The (Null) Effects of Clickbait Headlines on Polarization, Trust and Learning

March 31, 2019

Abstract

"Clickbait" has become a common form of online media, and headlines designed to entice people to click are frequently used by both legitimate and less-than-legitimate news sources. We present the results of a pair of experiments with different sets of subject pools: one conducted using Facebook ads that explicitly target people with a high preference for clickbait, the other using a sample recruited from Amazon's Mechanical Turk. We estimate subjects' individual-level preference for clickbait, and randomly assign sets of subjects to read either clickbait or traditional headlines. We find that older people and non-Democrats have a higher "preference for clickbait," but find no evidence that assignment to read clickbait headlines drives affective polarization, information retention, or trust in media.

1 The Rise of Clickbait Media

Trust in the news media has been declining steadily ever since the 1970s (Ladd, 2011), especially among conservatives. This same time period has seen a rise in "affective polarization"—the extent to which Republicans and Democrats dislike and distrust each other (Iyengar, Sood, and Lelkes, 2012). Cultural and technological changes in the media environment have been theorized as causes of the latter trend, with an increasingly fragmented political news industry able to target niche political audiences (Stroud, 2011) and the increasing range of entertainment options and decline of incidental exposure to the nightly news pushing low-political-interest moderates out of the electorate (Arceneaux and Johnson, 2013; Prior, 2007).

The economic model of the contemporary online news industry is distinct from print journalism. Although a small number of publications are financed by subscription revenue (the *New York Times* gets 60% of its revenue from subscriptions (Ember, 2018)), the primary business model is based on click-based advertisements. Competition comes from trying to attract readers' eyeballs by writing stories with headlines that entice them to click: "clickbait."

The concept of "clickbait" is best associated with the digital media upstart *Upworthy*. The "fastest-growing media site of all time," *Upworthy* implemented a new style of headline designed to entice consumption by strategically withholding information (Sanders, 2017).[1] Less than two years after its founding in March 2012, *Upworthy* had over 80 million unique visitors each month—more than the New York Times or Washington Post.

The following year, Merriam-Webster added "clickbait" to its dictionary, defining it as "something (such as a headline) designed to make readers want to click on a hyperlink especially when the link leads to content of dubious value or interest."

This initial conception of clickbait thus implies something like regret. The "Upworthy-style" information gap headline (the classic format is "XXXXXX...And You'll Never Believe What Happened Next!") played up the asymmetry inherent in the market for information goods. Consumers cannot evaluate the quality of information goods ex ante; consumption and evaluation happen simultaneously (Varian, 1999). Information gap clickbait profited from the intersection of the structure of the market and readers' naturally developed curiosity.

[1]This style of headline is also referred to as "forward-referring," especially amongs scholars of journalism (Blom and Hansen, 2015; Scacco and Muddiman, 2016).

However, the "market failure" entailed by this information asymmetry was detected and (largely) solved by Facebook. By measuring the time spent reading a given story, Facebook was able to quantify "regret," and subsequently downweighted stories that quickly led users back to Facebook (suggesting they had not been satisfied with their information consumption experience). After Facebook made this change in November 2013, *Upworthy*'s business collapsed. In November 2014, the site had only 20 million unique visitors (Karpf, 2016).

A more politically relevant form of clickbait is one that appeals directly to people's emotions, especially as it relates to their partisan identity. We propose to define this type of clickbait headline as *partisan emotional clickbait*: a headline which appeals directly and explicitly to the emotions of the partisan reader. This form of clickbait serves the twin purposes of inducing excitement by appealing to group competition (Abramowitz and Saunders, 2006; Mason, 2018), and being easily spread among online social networks, which tend to be homophilous (Centola, 2010). A paradigmatic example (from pre-internet clickbait experts at the *New York Post*, on May 23, 2016) would be "Democrats are freaking out over a possible President Trump." There is no information gap, but the headline directly primes the reader's partisan identity and tells them that people who share that identity are experiencing a strong emotion.

We argue that partisan emotional clickbait is currently a prominent form of clickbait headlines. However, there is no published academic research to this effect—in fact, there may never be. This kind of knowledge (about the current state of a massive, competitive and fast-moving system like the online media economy) is low in "temporal validity," and it decays faster than the cycle of academic publishing can keep up. As a result, we rely on industry analyses put out by Buzzsumo, an online content tracker and aggregator.[2]

Buzzsumo's 2018 *Content Trends Report* demonstrates that the market for clickbait headlines has continued to evolve. Facebook is a powerful actor. In 2016, they built a human-labeled classifier to detect posts that withheld information or mislead readers—and then punished *publishers* whom they found to be frequently posting clickbait. Then in 2017, they refined to classifier to target both individul posts and their publishers.

Buzzsumo documents the dramatic effects of these changes. Top "information gap" headlines before the 2017 change were shared on Facebook millions of times, but only

[2]Despite the unserious name, Buzzsumo is very influential in the digital research space. Academics have begun to use them as well; Allcott, Gentzkow, and Yu (2018)'s working paper on current trends in "fake news" diffusion is based on Buzzsumo data.

two such posts were shared more than 200,000 times post-2017 (Rayson, 2018). The report documents a general decline in social shares and notes that "Clickbait style headlines and listicles are far less effective." There is one important exception: "there has been more tribal and partisan sharing of content in recent years."

Another Buzzsumo report documents the headline formats with the highest engagement (from March to May 2017, after the Facebook Newsfeed changes) (Rayson, 2017). Their first conclusion is that "emotional headlines drive Facebook interactions," and the far and away more effective headline format contains the phrase "will make you." These headlines promise that the story "will have a direct impact on the reader, often an emotional impact."

We use these top headline formats to create what we call "partisan emotional clickbait." Due to the rapid pace of change in the online media market, there is no published research on the effects of partisan emotional clickbait, so we motivate our expectations for its effects from related findings in the literature.

Our pre-registered hypotheses[3] were that random assignment to read stories with partisan emotional clickbait headlines would exacerbate affective polarization, decrease trust in online news, and increase information retention; in all three cases across all of our studies, we observed null effects.

