Is there within-outlet demand for media slant? Evidence from US presidential campaign news*

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Abstract

Variation in political slant across media outlets, and demand for such slant, has been studied extensively. We conduct a novel within-outlet (and within-topic) analysis to enhance understanding of the demand for "congenially" slanted news. We study so-called horse race news from six major online outlets for the 2012 and 2016 US presidential campaigns. We find very limited evidence of greater demand for more congenial stories, and somewhat stronger evidence of greater demand for more *uncongenial* stories. However, we also find that, as expected, news is slanted congenially across outlets, counter-acting (and perhaps causing) any within-outlet preference for uncongenial slant. We discuss how our results are consistent with the three major mechanisms driving demand for slant studied in the theoretical literature, and help explain when each mechanism is more likely to come into play.

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1 Introduction

Over the last decade, the economics literature has made substantial contributions to the debate about the causes and consequences of political media slant. See Gentkzow et al. (2015) and Puglisi and Snyder Jr (2015a) for recent reviews. This literature focuses on studying political slant *across* news outlets, or effects of such slant, and it is well established that media consumers tend to prefer ideologically aligned news sources.[1] But the investigation of *within*-outlet demand for slant has been largely neglected so far. It is unclear whether, for a given trusted outlet, readers prefer more politically "congenial" news—news supporting one's preferred policies or party—or if consumers are indifferent to the slant of individual stories from such an outlet.

In this paper, we contribute to filling this gap in the literature. We present results from a within-outlet-topic analysis of the relationship between news slant and demand. Since both slant and consumer demand are correlated with news topics, it is crucial that our analysis also holds the news topic fixed. We do this by identifying a news issue reported on repeatedly by major outlets across the political spectrum: "horse race" news (news on competing candidates' chances of winning an upcoming election). We study horse race news for the 2012 and 2016 US presidential elections, constructing an original data set by scraping six news websites for each year. The sites are: the New York Times (NYT), Fox News, Wall Street Journal (WSJ), and Yahoo News in both 2012 and 2016; Google News and the Washington Post (WashPost) in 2016; and USA Today (USAT) and the Huffington Post (HuffPost) in 2012. For each year, we have two sites typically perceived as left-of-center (NYT, WashPost, HuffPost), two perceived as right-of-center (Fox News, WSJ), and two perceived as relatively neutral.[2] Our

[1] Studies of variation in slant across outlets include Chiang and Knight (2011), Puglisi and Snyder Jr (2015b), and Casas et al. (2016), who use explicit ideological standpoints to measure slant across newspapers, whereas Gentzkow and Shapiro (2010), Greenstein and Zhu (2012), and Garz et al. (2019) measure the slant of media outlets by comparing their language with that of ideological reference texts. A related approach uses citation counts of political think tanks (Groseclose and Milyo, 2005) and core topics (Larcinese et al., 2011; Qin et al., 2018) to capture outlet-level differences in slant. For evidence of alignment of slant between outlets and readers, see, e.g., Gentzkow and Shapiro (2010), Gentzkow and Shapiro (2011), and Flaxman et al. (2016).

[2] See, for example, https://www.allsides.com/media-bias/media-bias-chart for a reference

within-outlet-topic design holds fixed two key components of the information value of news. Consequently, if readers still prefer more congenial news, this behavior would most plausibly be driven by factors other than demand for accurate information, i.e., psychological factors, such as the desire to avoid cognitive dissonance and attain belief-based utility.

While we do not have micro-level click data for our main analysis, we use an innovative measure of demand: the websites' publicly reported lists of most popular articles. In addition to public availability, another advantage of the "most viewed" list data over most micro data is that the most viewed lists capture demand for the entire market, and not just a sample of users observed. To facilitate interpretation, we assume that the popularity, or lack thereof, of an article comes from an outlet's typical reader (i.e., popularity reflects news demand for the majority of readers ideologically aligned with the outlet). This assumption is grounded in the literature on selective exposure noted above. Moreover, it seems unlikely that the relationship between slant and aggregate most viewed status would be driven disproportionately by the minority of readers who are ideologically misaligned with outlets. Still, we discuss this assumption further as we proceed, and investigate it further with a complementary micro-level analysis, using data from incentivized surveys based on real-time news for a closely related, but distinct, topic, the presidential debates.

We discuss our web data in Section 2. Since articles attain most viewed status based on clicks, which are primarily based on headlines, we code the partisan congeniality of headlines, not the entire article content. Headlines are short, so we find it is most effective to use content analysis (human coding) rather than computational analysis to code them. We used a team of highly incentivized and closely supervised master MTurkers for this content analysis.

Prior to conducting the within-outlet-topic analysis, we examine general patterns in slant of the outlets' reporting. Note that we use the term slant throughout the paper to refer to favorability of the news to one party or the other, and not (necessarily) distortion from truth. We confirm that slant of all six outlets varies over time within each year, and each outlet's

to the outlets having these reputations. We are able to use four websites (including at least one from each reputational category) for both years: the NYT, Fox, WSJ, and Yahoo. We substitute USAT for Google, and HuffPost for WashPost, in 2012 due to data limitations, as we discuss in Section 2.

slant was correlated with poll averages in each year. However, in Section 3.1, we show there were also systematic differences in reporting across outlets, which largely corresponded to their ideological reputations. The HuffPost's headlines in 2012, and the NYT's headlines in 2016, were each slanted to the left of the "neutral" outlets, and Fox's headlines were slanted to the right of those outlets in both years by a substantial magnitude. We did not find significant evidence that these outlets were likely to slant news on the extensive margin (to report a story, or more stories, on the horse race depending on the current state of polls). However, perhaps surprisingly, the WSJ did appear more likely to report horse race stories when polls were more favorable to Democrats (i.e., uncongenial to Republican readers).

In Section 3.2 we present the within-outlet-topic analysis. We use simple linear probability models in which we regress a dummy variable for making an outlet's most popular list on slant-outlet interactions, with outlet and day fixed effects to account for general variation in article popularity driven by these factors. We find non-robust and only marginally significant evidence that more congenial stories were more popular for just one outlet, in one year (Fox in 2012). Point estimates for the NYT and HuffPost that year are near zero, with reasonably high precision. For 2016, we find somewhat more significant and robust evidence of non-null effects—that more *uncongenial* news was more likely to be popular—for both the NYT and Fox. Thus, the basic answer to our primary research question is that no, more congenial articles are not typically more popular (within-outlet-topic), and sometimes the opposite may be the case.[3]

In Section 4, we discuss interpretation of the various results in conjunction with one another with respect to the broader question of what drives demand for slant. Do media consumers prefer news from ideologically aligned outlets, which tends to be congenially slanted, because

[3]The survey results, presented in the appendix, also largely fail to yield significant preferences for congenial news from ideologically aligned outlets. The point estimates of preferences for congeniality from the NYT from Democrats and Clinton voters are near zero, and insignificant for Republicans for Fox, but we do obtain marginally (10%) significant results for a preference for congenial news from Fox for Trump supporters. This asymmetry in results across parties is directionally consistent with a similar asymmetry in the results for the most viewed list data, as Fox was the only outlet with any evidence of within-outlet preference for congeniality.

it is enjoyable to read or watch (for short, the "psychology" mechanism), or because they perceive it to be truly more informative? Moreover, within the information category, there are two major distinct mechanisms: instrumental value for decisions and trust (Gentkzow et al., 2015).

