonfarm Payrolls	nonfarm, payrolls, non farm
ISM Manufacturing	ISM Manufacturing
Retail Sales	Retail sales
GDP Quarterly Estimates	GDP, gross domestic product, economic growth, growth rate, growth
Affordable Care Act Enrollments	HHS, enrollment, sign up, signup, Obamacare, ACA, Affordable Care Act, enroll, healthcare, health care, insurance, health insurance, marketplace, healthcare.gov
The Employment Situation	unemployment, jobs, unemployment rate, job growth, employment, employed, unemployment benefits, labor force
Consumer Price Index	consumer price index, CPI, consumer prices, consumer price, inflation
Trade Deficit	trade, goods and services, goods, services, trade deficit, treasury, foreign trade balance, China, international trade

nomic indicators. Similarly, the Bureau of Economic Analysis releases quarterly reports, as well as revised estimates, of the Gross Domestic Product. We then searched for articles about the relevant topics on the date of the data report releases across each of our six news outlets. We started by using the advanced search tools on Google News, using keywords, restricting the date to the date of the data release, and the source to the news outlet of interest. The search terms used for each topic are listed in Table A1 below. After collecting headlines from Google News, we went to each outlet's website and used the same keyword searches and date restrictions, where applicable, to locate more headlines. Some websites, such as CNN, did not allow us to restrict search results by date, so we used the search terms and sorted the search results by date and scrolled through the list until we reached the data release date. We then cross-referenced these headlines with Lexis Nexis searches. Lexis Nexis worked well for media outlets, such as the New York Times, that have a physical print publication, but it was not comprehensive for news sources that do not have a print publication. Finally, we inspected the content of each article to make sure that it was about the intended topic.

Most statistic releases did not have corresponding headlines from every news source. After compiling a list of headlines for each release, we tabulated the news outlets most commonly having headlines for the releases. For the U.S., we found that the New York Times, USA Today, CNN, and Fox News most often covered the statistics we searched. We decided to use these four sources, and then selected the subset of releases that had headlines from all four of these news outlets. We then selected the four facts above from this list that covered different economic facts, including one U.S.-China fact, and that had headlines that we deemed modestly related to the fact of interest

Table A2: Headlines from U.S. experiment

Fact	Source	Headline
GDP growth 3rd quarter 2014	CNN	US economy grows incredible 5% in third quarter
GDP growth 3rd quarter 2014	Fox News	Oil Prices Up on Better-than-Expected GDP
GDP growth 3rd quarter 2014	New York Times	Economic Vital Signs in 3rd Quarter Were Strongest in a Decade
GDP growth 3rd quarter 2014	USA Today	U.S. economic growth surges past estimates in Q3
Job gains, May 2016	CNN	America's economy is stronger than weak jobs report
Job gains, May 2016	Fox News	Dollar Plunges After Dismal Jobs Report
Job gains, May 2016	New York Times	Sharp Fall in U.S. Hiring Saps Chance of Fed Rate Increase in June
Job gains, May 2016	USA Today	These stocks get hit hard by ugly job news
Yuan devaluation	CNN	China devalues yuan in shocking move
Yuan devaluation	Fox News	China's currency falls for second day after devaluation jolts global markets
Yuan devaluation	New York Times	Why Did China Devalue Its Currency? Two Big Reasons
Yuan devaluation	USA Today	Global stocks sink as China's yuan falls for second day

– often, the news article might mention the release but the headline would be on another topic, e.g. how the equity markets had fared. In sum, our goal was to identify four facts that covered important economic indicators that each had enough informative headlines from four consistent news sources to measure how subjects learned and if they attributed any bias to the news sources.

C Headlines

In this section, we present the headlines from each experiment. See Table C for the headlines from the U.S. experiment.

D Experiment instructions

The following pages present screen shots of the experimental instructions presented to participants along with the practice rounds each played.

Contest instructions

Instructions for the Game

In the next part of this study, you are invited to participate in a game. We are going to ask you about five different statements of fact over the course of 25 rounds. These statements of fact may be true or may be false. In each round, you will report how likely you believe the statement is true from 0 to 100. You have the opportunity to win $0.10, paid to you as a bonus. The contest works as follows:

We will present to you a statement of fact that may be true or false. In each round, you will indicate how likely you believe the statement is true, which is a number from 0 to 100 that indicates how likely you believe the statement is true. Zero means false beyond any doubt and 100 means true beyond any doubt. For example, if you were almost entirely certain the statement is true, you might enter 99. If you were almost entirely certain the statement is false, you might enter 1. If you were totally uncertain about the truth of the statement, you should enter 50. You might believe it likely to be true but not be fully certain and enter 70. In each round, please enter how likely you believe the statement to be true.

We ask that you please not look up the answer to the question during the contest.

On the next page, we'll present how your your response determines whether or not you win that round.

Instructions for the Game

Winning in each round of the game depends upon your response.

At the most basic level, in each round your task is to give your best guess about whether or not the statement is true. The contest is designed so that you will maximize your bonus by reporting your beliefs as accurately as possible.

You will maximize your chance of the highest possible bonus by being as accurate as possible in each round.