Our confidence in these null results is heightened because they were observed in two separate populations: the experiments were identical, but conducted on two different online samples. The first sample was recruited from Amazon's Mechanical Turk, a standard source of research subjects which has been shown to be generally reliable, producing experimental results which closely match results from nationally representative samples (Coppock, 2018; Mullinix et al., 2015; Snowberg and Yariv, 2018).

However, we theorize that age and digital literacy are two crucial moderators of online behavior like the propensity to consume clickbait news; survey data linked to Facebook data has revealed that age (in addition to ideology) strongly predicted the propensity to share fake news on Facebook during the 2016 US election campaign (Guess, Nagler, and Tucker, 2019). Evidence suggests that these two variables do not sufficiently vary within the Mechanical Turk population (Brewer, Morris, and Piper, 2016; Huff and Tingley, 2015).

To address these concerns, a second sample was recruited using a Facebook ad campaign. Although non-representative, this sample is of particular interest because

[3]https://egap.org/registration/3175

everyone in it – by dint of the recruitment process – had to have clicked on an attention-grabbing Facebook ad to be added to our sample. The Facebook sample is also considerably older than the MTurk sample (indeed, 55-75 year-olds are over represented compared to the US population), giving us sufficient variation on this theoretically important treatment moderator. However, the experimental results for this sample were also null.

We also provide evidence that certain types of people are more likely to select a partisan emotional clickbait headline. There is consistent evidence that older people and non-Democrats have a higher preference for clickbait. On other characteristics of interest, however, there are significant differences between the two samples, illustrating the importance of thoughtful sample selection when conducting research on digital media effects. The results suggest that the most important pathway by which clickbait could affect political outcomes is by changing *which* or *how many* news stories people consume. However, it bears emphasizing that the magnitude of respondents' preference for ideologically congruent headlines was much larger than any of these effects.

2 Experiments on the Determinants and Effects of Clickbait News Consumption

We begin by describing our research design. We conducted two survey experiments, one using Amazon's Mechanical Turk and the other using subjects recruited using Facebook advertisements.

The survey instrument was designed to take around ten minutes to complete, and contained an attention check and built-in delays to discourage respondents from giving low-quality answers.

The Mechanical Turk sample consisted of 2,803 total respondents across three slightly different experimental setups; in each case, because the pool of MTurk workers contains more Democrats than Republicans, we supplemented the first draw with a sample of self-reported Conservatives.[4] This sample was intended to serve as the baseline, as Mechanical Turk is a standard source of subjects for online survey experiments. Each Mechanical Turk subject was compensated $1.

The first session ($N = 1{,}140$) provided demographic information and non-experimental

[4] Mechanical Turk allows requesters the ability to specify the demographics of a given sample, including their ideological leaning.

preference for clickbait questions.[5] The second session ($N = 826$) included those same questions and also an experimental manipulation (described below). The final session ($N = 837$) replicated the experimental manipulation but dropped the pre-treatment preference for clickbait questions; we performed this analysis to check whether this portion of the instrument was dampening treatment effects. See Table 1(b) for a breakdown of the information drawn from each session.

The Facebook sample was recruited through a Facebook advertising campaign run by a Facebook page we created. We paid for an advertisement to appear on the News Feed of our potential subjects. The structure of Facebook's advertising platform meant that we only pay when a potential subject actually clicks on the ad. The overall cost paid to Facebook for the subject recruitment was \$1,858 for 2,766 subjects who clicked on our ad. We compensated subjects by entering them (the 1,232 who completed the survey) into a lottery to win a \$500 gift Amazon gift card, meaning that the overall cost per subject was \$0.85 for subjects who began the survey and \$1.91 for subjects who completed the survey. The advertisement we used is displayed in Figure 1.

The motivation for the lottery (and the design of the recruitment instrument) was twofold. First, one distinct advantage of Mechanical Turk over Facebook for subject recruitment is the former's built-in system for processing microtransactions. The need to perform an individual \$1 transaction for each subject would have represented a significant additional cost for the experiment.

More substantively, the advertisement was designed to be as eye-catching as possible. Facebook ads can be used with quota sampling to generate valid measures of public opinion (Zhang et al., 2018), but we were particularly interested in a non-representative sample of Facebook users: people who were most likely to click on an eye-catching ad.

The Facebook sample, then, is unbalanced on a number of important dimensions. Table 1(a) provides the descriptive statistics of the two samples. Some of the distributions are striking; in particular, a full 75% percent of the Facebook sample were women.

However, we cannot be sure whether this 3-1 gender ratio reflects the true rate at which people clicked on ads because there is some uncertainty about the way that the Facebook advertising software operates. As Zhang et al. (2018) points out, Facebook uses a multi-armed bandit algorithm to optimize the efficiency of ad buys throughout the duration of their run. For example, after detecting that women are slightly more

[5] This session did include an experimental manipulation, but it was unfortunately marred by a design flaw.