The systematic differences in slant across outlets could be due to the psychology mechanism. However, we cannot rule out that these systematic preferences are driven by the desire for information, either in addition to, or instead of, psychological factors. While it seems implausible that news reported with systematically congenial slant would provide greater instrumental value for decisions, it could be more trusted, as consumers may have perceived congenially slanted horse race stories as more informative (if consumers had priors biased toward their preferred candidate being more likely to win). However, the incentive for outlets to pander to these priors would decline as the election approaches, and we find it was not the case that actual slant declined in this way.

Consequently, we interpret the average outlet-level congenial slants to be likely driven at least partly, and perhaps largely, by the outlets pandering to the psychological desire for "good news". We interpret the lack of within-outlet demand for additional congeniality to be likely due to satiation of the psychology mechanism and/or perceptions that less congenial stories (within-outlet) were more credible and informative. We discuss why it is implausible that heterogeneity of reader behavior is the primary driver of these results. Moreover, we discuss how the extensive margin (WSJ) results perhaps best support the instrumental information theory of demand slant, and several subtle contextual factors that could influence the relevance of each mechanism. Our results hence provide support for each of the three major mechanisms, and argue against an either/or approach to understanding drivers of slant.

Before proceeding to the remainder of the paper, we briefly review other related literature. The demand for ideologically aligned news sources is often referred to as partisan selective exposure, especially outside of economics. See Hart et al. (2009) and Stroud (2011) for reviews of this research in psychology and communication studies, respectively, most of which relies on experimental settings.

See Golman et al. (2017) for a review of economics literature on the demand for congenial information outside of political media. For instance, Karlsson et al. (2009) find that investors exhibit the "ostrich effect," checking their portfolios more often when markets are rising rather than falling, consistent with what we call the psychology mechanism. Masatlioglu et al. (2017) investigate subjects' behavior in lotteries and show that the desire to manage anticipatory emotions dominates the preference for instrumental information in many situations. In contrast to most of the existing literature, our study offers an investigation of partisan selective exposure to news based on real-world data.

Two recent papers present experiments that study demand for belief-confirming information. Both of these papers fully abstract from psychological factors. Charness et al. (2018) study how variation in the nature of bias, which drives the optimality of seeking information sources biased either towards or against one's priors, affects choice of information source in a lab experiment. They find that subjects tend to excessively choose belief-confirming sources, despite the absence of any psychological motive. Montanari and Nunnari (2019) study a trade-off between alignment of a source's bias and source reliability using an online (Prolific) experiment. They find, perhaps surprisingly, excessive willingness to choose more reliable sources even when misaligned with the subject's prior and, perhaps less surprisingly, excessive responsiveness to confirmatory advice from sources aligned with the subject's prior.

A few studies explicitly investigate mechanisms underlying news demand, rather than demand for information in general. Using artificial news articles on controversial political topics, Metzger et al. (2015) find some support for the role of psychological utility, but stronger support for the importance of trust in driving news choices. Simonov and Rao (2018) show that exposure to pro-government news in Russia is shaped by the persistent preferences of consumers for certain outlets. Thaler (2019) conducts an MTurk experiment to cleanly distinguish motivated reasoning from Bayesian inference with heterogeneous priors as explanations for beliefs (or lack thereof) about "fake news", and finds evidence supporting motivated reasoning. We contribute to these studies in several ways, in particular, by evaluating demand mechanisms in the context of US presidential horse races, rather than politically-relevant information in a broad sense.

An especially closely related paper is Chopra et al. (2019). They conduct a survey experiment of demand for NYT news on effects of Trump's healthcare plan with a large sample size. They find that respondents prefer suppressed information, consistent with belief-based utility (what we refer to as the psychology mechanism). Our papers complement each other in that we examine different news issues, outlets, and use different methods; our paper also concludes that psychology is important, and discusses evidence of other mechanisms.

Finally, our research relates to previous studies of bias in horse race reporting. Searles et al. (2016) and Tremayne (2015) compare poll coverage with underlying poll results during the 2008 and 2012 US presidential campaigns, respectively. We confirm the result obtained by both studies that the coverage is slanted in favor of news outlets' average readers. However, in addition to using data from different outlets and a more recent year, our study is novel in that we combine data on slant with information on the popularity of stories among readers.

2 Data

For the 2016 presidential election, we started scraping news articles on July 27, 2016, well after the presumptive nominee for each party had been decided. The websites of Fox, WSJ, NYT, WashPost, Google, and Yahoo were scraped three times daily until the day of the election, November 8. We downloaded outlets' landing pages, politics sections, and most viewed lists. We chose these six outlets because of their prominence, ideological diversity, and because each of them publicly reports "top," "trending," "most popular," or "most viewed" stories; we use "most viewed" as shorthand to refer to all of these categories. The selection of Google's "top stories" is based on an algorithm, whereas the other five websites each use terms that explicitly or implicitly refer to stories being most frequently clicked on within a recent period of time.[4] Given the inclusion of Fox News, it would be natural to include the two other major cable news outlets, CNN and MSNBC. However, neither of these outlets report most viewed stories.

News data for the 2012 presidential election were collected by scraping snapshots of the outlets' websites stored by web.archive.org, also dating between July 27 and election day of

[4]Both Yahoo and Google aggregate news from other sources, occasionally including those in our sample, but these comprise a small fraction of Yahoo and Google's stories in total.

that year.[5] We were forced to make substitutions for Google and WashPost due to their snapshot data being unavailable and replaced them with USAT and the HuffPost, respectively. Since web.archive.org respects `robots.txt` advisory files, it did not collect data from Google and WashPost, and partly for Yahoo, which mandate `no follow`. We scraped the text for USAT and the HuffPost for 2016 as well but exclude them from the analysis to maintain consistency across years (i.e., to maintain an estimation sample with two outlets considered left-of-center, two considered right-of-center, and two relatively neutral). Moreover, USAT stopped reporting most viewed articles relatively early in the 2016 campaign. Scraping historical Google and WashPost data using the websites' sitemaps is not technically feasible, to our knowledge. Snapshots are available, but much more sparse, for 2008 and earlier election years, and so we do not collect snapshots for any years prior to 2012.

Both the archive and the live data include article date, time, URL, source, headline, text, author, and keywords, and, where applicable, the current rank in the most viewed list. Next, we identified a set of articles that were likely to be horse race stories. (Ultimately, whether or not a story is about the horse race will be determined by human coding, as we discuss below.) We used a fairly broad set of keywords to make the initial set inclusive and then narrowed this set down with human coding and additional restrictions. The initial set included any article with one of the following keyword combinations: At least one of the terms from the set {Obama (Clinton in 2016), Romney (Trump in 2016), president, white house, electoral} in the headline or URL and at least one term from {win, winning, momentum, lead (and not "leader"), bounce, bump, tied, gallup} in the headline. Through manual checks of random subsamples, these keywords were determined to lead to a very small fraction of false negative classifications (actual horse race stories that were not classified as horse race stories) at the expense of having a high number of false positives. We erred in this direction because the cost of cutting false positives with additional steps was relatively low, as compared to the cost of false negatives, lower sample size. We then dropped articles that included a clear indicator of

[5] We cannot scrape directly from the websites since, even if horse race stories from earlier years are still available on those sites, the sites do not provide access to the actual homepages presented to readers and most viewed lists from prior dates.

being an opinion piece in the headline, due to our focus on hard news stories. We used the following headline keywords, determined by inspection, to identify articles as opinion pieces: {opinion, schoen, goodwin, rove, strassel, power play, juan williams, bias alert, gainor, reich, douthat, dan rather, whalen, starnes}. This should reduce the prevalence of within-outlet variation in an article's credibility and information content. For example, some readers might perceive certain opinion writers to be particularly credible. With the exceptions of opinion pieces, readers do not see the author (if any) before clicking on the headline, in most cases.