Here is how your response generates a bonus in the game. You can skip these details if you are not interested in the underlying process. In each round, the computer will draw a random number from 0 to 100. Each number from 0 to 100 is equally likely to be drawn by the computer. We'll call this number Draw 1. How you win or lose that round of the contest depends on what number the computer draws for Draw 1 and your response:

1. If Draw 1 is less than your response, you win if the statement is true and do not win if the statement is false. For example, if you enter a response of 99, you are very likely to win if the statement is true and very likely to not win if the statement is false. The higher your response, the more likely you win if the statement is true. Similarly, the lower your response, the more likely you win if the statement is false.

2. If Draw 1 is greater than your response, then the computer will draw a second random

number from 0 to 100. As before, each number from 0 to 100 is equally likely to be drawn by the computer. We'll call this random number Draw 2. If Draw 2 is less than Draw 1, then you win the round. If Draw 2 is greater than Draw 1, then you do not win the round.

The contest is designed so that you have the best chance for earning a bonus by being as accurate as possible with your response. The random numbers and payment calculations happen behind the scenes. You will not see the draws in any round.

Finally, you will have 20 seconds to submit your response on each screen.

Instructions for the Game

We will ask your belief about whether the statement is true for each of 25 rounds of the contest. We will present the same statement more than once.

Sometimes when we repeat a statement, the computer will provide you with a signal about the correct answer. The computer will present you a signal "TRUE" or "FALSE." Part of the contest is that three out of every four signals from the computer are correct, on average. That is, if the statement is true, the computer will signal "TRUE" three out of four times and "FALSE" one out of four times, on average. If the statement is false, the computer will signal "FALSE" three out of four times and "TRUE" one out of four times, on average. You will not know, however, whether or not each signal you see is correct.

We again emphasize that this is a NO DECEPTION study. The signals you receive from the computer will be correct three out of four times, on average.

Other times when we repeat a statement, the computer will provide to you a news headline related to the fact. The headline is an actual headline from an actual news media provider published within a few days of the fact. You may want to use the headline to change how likely you believe the fact is true or false.

You may use any information from the computer signal or from news headlines to change your response in that round from what you had said earlier.

After you have completed the survey, we will calculate how many rounds you won and pay you your total bonus payment given the 0 to 100 responses you gave in each round and whether or not the statement of fact was actually true or false.

Here is an example of what the contest will look like. Note: you are not being paid for these practice responses.

Factual statement:
* Please tells us how likely you believe this statement is true:
It rained (more than 0.00 inches of precipitation) in Santa Fe, New Mexico on July 7, 2004.

How likely you believe that the statement is true (for example, 1 if you believe it is almost certainly false, 99 if you believe it is almost certainly true, 50 if totally unsure):

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Here is an example of what the contest will look like WHEN YOU RECEIVE A SIGNAL FROM THE COMPUTER (timer not used here, but will be used in actual contest):

Factual statement:
* Please tells us how likely you believe this statement is true:
It rained (more than 0.00 inches of precipitation) in Santa Fe, New Mexico on July 7, 2004.

Last response:
* Your last response was ${q://QID72/ChoiceTextEntryValue}.

Computer signal:
* The computer has produced a signal for you. Remember, three out of four times this signal will be accurate and one out of four times it will be inaccurate.

*** THE SIGNAL FROM THE COMPUTER IS "FALSE."**

How likely you believe that the statement is true (for example, 1 if you believe it is almost certainly false, 99 if you believe it is almost certainly true, 50 if totally unsure):

Here is an example of what the contest will look like WHEN YOU RECEIVE A NEWS HEADLINE (timer not used here, but will be used in actual contest):

Factual statement:
* Please tells us how likely you believe this statement is true:
It rained (more than 0.00 inches of precipitation) in Santa Fe, New Mexico on July 7, 2004.

Last response:
* Your last response was ${q://QID75/ChoiceTextEntryValue}.

News headline:

* This news headline was published soon after the information relevant to the factual statement was made available from official sources:

ENGINEER, CALL HALT TO WATER-CZAR SCHEME

How likely you believe that the statement is true (for example, 1 if you believe it is almost certainly false, 99 if you believe it is almost certainly true, 50 if totally unsure):

Here is what will be going on "behind the scenes" after you submit your response in each round.

Your last belief that the statement, "It rained in Santa Fe, New Mexico on July 7, 2004" was true was
${q://QID77/ChoiceTextEntryValue}.

According to Weather Underground (www.wunderground.com), there were 0.00 inches of precipitation in Santa Fe, New Mexico on July 7, 2004.
The correct answer is that the statement is FALSE.

If the random number drawn by the computer (Draw 1) was less than your response ${q://QID77/ChoiceTextEntryValue}, because the statement is FALSE you would not have won.

If Draw 1 was greater than your response ${q://QID77/ChoiceTextEntryValue}, the computer would draw a second number at random from 0 to 100 (Draw 2). If Draw 2 is less than Draw 1, you win, if Draw 2 is greater than Draw 1, you do not win. Again, **you will be most likely to win each round when you accurately report your belief**.

In the rest of the survey, you will not see the outcome of the random draws or your wins and losses. After the study, we will calculate your winnings based on your responses and random numbers drawn by the computer, and pay these to you as a bonus.