Figure 1: Recruitment Instrument for Facebook Sample

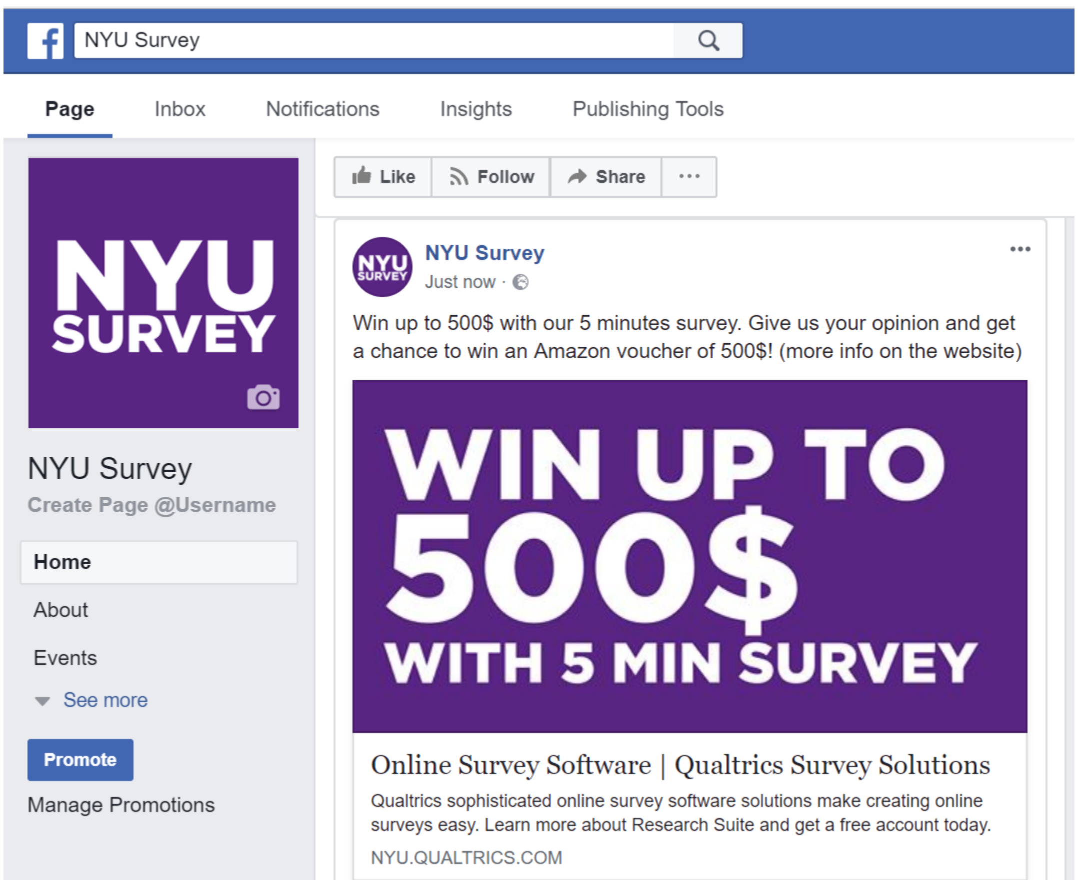


Table 1: (a) Summary Statistics of MTurk and Facebook Samples

	MTurk	Facebook
% Female	46%	75%
Mean Age	37	49
75th Percentile Age	43	63
% Finished College	58%	42%
% Republican	33%	21%
% Independent	29%	28%
% Internet > 1/day	96%	93%
% Facebook > 1/day	52%	90%
N	1,903	2,382

(b) MTurk Samples and Results

	N	PfCB	Experiment
Session 1	1,140	X	
Session 2	826	X	X
Session 3	837		X

likely to click the ad than are men, the algorithm would start displaying the ad to more women.

This does not seem to be driving results in this case, as the proportion of women in the beginning and end of the ad run are identical. Even so, given the opacity of the Facebook algorithm, we should not read the proportions from the Facebook sample as necessarily reflecting the true population of people who might have clicked on the ad.

In each experiment, respondents were directed to a Qualtrics survey in which they first reported demographic information, including partisan affiliation and their frequency of internet/Twitter/Facebook use. We then gave them a series of nine tasks, one of which was an attention check. In each task they were shown four headlines, and asked which they would most like to read. Note that respondents were not actually given links to these stories nor asked to actually read the stories at this point. In each task, there were two political stories (one Democrat-favorable, one Republican-favorable) and two non-political stories (one sports, one entertainment).[6] One of the two political headlines (either the Democrat-favorable or Republican-favorable) in each decision set was turned

[6] The inclusion of non-political stories has been shown by Arceneaux and Johnson (2013) to provide more reliable estimates of media choice.

into a clickbait headline through the addition of an attention-grabbing phrase to the beginning, so that there were four instances in which the Democrat-favorable headline was clickbait and four instances in which the Republican-favorable was clickbait.In the task set up as an attention check, one of the four answers read "Survey taker: always select this option, ignore the other choices."

The purpose of this part of the survey was to calculate individual-level *preference for clickbait* (PfCB): how often each respondent claimed they would prefer to read the clickbait headline rather than the non-clickbait headline, ignoring the preference for non-political headlines.[7] This process was non-experimental; our goal was to see how PfCB varied across respondent demographics, and to see how the experimental treatment effect (described below) varied with individual-level PfCB.

Respondents were then randomly assigned to one of four treatment conditions plus a fifth "placebo" condition (in which respondents were given a story about sports) through a 2x2 treatment design that varied the partisan leaning of a headline and whether the headline was clickbait. In each case, respondents were presented with a hyperlinked headline; when they clicked the headline, they were directed to a separate tab which displayed the given headline and a news story. The text of the news story was held constant across the conditions.

After respondents read the story and closed the tab, they were asked "feeling thermometer" rating questions for Republicans, Democrats, online media and traditional media, as well as a multiple-choice question about their trust in online media and traditional media.[8] On the next page, they were asked three multiple-choice questions based on facts presented in story they had been given to read plus an additional, placebo factual question about the sports story.

The text of the story used in this experimental manipulation summarized the findings from the October jobs report and was taken from a politically neutral news source: CNN Money.

The treatment headlines for the experiments are displayed in Table 2.

The headlines displayed in Table 2 are symmetric, adding only a "not" to switch

[7]This process balances the concern expressed in Leeper (2016) for measuring media treatment effects on the relevant population (those who would actually consume the given media) with the fact that we needed to disguise the nature of the manipulation from the respondent.

[8]Feeling thermometer questions ask respondents to rate how they feel about the category in question (could be a person, industry, organization, group of people, etc.) on a scale from 0 to 100, where 0 is "Very cold or unfavorable feeling" and 100 is "Very warm or favorable feeling." This question has a long history of use in the American National Election Study, and is the standard measure for measuring affective polarization (i.e., feeling thermometer rankings for the Democrat and Republican parties).

Table 2: Treatment Headlines

R: Baseline	Trump economic policies working
R: Clickbait	Democrats won't like this economic news: Trump policies working!
D: Baseline	Trump economic policies not working
D: Clickbait	Republicans won't like this economic news: Trump policies not working!

the partisan leaning. The emotion appealed to in this version of emotional clickbait is—quite explicitly—negative partisan excitement: the idea that your opponents being angry about something implies that you will excited by it (Abramowitz and Saunders, 2006).