Because headlines are short, the degree to which they favored one party or the other is relatively easy to manually code, and difficult to do so computationally, as we discuss further below. We therefore used manual content analysis for the coding of headline congeniality. We assigned three "master" MTurk workers, having them each rate every headline on a five point scale—"very good news" or "good news" for either the Democratic or Republican candidate's chances of winning, or "neutral"— with two additional options, "ambiguous or unclear" or "not relevant [to the candidates' chances of winning the election]". The exact instructions provided to MTurkers are in Table A1 in the Online Appendix. We did not allow the Mturkers to see the names of the outlets, so that ratings are based on headline content and comparable across outlets.[6] These workers each passed initial screens of the quality of their work. To incentivize continued effort, while avoiding excessive monitoring and potential demand effects, we kept instructions intentionally vague. We did not specify additional payment for particular results, but simply offered the incentive of generously paid additional work (coders were paid $3 for each batch of 40 headlines) if the work was done "carefully and reasonably." We monitored the coding done by these MTurkers by choosing four headlines with relatively unambiguous favorability to one party or the other, and spot-checked each worker's ratings for these headlines, for each batch of 40 headlines. These spot-checked ratings were consistent with our expectations in all but one batch (out of dozens of batches across the three coders); we manually checked the other headlines in that batch, and they seemed reasonable, so we continued to invite the worker to do additional work. We used the same three coders for the

[6]Some headlines did refer to Fox News polls; results are largely similar when these are dropped.

vast majority of the coding for consistency and because accuracy may have improved with experience.

There were 2,025 headlines coded in total.[7] Krippendorff's α, a standard measure of inter-coder reliability, for all the coded headlines is 0.313. Condensing to an ordinal three-point scale—good news for the Democrats, good news for the Republicans, or neutral or ambiguous—increases α to 0.816, exceeding the standard threshold of 0.80.[8] Of the 1,177 headlines that were not rated as irrelevant by any of the coders, the α for the five-point scale is 0.405, and for the three-point scale, it is 0.859. Of the 871 headlines that were not rated as irrelevant or ambiguous by any of the coders, the α for the five-point scale is 0.440, and for the three-point scale, it is 0.900. Thus, the three-point scale appears much more valid than the five-point scale, which is perhaps unsurprising (it is easier to code whether a headline simply favors one side or the other than the strength of favoritism toward that side). Consequently, we only use the three-point scale going forward, with very good or good news for Democrats coded as -1, very good or good news for Republicans coded as 1, and neutral and ambiguous news coded as 0. Restricting the sample to headlines that all three raters agreed were relevant and unambiguous increases the validity, but results in a substantial loss of observations. Thus, for transparency and to examine robustness, we consider three variations of the measure for all of our analyses: $Slant_1$ = mean slant of headlines rated as irrelevant or ambiguous by at most one coder; $Slant_2$ = mean slant of headlines not rated as irrelevant by any coder; $Slant_3$ = mean slant of headlines not rated as irrelevant or ambiguous by any coder. Headlines used for $Slant_3$ are a strict subset of those used for $Slant_1$. Most, but not all, $Slant_2$ headlines are also $Slant_1$ headlines. As noted in the introduction, $Slant_i$ simply measures favorability of a headline to one party or the other and not necessarily distortion or any type of misreporting.

[7] We study slant of just headlines and not article content throughout. We do this to be consistent across analyses and because headlines are likely the main driver of variation in demand (clicks) within outlets, see, e.g., Powell et al. (2019). Furthermore, headline and article congeniality are generally well aligned as shown by, e.g., Tremayne (2015), which we confirm in spot checks. A typical horse race headline will summarize new poll results, while the article discusses details of the results for different demographic groups.

[8] For the three-point scale, we used the ordinal method to calculate the Krippendorff α and thus coded "not relevant" as missing values. For the five-point scale, Krippendorff α values were very similar whether we used ordinal or nominal methods.

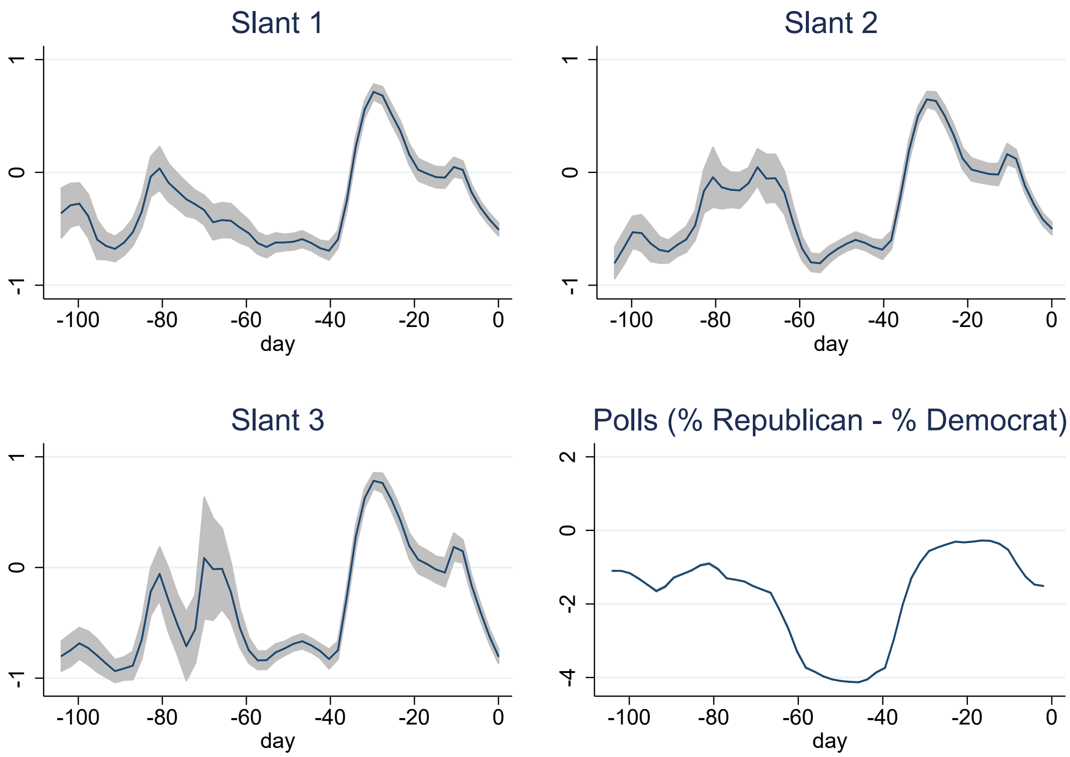
Figures 1 and 2 present smoothed plots of daily means of each slant measure versus daily poll averages (percent planning to vote Republican minus percent planning to vote Democrat; obtained from R's "pollstR" library) in 2012 and 2016, respectively.[9] The plots are quite similar to one another, and to the polling average, supporting the validity of all three slant measures. However, a number of results presented in Section 3 are significant for one measure of slant but not for others, and so it could be misleading to restrict the analysis to just one of these measures. To provide direct examples of the coding, Table A2 shows the three slant ratings for all headlines that contained the appropriate keywords for the day before the 2016 election (November 7, 2016). Most of the ratings seem very reasonable; sometimes $Slant_2$ and/or $Slant_3$ seem to appropriately drop a non-horse race headline (e.g., "Trump urges voters to deliver justice at polls"); sometimes these more restrictive versions seem to mistakenly drop a horse race headline (e.g., "polls Trump and Clinton virtually tied in key swing states"). Thus, the table also supports the use of the various $Slant$ measures in the analysis.