3 Hypotheses

The first question this study aims to answer is exploratory: what kinds of people are more likely to consume *partisan emotional clickbait?* There is not any strong extant theory here,[9] so the analysis related to this research question should be treated as descriptive and exploratory rather than confirmatory.

Research Question: *What kinds of people are more likely to consume emotional clickbait?*

Our experimental investigation of the effects of partisan emotional clickbait is novel, so our hypotheses do not follow directly from published results. Instead, we synthesize findings about the effects of theoretically relevant media developments to motivate our hypothesis. The outcomes of interest—affective polarization, trust in media, and information retention—are of particular interest to public opinion scholars today and are related to media consumption.

Our expectations about the individual-level effects of partisan emotional clickbait are tempered by the overall socio-technical media environment; fractured and elective media consumption entails minimal effects (Bennett and Iyengar, 2008). Even constant elective exposure to biased media may not be enough to cause polarization, at least

[9]The most related result is a paper – published after we pre-registered our hypotheses – on the "Demand for Spam" (Redmiles, Chachra, and Waismeyer, 2018). Researchers at Facebook used proprietary data to demonstrate that women, older people and people with less experience using Facebook (those lower in Facebook literacy) are more likely to click on spam. Encouragingly, we find similar results.

during the time frame of a single study (Peterson, Goel, and Iyengar, 2018). However, the novelty and prominence of partisan emotional clickbait motivate our desire to test the minimal effects framework in this case. Furthermore, the minimal effects paradigm does not have strong implications for the effect of partisan emotional clickbait on either information retention or trust in media.

The primary mechanism by which we theorize partisan emotional clickbait to operate is *increased arousal*. In a book-length investigation of the effects of arousal caused by televised close-ups of partisan incivility, Mutz (2015) defines arousal as when "a person becomes psychologically and physiologically prepared to respond to stimuli of some kind." Mutz investigates the effect of adding emotion to a partisan broadcast—a theoretical analogue our current investigation. Mutz finds that increased arousal is responsible for increased information retention and affective polarization—the latter primarily in the form of decreased warmth towards the out-party.

The literature on affective polarization suggests that the primary driver is decreased warmth towards the out-group. This is what Abramowitz and Webster (2016) call "negative partisanship"—out-partisan animosity is a powerful motivator for a range of political behaviors. Mason (2016) finds experimental support for the presence of anger in response to partisan threats, and Mason (2018) presents extensive evidence of the effect of partisan emotion on affective polarization.

Furthermore, one of the few studies conducted on "information gap" clickbait provides support for this mechanism by using eye tracking data and self-reported arousal. Pengnate (2016) find that subjects exposed to clickbait headlines experienced increased arousal.

The theory, then, is that partisan emotional clickbait increases arousal, which increases affective polarization, leading to Hypotheses 1 and 2:

Hypothesis 1 *The Republican-favorable conditions will **increase** reported affect toward Republicans. The Democrat-favorable conditions will **decrease** reported affect toward Republicans.*

Hypothesis 2 *The effects predicted in Hypothesis 1 will be larger in the partisan emotional clickbait than the baseline conditions.*

Hypothesis 1 is essentially a replication of research suggesting that exposure to partisan media or campaigns increases affective polarization (Iyengar, Sood, and Lelkes, 2012; Levendusky, 2013). In the current case, the Republican president is the primary political actor mentioned in the headline, so Hypothesis 1 predicts a change in the way that subjects feel about the Republican party. Hypothesis 2 is that partisan emotional clickbait will enhance these effects.

Arousal is also theorized to increase information retention. Mutz (2015) motivates her findings to this effect with reference to a broad literature in psychology that investigates the connection between memory and arousal. There is an ongoing debate about the precise nature of this relationship—under different conditions, arousal can either improve or impair recall—but the theory of "affect-based attention" predicts that emotional arousal will increase the attention paid to (and the subsequent recall of) affectively relevant information (Todd et al., 2012). The information retention questions we ask pertain to facts (the unemployment rate, the employment rate, and wage growth) directly relevant to the "Trump economic policies" headlines used in the experiment.

Hypothesis 3 *Respondents assigned to read emotional clickbait will retain more information.*

The public's general attitude towards clickbait is negative; complaints about clickbait were what drove Facebook to punish it. Hypothesis 4 is thus that partisan emotional clickbait will decrease trust in (online) media. Just as Ladd (2011) demonstrates in the case of "tabloid news," we expect that subjects who are assigned to the clickbait condition will report lower trust in media.

Research on alternative clickbait formats suggests that they can decrease readers' attitude toward the headline and associated story. Scacco and Muddiman (2016) find evidence for this effect with "question-based" clickbait, but not with "forward-reference" clickbait. Still, the best evidence for this effect is likely proprietary—media companies experiment with headlines and want to balance attracting readers with maintaining their credibility. Citing a personal conversation with editors at the *Washington Post*, Hindman (2018) reports that "the *Post* found that headlines chosen for maximum clicks actually *lowered* traffic...[they] turned off those readers most inclined to visit the second or third article."

Hypothesis 4 *Respondents assigned to read emotional clickbait will report lower trust in (online) media.*

The final hypothesis was not pre-registered; the null results found in the experiment conducted on the MTurk subjects motivated us to think about the limitations of that sample. We hypothesized that the MTurk sample did not sufficiently vary in potential treatment moderators (age and digital literacy), and we sought out the Facebook sample in order to test this theory.

Hypothesis 5 *The treatment effects in Hypotheses 1-4 will be larger among subjects with lower levels of digital literacy and thus larger among the Facebook sample than among the MTurk sample.*

These hypotheses did not vary across samples. The R file containing all of the code used to analyze the experimental data was included with our pre-registration as part of the pre-analysis plan. In addition to pre-registering the hypotheses listed above, we specified in advance the precise coding and data manipulation decisions we would make in testing those hypotheses.[10]

4 Results

4.1 Preference for Clickbait

To analyze the individual-level preference for clickbait (PfCB), we compare the results from the MTurk and Facebook experiments. PfCB is calculated by estimating what percentage of the political stories the subjects selected to read were clickbait. We also estimate the individual-level preference for Republican (PfR) news. Note that these two quantities are structurally (negatively) correlated: an individual who selected 8 out of 8 clickbait stories would necessarily have selected 4 out of 8 Republican stories.

Partisans made the expected choices: the mean PfR was .61 for Republicans and .36 for Democrats, including leaners, in both samples. For Republicans (including leaners), the mean PfR was .60 in the Facebook sample and .64 in the MTurk sample. Restricting to strong partisans heightens these trends only slightly. This preference for co-attitudinal news restricts the range of possible values for PfCB.

Still, the overall results were surprising: the overall PfCB was negligible. The rate of selecting the clickbait political stories was in fact slightly lower than the non-clickbait political stories (median PfCB = .50, mean PfCB = .47); this rate did not vary across the samples.

[10]Note that the specific language used to describe the hypotheses has been changed from the pre-registration to match the terminology employed in the rest of this paper.

In addition to the restricted range discussed above, this result illuminates two limitations of the current research design. First, stories shared on Facebook or Twitter consist of more than just a headline—they are almost always accompanied by a picture and a source. The equivalency in legitimacy this creates between stories shared from, say, the *New York Times* and *Upworthy* may be a significant component of why clickbait is a viable strategy. A headline devoid of this visual signifier might be perceived as too obviously low-quality.[11]

With this caveat, though, we can still estimate the subjects' *relative* PfCB. Table 3, columns 1 (Mturk) and 2 (Facebook), displays the results of an OLS regression taking PfCB as the dependent variable and all of the demographic information collected from users as independent variables. Questions about frequency of Facebook use, Twitter use, Internet use, reading online news stories and reading offline news stories are on an 8-point increasing categorical scale.

Across both samples, the only consistent results predicting PfCB are that older individuals have a higher PfCB and Democrats have a lower PfCB. Many of the other coefficients are estimated to have significant relationships in one sample and negligible relationships in the other. Neither of these samples is representative of the US population, but the attention-grabbing Facebook ads we used to recruit that sample suggests that those subjects are precisely the type of people who drive clicking behavior online. Such findings are particularly interesting in light of recently published work finding the same populations – older Americans and non-Democrats – were more likely to share fake news on Facebook in the 2016 US election campaign (Guess, Nagler, and Tucker, 2019).

Subjects recruited via Facebook have higher values for PfCB when all of the covariates take the value of 0. However, it is possible that these factors behave differently in subjects in the different samples, so Table 5 in Appendix A combines these two samples analyzed separately in Table 3 with models that fully interacted with a dummy for which sample a subject was drawn from. There are no significant interaction effects in the models that estimate the PfR, but there are a few in the models of PfC. The difference between Democrats' and Republicans' PfC is less pronounced among the Facebook sample, and increased Facebook use is increased with PfC only among the

[11]Thus, we do not take these results as evidence that clickbait "doesn't work." Dozens of competing media firms have in effect demonstrated that clickbait does work by adopting it as a prominent format for news headlines, sometimes using explicit A/B testing. The specific way we operationalize partisan emotional clickbait in this study is motivated by the industry research cited in the introduction.

Table 3: Preference for Clickbait

	Dependent variable:			
	Preference for Clickbait		Preference for Republican	
	MTurk	FB	MTurk	FB
Facebook use	0.003	0.015^{***}	0.004	0.007
	(0.003)	(0.006)	(0.003)	(0.007)
Twitter use	0.003	0.002	-0.001	-0.001
	(0.003)	(0.002)	(0.003)	(0.002)
Internet use	0.009	-0.009^{*}	0.002	0.009
	(0.008)	(0.005)	(0.009)	(0.006)
Age	0.001^{*}	0.001^{***}	0.001	-0.0001
	(0.0005)	(0.0003)	(0.001)	(0.0003)
Education	-0.005	-0.014^{***}	-0.001	-0.007
	(0.007)	(0.004)	(0.008)	(0.005)
Offline news consumption	0.009^{**}	0.001	-0.0001	-0.001
	(0.004)	(0.002)	(0.004)	(0.002)
Offline news consumption	0.006	0.005^{*}	-0.002	-0.012^{***}
	(0.005)	(0.003)	(0.005)	(0.003)
Democrat	-0.052^{***}	-0.020^{*}	-0.129^{***}	-0.096^{***}
	(0.016)	(0.010)	(0.018)	(0.012)
Lean Democrat	-0.032^{*}	-0.032^{**}	-0.082^{***}	-0.090^{***}
	(0.019)	(0.015)	(0.021)	(0.018)
Lean Republican	0.067^{***}	0.012	0.112^{***}	0.103^{***}
	(0.018)	(0.017)	(0.020)	(0.020)
Republican	0.036^{**}	0.021	0.135^{***}	0.165^{***}
	(0.018)	(0.014)	(0.020)	(0.016)
Constant	0.308^{***}	0.364^{***}	0.450^{***}	0.448^{***}
	(0.063)	(0.046)	(0.071)	(0.053)
Observations	1,889	2,256	1,889	2,256
Adjusted R^2	0.033	0.029	0.117	0.153

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Facebook sample.

4.2 Pre-Registered Experimental Results

Turning to the results from the experimental condition, we want to be explicit about our central result: following the analysis code that we pre-registered in our pre-analysis plan, we found null results. After performing the appropriate Bonferroni correction to account for multiple comparisons (and, in fact, in almost every case without this correction), we estimate that each of the hypothesized treatment effects on the relevant outcome variable was significantly indistinguishable from zero. The sample sizes of the two experiments, drawn from entirely distinct samples, gives us confidence in the lack of the expected effects.

There is evidence that the reason the treatments did not have the hypothesized effects is not due to a lack of uptake from the factual knowledge questions. Figure 2 displays these results. There were three information retention questions in addition to a sports-related placebo information retention question.[12]

In both the Mechanical Turk and Facebook samples, subjects in the placebo condition answered far fewer questions correctly. This is evidence that subjects were in fact reading the stories carefully and retaining the information, rather than relying on their *ex ante* knowledge. The one exception is the sample of Republicans recruited from Facebook; their rate of correct answers was similar across all five conditions, but their overall average correct was similar to Democrats.