We also experimented with several formulaic text-based measures of slant, and found that coding headlines as favoring a candidate if they contain the candidate's last name and "win" (which could be part of winning or winner) and "lead" (which could be part of leading) and do *not* contain the opponent's name, or "[candidate's name] lead" (e.g., "Trump leads" or "Trump leading") yielded the largest correlations with our manually coded slant measures (average correlation of 0.33 with $Slant_i$). However, the correlation with the daily poll average was negligible (0.01), and correlations were similarly very small for other text-based measures. The correlation of each of the manually coded $Slant_i$'s with the polls is approximately 0.42, which supports the superiority of the human-coding approach (as expected, given the small amount of text in each headline) and the use of these measures in the analyses.

Appendix Figures A1 and A2 present smoothed $Slant_1$ plots broken out by outlet and most viewed/other articles. Patterns of slant over time are generally similar across outlets, and in unreported results we find that the slant of each outlet's articles is significantly correlated

[9]Figures A1 and A2 in the appendix show equivalent plots of $Slant_1$ for the individual outlets and news categories.

Figure 1: Mean $Slant_i$ and poll average versus day relative to election day (day 0) in 2012.

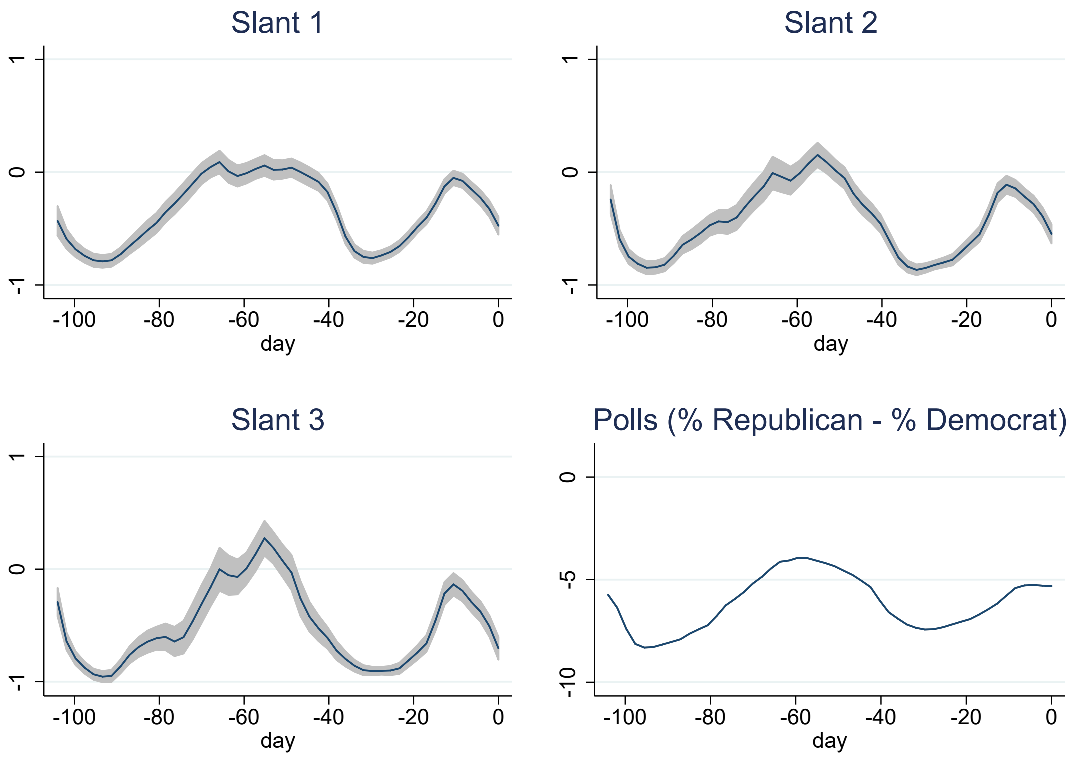


Note: Curves are kernel-weighted smoothed local polynomials with 95% confidence interval bands. Positive values of *Slant* denote better chances of winning for the Republican candidate, whereas negative values indicate better chances for the Democratic candidate.

with poll results (whether studied separately by outlet or pooling articles for all outlets). These results suggest that for each outlet, horse race stories are fundamentally driven by what is truly occurring in the campaign at the time. Table 1 implies a somewhat different story. This table reports the number of unique most viewed and other articles per outlet, and their means for various slant measures.[10] The average slants vary across outlets substantially,

[10]The number of headlines reported in this table is less than the corresponding number referred to in the Krippendorff α analysis (2,025) because the sample used in this table, and for most of the subsequent analysis, differs for two reasons. First, even the broadest slant definition that we use for the main analysis, $Slant_1$, is restricted to headlines coded as irrelevant or ambiguous by at most one coder, and therefore excludes many of the original 2,025 headlines. Second, the story-level data set collapses headlines with slight variants in wording to a unique observation, whereas the MTurkers coded multiple variants of headlines, with wording that slightly differed, for some stories (such as "FOX NEWS POLL Clinton leads Trump by 10 points both seen as flawed presidential candidates" and "Fox News Poll Clinton Leads Trump by 10 Pts Yet Both Flawed Say Voters"). Including these variants in the α calculations should not bias results since the coders are as likely to disagree on variants

Figure 2: Mean $Slant_i$ and poll average versus day relative to election day (day 0) in 2016.



Note: Curves are kernel-weighted smoothed local polynomials with 95% confidence interval bands. Positive values of *Slant* denote better chances of winning for the Republican candidate, whereas negative values indicate better chances for the Democratic candidate.

largely consistently with the outlets' reputations. Panel A of the table, on the 2012 data, also suggests that the most viewed stories were slanted to the left of other stories for all outlets except for Fox. Panel B (on the 2016 data) suggests that both Fox's and the NYT's most viewed stories were more neutral than the outlet's other stories. We analyze these differences more formally in the next section.

3 Analysis

3.1 Slant across outlets

As noted above, the study of slant across outlets has been a focus of prior literature. We also address the question if and how mean slant of headlines varied across outlets and years to facilitate the interpretation of our within-outlet analysis. Across-outlet slant is also worth

of headlines for a given story as they are on a single version of a headline.

studying unto itself, given that our context and data are distinct from prior literature.

There are two basic ways across-outlet slant could occur: on the intensive margin (how does mean horse race slant vary by outlet, given the "true" horse race news?) and on the extensive margin (how many horse race stories were published, given the "true" horse race news of the day?). To address the former, we use a story-level data set to estimate a separate regression for each definition of $Slant_i$ ($i \in 1, 2, 3$) of the following form:

$$Slant_{ijkt} = \alpha + Outlet_j + Day_t + \epsilon_{ijkt}. \quad (1)$$

$Slant_i$ of each story k published by outlet j on day t is regressed on outlet and day fixed effects, yielding the estimates of the $Outlet_j$'s and Day_t's. The day fixed effects account for mean slant across outlets on the first day that the story was reported driven by new poll results or other factors. We do not include daily polls and poll changes as covariates, as they are fully collinear with the day fixed effects. Results are similar, with somewhat smaller standard errors and lower R^2 values, when we replace the day fixed effects with a date polynomial to preserve degrees of freedom.