Figure 3 presents the results for trust in online and offline media. The expectation that the clickbait treatments would decrease trust in media was not realized. The one exception is a marginally significant ($p = .09$, non-Bonferroni corrected) reduction in trust in online media among the MTurk sample.

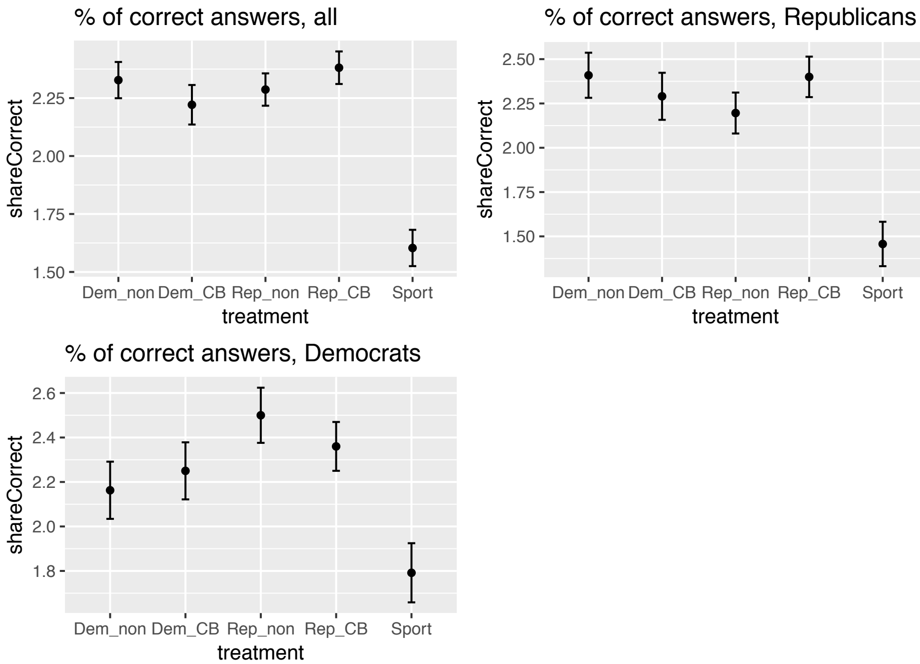
4.3 Post Hoc Analysis of Experimental Results

To further validate that the experimental manipulation was not entirely ignored, and to learn as much as possible from the data, we present the results from post hoc mod-

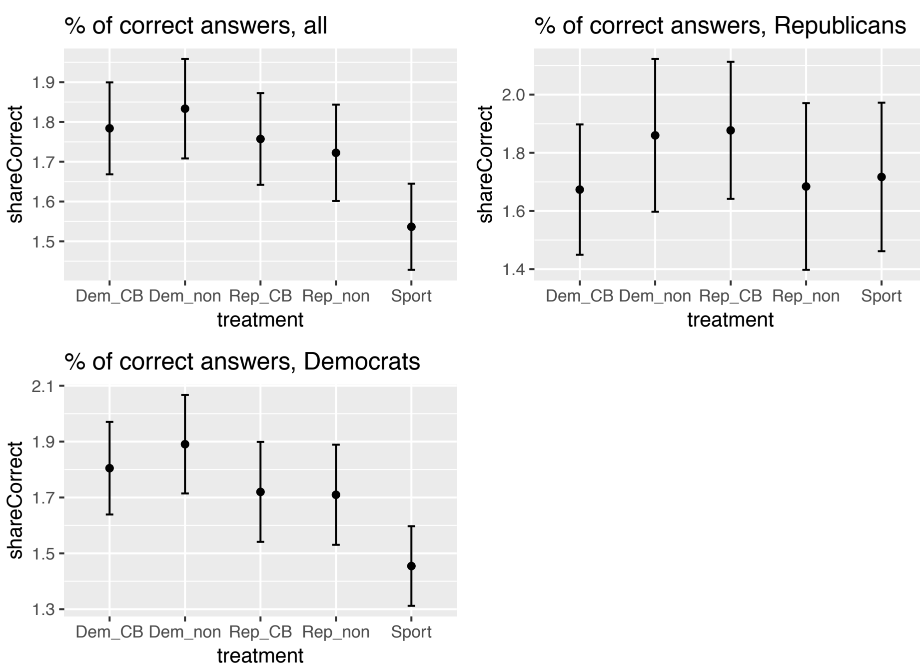
[12] All of the information retention questions were based on information provided in the body of the treatment news story. Because these were taken from existing news stories based on recent political news stories, it is possible that respondents could have known the correct answers *ex ante*. To minimize this problem, the questions concerned specific details from the stories that were not particularly salient to the overall political discussion.

Figure 2: Effects of Clickbait on Information Retention

MTurk



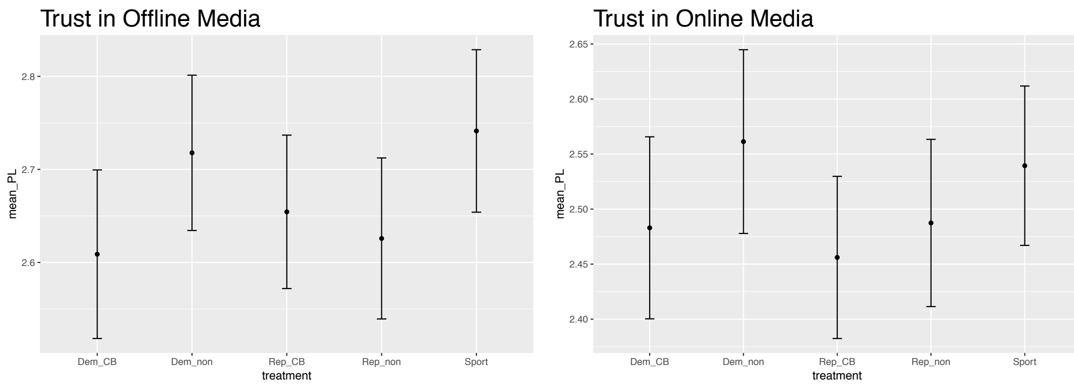
Facebook



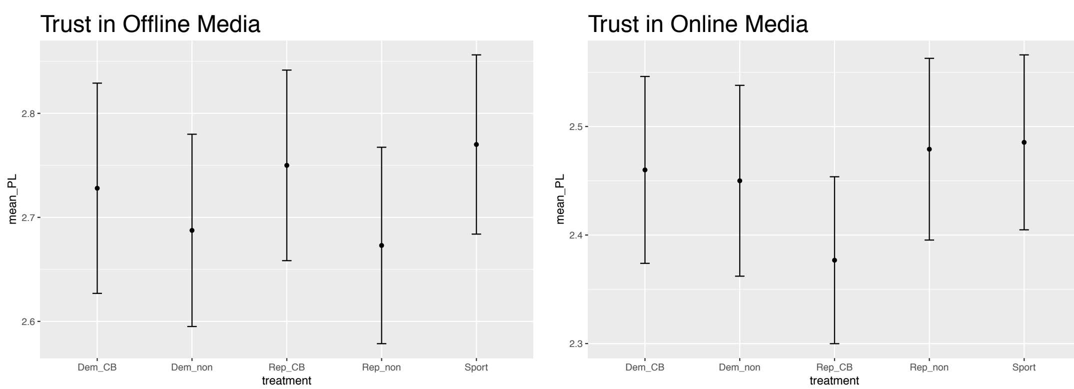
Bars represent 95% confidence intervals.

Figure 3: Effects of Clickbait on Trust in Media

MTurk



Facebook



Bars represent 95% confidence intervals.

ifications to our pre-registered analysis plan. The primary modification is to interact the treatments with the party identification (on a five-point scale) of the respondents.

Table 4 presents two models that estimate the effects of our four treatment conditions interacted with the party identification of the respondents on affect towards the Republican party, as measured with the 0-100 feeling thermometer.[13] The straightforward effect of party ID dominates, as expected, but in the model using the Mechanical Turk sample, we find the two Republican-leaning headlines cause a significant reduction in warm feelings toward the Republican party; the two Democrat-leaning headlines cause a non-significant reduction.

These reductions are more than counterbalanced by the positive and significant interaction terms when the treatment effects are estimated on Republicans and Republican leaners. The ignored category in the party ID variable is Independents, so in the aggregate we can summarize the results of Table 4: the Republican-leaning treatment conditions caused a reduction in warm feelings toward the Republican party among Independents, had no effect on Democrats, and increased warm feelings among Republicans.

We do thus find support for Hypothesis 1, although this is a straightforward replication of the large literature on partisan priming. The fact that this result replicates in our dataset should increase our confidence that the null results in comparing clickbait and non-clickbait headlines are legitimate estimates of the true effect of clickbait.

However, we only find the significant results of partisan cues in the Mechanical Turk sample. One plausible explanation for our failure to replicate these results on the Facebook sample is that there was massive attrition from this sample at the stage of assigning treatment, leaving us with a non-random half of the original sample.

The experimental treatment involved clicking on a hyperlinked headline that opened up the news story in a separate tab. At this point in the survey, 6% of the Mechanical Turk sample dropped out, compared to 31% of the Facebook sample. This dramatically reduces the statistical power to detect any treatment effects in the Facebook case, but because this attrition could be non-random, it could also produce biased estimates of treatment effects.

In particular, much of our motivation for using the Facebook sample to confirm our null results from the Mechanical Turk sample was that we were concerned that the latter did not contain enough people with low digital literacy, and that these are

[13]We do not present a similar breakdown with models of the other recorded dependent variables of interest (trust in media and factual information retention) because there are no significant results.

Table 4: Treatments Interacted with Party ID

	Republican Feeling Thermometer	
	(Mturk)	(Facebook)
Shortened Survey	4.255***	
	(1.258)	
Dem CB	−3.692	−4.423
	(3.788)	(3.646)
Dem non CB	−5.107	−1.939
	(3.743)	(3.734)
Rep CB	−7.711**	2.345
	(3.664)	(3.487)
Rep non CB	−7.820**	−4.743
	(3.593)	(3.601)
Democrat	−22.476***	−18.664***
	(3.812)	(3.334)
Lean Democrat	−15.184***	−10.067**
	(4.497)	(5.084)
Lean Republican	11.564***	18.626***
	(4.379)	(5.706)
Republican	24.272***	41.889***
	(4.530)	(4.728)
Dem CB X Democrat	2.814	6.898
	(5.444)	(4.801)
Dem non CB X Democrat	4.393	1.292
	(5.335)	(4.904)
Rep CB X Democrat	3.500	−0.124
	(5.332)	(4.693)
Rep non CB X Democrat	9.971*	8.403*
	(5.356)	(4.745)
Dem CB X Lean Democrat	0.439	3.016
	(6.923)	(7.295)
Dem non CB X Lean Democrat	0.502	−4.913
	(6.423)	(7.235)
Rep CB X Lean Democrat	7.784	−6.994
	(6.249)	(7.016)
Rep non CB X Lean Democrat	4.766	2.290
	(6.684)	(7.465)
Dem CB X Lean Republican	1.579	16.232*
	(6.345)	(9.291)
Dem non CB X Lean Republican	13.020**	9.794
	(6.346)	(7.964)
Rep CB X Lean Republican	12.840**	−2.184
	(6.045)	(7.785)
Rep non CB X Lean Republican	11.056*	7.024
	(6.210)	(7.973)
Dem CB X Republican	9.881	−2.072
	(6.346)	(6.530)
Dem non CB X Republican	12.913**	−2.817
	(6.232)	(6.940)
Rep CB X Republican	15.002**	−9.679
	(6.082)	(6.566)
Rep non CB X Republican	13.425**	−2.510
	(6.145)	(6.563)
Constant	46.693***	39.474***
	(2.690)	(2.578)
Observations	1,608	1,303
R^2	0.377	0.404

precisely the people who should be most likely to consume and be affected by emotional clickbait.

As a result, we cannot be sure that the treatment effects estimated on the sample of Facebook users who completed the survey generalize to *any* relevant population: to the population of "people who click on Facebook ads" from which the entire sample was drawn, or to the population of Facebook users (Coppock, 2018).