We use Yahoo as the reference category in 2012, and Google in 2016, given these outlets' relative neutrality and the large number of horse race stories in their respective years. The $Outlet_j$ estimates thus represent the mean difference in slant for outlet j as compared to Yahoo in 2012, and Google in 2016, conditional on mean slant of stories reported on that day across outlets. Results are very similar with various alternative controls, such as a dummy for whether or not the story made the most popular list, or interactions of this dummy with day fixed effects. We cluster standard errors by day.

Table 2 presents results. In both years, there is robust evidence that Fox's stories were slanted to the right of the other outlets. The leftmost stories on average in 2012 were from the HuffPost, and NYT's stories were left of Yahoo's (at 5% significance) in one model. The point estimates for each non-Yahoo fixed effect are all largest for the $Slant_3$ models, implying that Yahoo's slant shifted left for this measure, which is also true for Yahoo in 2016. This could mean that Yahoo used relatively ambiguous wording for headlines more favorable to

Republicans. In 2016, the NYT was significantly to the left of Google at the 1% level for two specifications, and the WashPost and WSJ were both left of Google at 5% for two specifications. The magnitudes are on average largest for the WSJ and next largest for the NYT. The magnitudes of the significant effects are typically large, often close to 0.5 on a scale from -1 to 1.

To estimate slant on the extensive margin, we construct outlet-level daily time series data sets. We cannot use story-level observations here as we need to account for days in which horse race stories were not reported. We run separate regressions for each outlet of the following form:

$$\#HR\,Stories_{jt} = \alpha + \beta Slant_t^{true} + f(\#HR\,Stories_{-j,t}) + \epsilon_{jt}. \tag{2}$$

The left-hand-side variable is the number of horse race stories reported by outlet j on day t. $Slant_t^{true}$ is a measure of "true" slant on day t, equal to either: 1) the average slant of stories reported by other outlets that day or 2) the pollstR average difference in polls that day. Results are largely similar when we also include recent poll changes in the second specification, but cleaner to report when these are omitted. The term $f(\#HR\,Stories_{-j,t})$ is a control for the importance of horse race news on day t, a flexible polynomial of the total number of horse race stories reported by other outlets that day.[11] For models using other outlets' slant as the measure of $Slant_t^{true}$, we also include a 4th order date polynomial, to further control for general trends in horse race news interest. We do not include this polynomial when we use the pollstR measure of $Slant_t^{true}$ because these variables are highly collinear. We use Poisson regressions because the left-hand side is a count variable, with bootstrap standard errors; results are similar when we use OLS with Newey-West standard errors.

Results are presented in Table 3. For the Fox 2012 sample, only one estimate is significant, and at just 10%, but all of the estimates have signs consistent with congeniality slant (i.e., a greater number of stories on days with more favorable news from a Republican perspective).

[11] The degree of the polynomial is arbitrary and results are similar for other flexible polynomials. We cannot use day fixed effects in these models because there is only one observation per day.

There are also two significant estimates consistent with congeniality for the NYT in 2016 (i.e., a greater number of stories when the news is more favorable to Democrats). The strongest and more robust results, however, are for the WSJ. Half or more of the estimates in both years are significant at least at the 10%-level and indicate that the WSJ reported more horse race stories on days when news was *less* favorable to Republicans. We discuss these findings further in Section 4.

3.2 Within-outlet news demand

In this subsection, we present the analysis addressing our primary research question. We estimate the within-outlet relationship between slant and story popularity with variants of the linear probability model:

$$MostViewed_{jk} = \alpha + Outlet_j + \beta_j Slant_{ijk} + \Sigma_t Day_t^{jk} + \epsilon_{jk}. \tag{3}$$

$MostViewed_{jk}$ is a dummy for whether story k (ever) made its outlet's (j's) most viewed list, which we regress on outlet fixed effects (to account for different mean probabilities of making the most viewed list by outlet) yielding estimates of $Outlet_j$, a different slant term for each outlet j (i.e, an interaction of a dummy for outlet j and $Slant_{ik}$) yielding the estimates of β_j's (one for each outlet), and a fixed effect for *each* day that a story was available online ($Day_t^{jk} = 1$ if story jk was available on day t). These account for unobservables changing horse race news demand over time, such as James Comey's press conference in 2016, and interest in the election increasing as it approaches. We also consider a model with a date polynomial. The β_j's are the coefficients of interest, as each represents the marginal effect of slant on the probability of being most viewed for outlet j. We present results both with and without additional controls for the number of competing horse race headlines at the same time and from the same outlet.

Results are presented in Table 4. There is some evidence of a congeniality effect for Fox in 2012, but this is significant for $Slant_1$ only, and only at 5%. The magnitude of the $Slant_1$ estimates imply that a one unit increase in slant predicts a 17 percentage point increase in being most viewed. There are no other significant results for that year. For 2016, there are several results significant at 10% or 5% for Fox and NYT, but each indicates that *less* congenial stories were the ones more likely to be most viewed. The significant effects for Fox are 13–19 percentage points per unit decrease in congenial slant, and for the NYT, 19–31 percentage points. The standard errors for the insignificant estimates for the HuffPost, WashPost, and NYT in 2012 are all less than 0.1 (10 percentage points per unit change in slant), implying reasonably good power.

The 2016 results only become stronger when we replace the day fixed effects with a date polynomial, while the 2012 Fox effects disappear in this case (see Table A3). We also consider a specification in which we split out the measure of slant into congenial and uncongenial effects for each outlet. It is possible that avoiding negative news is more important than seeking positive news, or vice versa. We analyze this specification (results unreported but available on request) and find no systematic patterns.

3.3 Alternative explanations

The most viewed data could be misleading if total website traffic changed depending on the congeniality of horse race news at the time. For example, suppose Republicans were less likely to visit foxnews.com on days when horse news for Republicans was less congenial, and Fox horse race stories were indeed less congenial those days. Even if these stories were more likely to make the most viewed list than a horse race story on a more congenial news day, it is possible these uncongenial stories received fewer total clicks than the more congenial stories. We do not have daily total website click data to directly address this issue, but can use other publicly available data to shed some light on it. Figure A3 presents smoothed polynomials of Google Trends data on Google searches for "fox news" and "new york times" for the election seasons of 2012 and 2016. The curves all generally trend up over time, more sharply in the final two weeks before the election. There is no evidence of the trends differing between the two outlets in a given year, or of any correlation between these trends and the trends presented in earlier figures using poll and $Slant_i$ data. Thus, there is no evidence that Google searches are correlated with the congeniality of horse race news on a given day. Google searches likely only account for a small fraction of total website traffic. Still, if total traffic was substantially correlated with congeniality, we would expect to see some sign of this correlation in the search data as well.