5 Conclusion

Clickbait news media is here to stay. Although Facebook and other online platforms try to combat deceptive or regret-causing headlines to improve the experience of their users, the fundamental economic dynamic of the social media feed is that it incentivizes media companies to compete on the level of individual stories. Crafting attention-grabbing headlines is essential: with a near-infinite amount of news content available, media companies need to make readers choose their stories. With the proliferation of online media outlets enabled by the reduced cost of producing news content, one strategy has been to create headlines that appeal directly to readers' identities via the mechanism of emotional arousal.

In the context of politics, these identities tend to be partisan. "Partisan emotional clickbait" headlines include explicit cues about how partisans should feel in response to a given piece of news. This phenomenon has become more relevant with the increasing alignment of partisan identities with other social identities; partisans tend to experience political news in terms of it being good or bad for their party, and partisan media reinforces this tendency (Mason, 2018).

We hypothesized that random assignment to read an emotional clickbait headline would provide evidence that this media trend might be able to explain some of the worrying trends among American partisans. The concerns about sample attrition discussed above notwithstanding, the experimental results presented in this paper failed to provide evidence for the hypotheses that emotional clickbait has direct effects on affective polarization, information retention or trust in media. We have complete data from 1,608 Mechanical Turk respondents (half of whom participated in a shortened version of the survey out of concern for dampened treatment effects) and 1,303 Facebook respondents. Using our pre-registered code to analyze this data, we find null results. Even a post hoc analysis of the data which confirms the replication of the well-known effects of partisan cues fails to find evidence of the effect of clickbait headlines.

The experimental manipulation we implemented was relatively small—we only changed the headlines of the news story, keeping the text of the story constant—which should bias against finding treatment effects of clickbait. It is also possible that a larger (and in some ways more realistic) experimental setup that varied the body of the story to mirror the tenor of the headline might find a larger effect.

Our non-experimental analysis, however, allows for another pathway by which clickbait could affect American politics: by differentially changing the media diets of different types of social media users. We find evidence of heterogeneously distributed preference for clickbait; in both of our samples, older respondents scored higher on this dimension while Democrats scored lower. We also found some variables that were significantly associated with PfCB in one sample but not the other.

We argue that the Facebook sample is more relevant because it is drawn from the population of interest: people opted into the sample because they clicked on our recruitment ad on Facebook. Among this sample, there are two particularly strong relationships: more frequent Facebook users have a higher PfCB, while more educated respondents have a lower PfCB.

The upshot of these descriptive findings is that we need to realize that the impact of social media use on behavior and attitudes is *heterogeneous*.

The heterogeneity of the effects of different media technologies is well established in political science. The clearest example comes from Prior (2007), who conceptualizes two populations of television consumers: those with a high preference for entertainment (PfE), who will always chose to watch non-news programs, and those with low PfE. In the broadcast era, these groups were indistinguishable because of the lack of choice among the three broadcast providers. Broadcast television thus had a relatively *homogeneous* effect on viewers' political attitudes and information levels. With the advent of cable television, however, people with high PfE avoided news programs. The effect of cable television viewing was thus *heterogeneous* in the viewer's PfE; cable television led to a more polarized electorate as moderates became less politically engaged.

Changing the number of images simultaneously possible to view from 3 to 50 (broadcast to cable television) increased the heterogeneity of the effects of television. The internet and social media have made that number of possible images essentially infinite; you can never step in the same News Feed twice.

Heterogeneity should thus be central to any study of media or persuasive effects on social media. Average treatment effects on a representative population might be deceptively low, disguising effects in politically relevant sub-populations.[14] Future research will be wise to address this point more explicitly, both in terms of theory and empirical research design.

[14] There is growing evidence for this view in the context of political engagement. Using web-tracking data, Guess, Nyhan, and Reifler (2017) conclude that the average number of times US internet users viewed Fake News during the 2016 election was quite low. This average masks the fact that "almost six in ten visits to Fake News websites came from the 10% of Americans with the most conservative information diets." It should be noted that this observational "preference for Fake News" finding closely mirrors our results about the preference for clickbait.

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A Fully Interacted Models

Table 5: Preference for Clickbait: Fully Interacted Models

	Dependent variable:	
	PfCB	PfR
Facebook sample	0.057	−0.002
	(0.077)	(0.087)
Facebook use	0.003	0.004
	(0.003)	(0.003)
Twitter use	0.003	−0.001
	(0.002)	(0.003)
Internet use	0.009	0.002
	(0.007)	(0.008)
Age	0.001**	0.001
	(0.0004)	(0.0005)
Education	−0.005	−0.001
	(0.006)	(0.007)
Offline news consumption	0.009***	−0.0001
	(0.003)	(0.004)
Online news consumption	0.006	−0.002
	(0.004)	(0.005)
Democrat	−0.052***	−0.129***
	(0.014)	(0.016)
Lean Democrat	−0.032*	−0.082***
	(0.017)	(0.019)
Lean Republican	0.067***	0.112***
	(0.016)	(0.018)
Republican	0.036**	0.135***
	(0.016)	(0.018)
Facebook use X Facebook sample	0.012*	0.002
	(0.007)	(0.008)
Twitter use X Facebook sample	−0.001	0.0001
	(0.003)	(0.004)
Internet use X Facebook sample	−0.017*	0.007
	(0.009)	(0.011)
Age X Facebook sample	0.0003	−0.001
	(0.001)	(0.001)
Education X Facebook sample	−0.009	−0.006
	(0.008)	(0.009)
Offline news X Facebook sample	−0.008*	−0.001
	(0.004)	(0.005)
Online news X Facebook sample	−0.0005	−0.010*
	(0.005)	(0.006)
Democrat X Facebook sample	0.032*	0.033
	(0.018)	(0.021)
Lean Democrat X Facebook sample	−0.0002	−0.007
	(0.024)	(0.027)
Lean Republican X Facebook sample	−0.055**	−0.009
	(0.025)	(0.029)
Republican X Facebook sample	−0.015	0.030
	(0.023)	(0.026)
Constant	0.308***	0.450***
	(0.056)	(0.064)
Observations	4,145	4,145
R^2	0.037	0.149
Adjusted R^2	0.032	0.145
Note:	*p<0.1; **p<0.05; ***p<0.01	