Another issue is the aggregate nature of the web data. While (as noted above) the outlets' reputations are aligned with the ideologies of the majority of the outlets' readers, there is still ideological heterogeneity in the outlets' readerships. Unfortunately, our web data do not allow us to address heterogeneity since the data do not contain information on who is doing the clicking. It is possible that what we refer to as demand for uncongenial news was actually driven by clicks from an outlet's ideological minority. For example, the clicks on NYT stories favorable to Republicans may have mostly come from Republican readers. To address this issue, and complement the web data analysis more generally, we collect additional micro-level data from incentivized surveys on a related topic, presidential debates. We explain the design for this analysis and present results in Appendix A.2. We find that neither Democrat demand for NYT news, nor Republican demand for Fox news, are significantly affected by the congeniality of such news. There is, however, marginally significant evidence that Trump supporter demand for Fox news increases in congeniality of that news (but not for Clinton supporter demand for NYT news). This asymmetry across parties is consistent with the 2012 aggregate results also indicating right-of-center consumers have a greater within-outlet preference for congenial news. There is also significant evidence that Democrat demand increased in the congeniality of Fox news, but we discuss how this result may have been an artifact of the survey design. Republican demand for NYT news was unaffected by the congeniality of that news. Altogether, these results support our priors for NYT web news demand (that it was mostly driven by Democrats), but make the interpretation of Fox web news demand perhaps less clear.

4 Discussion

Before providing further interpretation of our main (most viewed list) results we briefly review relevant theory. As noted in Section 1, there are two main categories of explanations for demand for media slant. The first is that slant provides direct psychological value. News that confirms one's prior beliefs or outcomes that one hopes to occur may be pleasant, and belief-challenging news unpleasant, due to cognitive dissonance, ego and identity support, anticipation utility, and related factors; see, for example, Iyengar and Hahn (2009), and from economics, Mullainathan and Shleifer (2005) and Bernhardt et al. (2008).

The second explanation for demand for slant is that congenially slanted news is perceived as more informative. Gentkzow et al. (2015) distinguish between two mechanisms for this case, which they refer to as "delegation" and "reputation". Delegation is the case of consumers rationally preferring a like-minded news source because it provides optimal instrumental value for decisions (e.g., Burke, 2008; Chan and Suen, 2008; Oliveros and Várdy, 2015; Fang, 2016). For example, in Chan and Suen's model, like-minded news sources provide media consumers with more useful information about whom to vote for. The reputation mechanism occurs when media consumers prefer like-minded sources because those sources are more trusted—perceived as objectively more credible (Gentzkow and Shapiro, 2006), though perhaps mistakenly (Vallone et al., 1985; Stone, 2011; Kelly, 2018).[12] Welfare implications of political slant are generally worst when slant is due to psychology, and best when due to delegation.

Now returning to our main results, to briefly recap: we find very limited evidence of greater demand for more congenial stories within-outlets, and somewhat stronger evidence of greater demand for more uncongenial stories within-outlets.[13] Within-outlet demand for congenial stories would be relatively clean evidence in support of the psychology mechanism, so our results may appear at odds with this mechanism. But of course absence of evidence is not always evidence of absence. For our context, since we also find that horse race news is systematically congenially slanted across outlets, the within-outlet effects must be interpreted

[12] Note that in both this case and the instrumental value case, consumers are information-seeking. But these two mechanisms differ in two key ways: 1) the instrumental value theory implies that consumers agree on the accuracy and slants of the different outlets, while the credibility theory implies disagreement; 2) the instrumental value theory only applies to decision-relevant news, while the credibility theory applies to information with either instrumental or intrinsic value.

[13] In this section, in the interest of brevity, we do not discuss asymmetry across parties in these effects.

accordingly. The systematic outlet-level congenial slant could also be due to outlets pandering to reader psychology, and could even satiate the psychological desire for "good news", which could explain the lack of additional demand for particularly congenial news from such typically congenial outlets. We present a highly stylized model illustrating this point in Appendix A.4.

Could across-outlet congenial slant for horse race news also be explained by an information mechanism? It seems unlikely that this would be delegation. While horse race news could be relevant to some decisions such as campaign activism, horse race news has been criticized for being relatively non-substantive (Zoizner, 2018). It is especially implausible that a general slant favoring a reader's ex ante preferred party would be useful for decisions. However, this slant could be at least perceived as yielding more accurate news, if readers had priors biased toward favoring the chances of their preferred candidates. Thus, congenially slanted news by an outlet could increase or confirm a reader's trust in that outlet. There is evidence that individuals do have such priors and draw inferences like this about quality of news (Stiers and Dassonneville, 2018; Madson and Hillygus, 2019). However, this type of pandering to readers' beliefs should decline as the election approached, as the election outcome provides feedback on the accuracy of prior horse race reporting. In unreported results, we find that this is not the case (congenial slant does not decline as the election approaches), supporting psychology being at least part of the explanation for across-outlet slant.

The questions of why would demand be higher for uncongenial news (and why in 2016 only), and why would an outlet provide systematically uncongenial news (the extensive margin results for the WSJ), remain. Our survey results provide some evidence against this being driven by heterogeneity. Furthermore, for our web results to be consistent with readers preferring congenial stories even within-outlets, the greater popularity in 2016 of pro-Republican stories on the NYT, and of pro-Democrat stories on Fox, would both have to be driven by ideologically misaligned minorities. This would mean that Democrats would have to have a stronger preference for congeniality than Republicans for Fox stories *and* Republicans would have to have a stronger preference for congeniality than Democrats for NYT stories. These differences in preferences would have to be sufficiently large to outweigh the misaligned readers' minority status, which as we have noted is arguably quite unlikely, though possible.

However, both of the information mechanisms, especially reputation, could plausibly explain greater within-outlet demand for uncongenial news. If there was variation in credibility of stories within outlets, and headlines provided a signal of credibility of the article's content, then uncongenial headlines might have signaled high credibility for stories from an outlet that is typically congenial. For example: if readers knew the NYT had typically published stories implying that Clinton's chances of winning the upcoming election are high, and saw an NYT headline implying Clinton's chances are now ambiguous or even low, readers might have inferred that the underlying evidence for the story was particularly compelling. The appendix model provides a related (but distinct) illustration of this idea.

The negative within-outlet slant-demand relationship could arguably even be compatible with instrumental information seeking, if readers drew inferences on candidate quality from horse race news, as negative horse race news about a preferred candidate is more likely to be decision relevant than positive. For instance, it is perhaps possible that Fox readers could have been more likely to click on pro-Clinton headlines because of the value of this information for changing choices related to campaign involvement (donations, activism), or even whom to vote for or whether to turn out to vote (Bursztyn et al., 2017). Both mechanisms could be stronger in 2016 due to stronger average congenial slant in 2016 or changes in other contextual factors such as the nature of the candidates or overall media landscape.

Similarly, the uncongenial outlet-level slant for the WSJ is also plausibly explained by the delegation mechanism. If the WSJ's readers lean Republican and are relatively affluent, then these readers may have been more likely to make campaign contributions to Republican candidates when they were down in the polls. In fact, it is especially plausible that this type of instrumentally valuable is relevant to WSJ readers given their demographics.[14]

We also note (cognitive dissonance-minimizing) psychology, delegation, and reputation are not the only factors driving demand. Another factor worth considering is the distinct psychological factor of surprise (Ely et al., 2015). If consumers are more likely to click on

[14] An alternative explanation for this result is that the WSJ is a distinct type of outlet, attracting right-leaning readers via its business coverage even while the news staff leans left for other reasons (Groseclose and Milyo, 2005).

more surprising news, this could also cause a negative within-outlet relationship between congeniality of slant and demand for typically congenial outlets. We investigate this possibility by constructing a variable intended to directly measure the degree to which the slant of a story was surprising for each outlet given trends and polls. We do this by, first, estimating a separate regression model for each outlet with $Slant_i$ on the left-hand side, explained by average pollstR levels and the previous week's changes in relative Republican support, as well as a third-order date polynomial. We use predicted values from these models to extract the surprise component in slant, by calculating the absolute value of the difference of actual slant of any horse race story reported and the predicted value of slant for that story. We then replace $Slant_i$ with the surprise component in the models of Table 4. This captures surprise in headline slant given the outlet's trend in slant and how the outlet typically reports on recent poll results. Results (available on request) are insignificant, which suggests that surprise does not play a major role in explaining the popularity of uncongenial stories in 2016.

5 Concluding remarks

We conduct a novel analysis of the relationship between within-outlet article popularity and headline slant. We find that this relationship is weak in aggregate horse race news data, and there is even evidence that articles with uncongenial headlines for an outlet's typical reader are relatively popular. However, outlets across the spectrum do provide news that is slanted congenially on average for the outlets' typical readers. We discuss how various aspects of our results provide support for the three major mechanisms for demand for slant studied in the theory literature. A significant caveat to our work is that for our main analysis we only use aggregated data.

Our results also help clarify the connection between two of these mechanisms, trust and psychology. While they are modeled as distinct factors in some theory papers, they are related. Trust can be influenced by psychological factors. Cognitive dissonance and confirmation bias might affect reactions to information observed in the past. These factors may be the primary reasons that perceptions of news source credibility vary so much across the population (Kelly, 2018). A more subtle point that our results on the reasonably robust demand for "bad news" across the spectrum help us to see is that the psychological value of news also likely depends on trust. As in the case of self-signaling models that incorporate credibility (Bénabou and Tirole, 2016), "good news" does not make one feel good unless one thinks this good news is believable. This factor implies possibly natural limits to the degree of psychology-driven news distortion: if distortion becomes too extreme, it destroys credibility, defeating this purpose. This trade-off is likely especially relevant to issues reported on repeatedly, and especially when true outcomes are eventually revealed, both of which are the case for horse race news.

Future work building on our paper could consider more detailed individual click-level web data or social media data. The complexity of our results demonstrates (or reminds us) that both media and reader behavior can vary substantially over time and across outlets. In 2016, Fox may have moved to the right of its readers, and the NYT may have moved further left. The WashPost and NYT have similar ideological reputations, but there are differences in their reporting and reader behavior. The WSJ's reporting appears quite distinct from its reputation, as opposed to that of Fox and the NYT. These nuances in our findings emphasize the importance of considering context in interpretation, and the limitations for extrapolating results. While this is always true in empirical work, this point may be especially relevant to the analysis of media in recent years, due to the fast-changing environment and uniqueness of the various outlets.

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Table 1: Average headline slants and article counts by outlet (samples for each $Slant_i$ defined in text)

Outlet	Type	$Slant_1$	N	$Slant_2$	N	$Slant_3$	N
Panel A: 2012							
Fox	Other	0.27	38	0.33	31	0.38	23
	Most viewed	0.37	25	0.34	27	0.42	22
WSJ	Other	-0.37	6	-0.37	6	-0.28	6
	Most viewed	-0.53	7	-0.52	7	-0.53	7
USAT	Other	0.10	13	0.00	9	0.00	8
	Most viewed	-0.31	19	-0.24	20	-0.29	16
Yahoo	Other	-0.12	76	-0.23	50	-0.31	31
	Most viewed	-0.23	30	-0.21	32	-0.36	22
NYT	Other	-0.17	59	-0.15	58	-0.21	42
	Most viewed	-0.48	21	-0.31	24	-0.48	14
HuffPost	Other	-0.58	119	-0.50	102	-0.59	76
	Most viewed	-0.56	12	-0.37	16	-0.50	10
Panel B: 2016							
Fox	Other	0.35	23	0.50	12	0.67	8
	Most viewed	0.00	47	-0.11	33	-0.16	25
WSJ	Other	-0.65	12	-0.90	7	-1.00	6
	Most viewed	-0.67	11	-0.93	9	-0.93	9
Google	Other	-0.23	270	-0.28	205	-0.33	161
	Most viewed	-0.16	46	-0.36	34	-0.42	26
Yahoo	Other	-0.27	85	-0.42	60	-0.68	39
	Most viewed	-0.50	8	-0.33	6	-0.33	6
NYT	Other	-0.65	33	-0.79	24	-0.90	21
	Most viewed	-0.37	22	-0.35	19	-0.61	11
WashPost	Other	-0.38	96	-0.46	60	-0.61	45
	Most viewed	-0.36	43	-0.40	32	-0.51	24

Table 2: Estimated mean differences in headline slant across outlets

Outlet	$Slant_1$	$Slant_2$	$Slant_3$
Panel A: 2012 (Reference outlet = Yahoo)			
Fox	0.340**	0.471***	0.648***
	(0.130)	(0.125)	(0.176)
WSJ	-0.306*	-0.165	0.059
	(0.176)	(0.170)	(0.227)
USAT	-0.117	0.012	0.037
	(0.182)	(0.175)	(0.245)
NYT	-0.312**	-0.161	-0.142
	(0.121)	(0.131)	(0.206)
HuffPost	-0.499***	-0.335***	-0.236
	(0.108)	(0.114)	(0.178)
Adj R^2	0.412	0.407	0.494
N	425	382	277
Panel B: 2016 (Reference outlet = Google)			
Fox	0.238**	0.308**	0.353*
	(0.116)	(0.149)	(0.191)
WSJ	-0.235	-0.506***	-0.479**
	(0.179)	(0.171)	(0.203)
Yahoo	-0.082	-0.143	-0.360**
	(0.130)	(0.150)	(0.149)
NYT	-0.363***	-0.230*	-0.411***
	(0.097)	(0.120)	(0.120)
WashPost	-0.162**	-0.118	-0.260**
	(0.079)	(0.092)	(0.120)
Adj R^2	0.250	0.332	0.434
N	696	501	381

Note: OLS estimates, using story-level data. Left-hand side variable: $Slant_i$, and coefficients presented in table are outlet fixed effects ($Outlet_j$ from equation (1)). All models include fixed effects for the first date a story was reported. The 2016 models also include dummies for Yahoo stories' first date occurring during one of two time-frames in which Yahoo data collection changed. Standard errors are clustered by the first date the story was available. *, **, *** denote 10%, 5%, 1% significance.

Table 3: Effects of slant and poll means on the daily number of horse race stories

	Fox	WSJ	NYT	HuffPost
Panel A1: RHS = mean slant of other outlets (2012)				
$Slant_1$	0.251	-0.038	0.284	-0.075
	(0.253)	(0.504)	(0.224)	(0.265)
$Slant_2$	0.309	-0.740	0.182	0.014
	(0.258)	(0.665)	(0.221)	(0.210)
$Slant_3$	0.202	-0.624	0.224	-0.335
	(0.267)	(0.647)	(0.207)	(0.207)
Panel A2: RHS = mean Republican poll advantage (2012)				
$Slant_1$	0.077	-0.584**	-0.067	0.051
	(0.089)	(0.292)	(0.091)	(0.089)
$Slant_2$	0.135	-0.437*	-0.027	0.037
	(0.098)	(0.228)	(0.096)	(0.084)
$Slant_3$	0.186*	-0.447**	-0.040	-0.006
	(0.112)	(0.193)	(0.093)	(0.103)
	Fox	**WSJ**	**NYT**	**WashPost**
Panel B1: RHS = mean slant of other outlets (2016)				
$Slant_1$	-0.091	-0.417	-0.367	0.224
	(0.269)	(0.781)	(0.321)	(0.212)
$Slant_2$	-0.198	-1.078*	-0.787***	0.216
	(0.350)	(0.635)	(0.291)	(0.247)
$Slant_3$	-0.146	-1.206	-0.609**	0.233
	(0.315)	(0.773)	(0.273)	(0.278)
Panel B2: RHS = mean Republican poll advantage (2016)				
$Slant_1$	0.204**	-0.335*	-0.155	0.107**
	(0.087)	(0.175)	(0.105)	(0.050)
$Slant_2$	0.134	-0.363	-0.156	0.122*
	(0.085)	(0.229)	(0.118)	(0.069)
$Slant_3$	0.091	-0.341**	-0.128	0.076
	(0.112)	(0.165)	(0.140)	(0.087)

Note: Poisson regressions, using daily outlet-level time series, with bootstrap standard errors. Left-hand side variable: number of horse stories of the outlet listed in the column header. Mean $Slant_i$ of other outlets equals 0 if no horse race stories of type i are available on a given day. All models include the 4th order polynomial of the number of horse race stories reported by all other outlets. Models in Panels A2 and B2 also include a 4th order date polynomial. N=103 and 101 for Panels A1 and A2, and N=105 for Panels B1 and B2. *, **, *** denote 10%, 5%, 1% significance.

Table 4: Probability of story making most viewed list

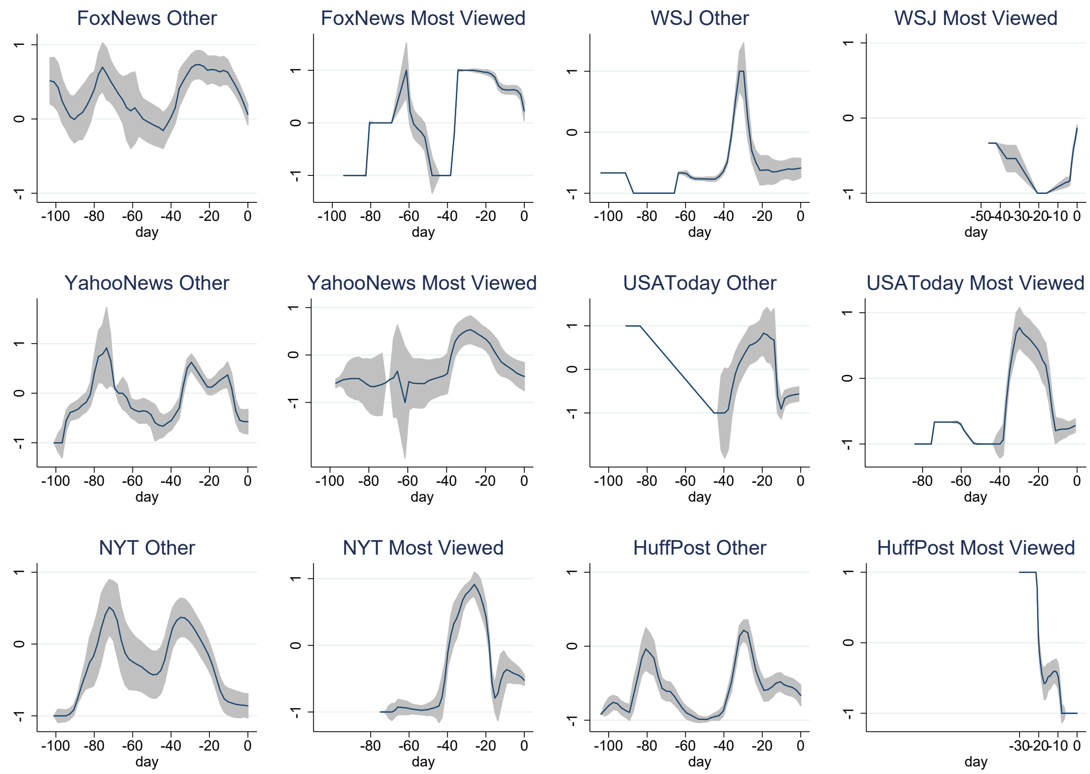
	$Slant_1$	$Slant_2$	$Slant_3$	$Slant_1$	$Slant_2$	$Slant_3$
Panel A: 2012						
Fox $\times Slant$	0.170**	0.096	0.116	0.172**	0.079	0.100
	(0.083)	(0.103)	(0.135)	(0.085)	(0.104)	(0.143)
WSJ $\times Slant$	-0.010	0.024	0.001	-0.042	-0.003	-0.055
	(0.202)	(0.210)	(0.186)	(0.195)	(0.201)	(0.180)
USAT $\times Slant$	-0.106	-0.087	-0.088	-0.110	-0.096	-0.118
	(0.088)	(0.115)	(0.111)	(0.091)	(0.120)	(0.114)
Yahoo $\times Slant$	-0.043	-0.038	-0.027	-0.027	-0.023	-0.027
	(0.043)	(0.053)	(0.064)	(0.040)	(0.047)	(0.056)
NYT $\times Slant$	-0.013	0.024	0.026	0.001	0.037	0.032
	(0.072)	(0.076)	(0.087)	(0.071)	(0.076)	(0.085)
HuffPost $\times Slant$	0.010	0.029	0.021	0.020	0.035	0.009
	(0.048)	(0.054)	(0.068)	(0.052)	(0.058)	(0.077)
Competing headline controls?				✓	✓	✓
Adj. R^2	0.379	0.408	0.353	0.380	0.410	0.340
N	425	382	277	425	382	277
Panel B: 2016						
Fox $\times Slant$	-0.131*	-0.189**	-0.179*	-0.128*	-0.171*	-0.176
	(0.069)	(0.087)	(0.094)	(0.075)	(0.099)	(0.108)
WSJ $\times Slant$	-0.043	-0.187	0.389	-0.029	-0.091	0.463
	(0.244)	(0.523)	(0.293)	(0.247)	(0.546)	(0.285)
Yahoo $\times Slant$	-0.021	-0.009	0.089	-0.034	-0.061	0.022
	(0.087)	(0.116)	(0.141)	(0.093)	(0.137)	(0.209)
Google $\times Slant$	0.016	-0.026	0.009	0.023	-0.018	0.018
	(0.029)	(0.029)	(0.032)	(0.030)	(0.032)	(0.032)
NYT $\times Slant$	0.193*	0.284**	0.511	0.194*	0.314**	0.539
	(0.111)	(0.130)	(0.324)	(0.110)	(0.129)	(0.330)
WashPost $\times Slant$	-0.043	-0.013	0.019	-0.048	-0.046	-0.003
	(0.056)	(0.072)	(0.082)	(0.057)	(0.073)	(0.093)
Competing headline controls?				✓	✓	✓
Adj. R^2	0.286	0.378	0.371	0.286	0.392	0.371
N	696	501	381	696	501	381

Note: OLS estimates, using story-level data. Left-hand side variable: most viewed (yes/no). All models include the constituent terms of the interactions and day fixed effects. The 2016 models also include dummies for Yahoo stories' first date occurring during one of two time-frames in which Yahoo data collection changed. Competing headlines controls are fixed effects for number of headlines with $Slant_1$ value for the outlet on first day that story was reported. Standard errors are clustered by the first date the story was available. *, **, *** denote 10%, 5%, 1% significance.

A Appendix

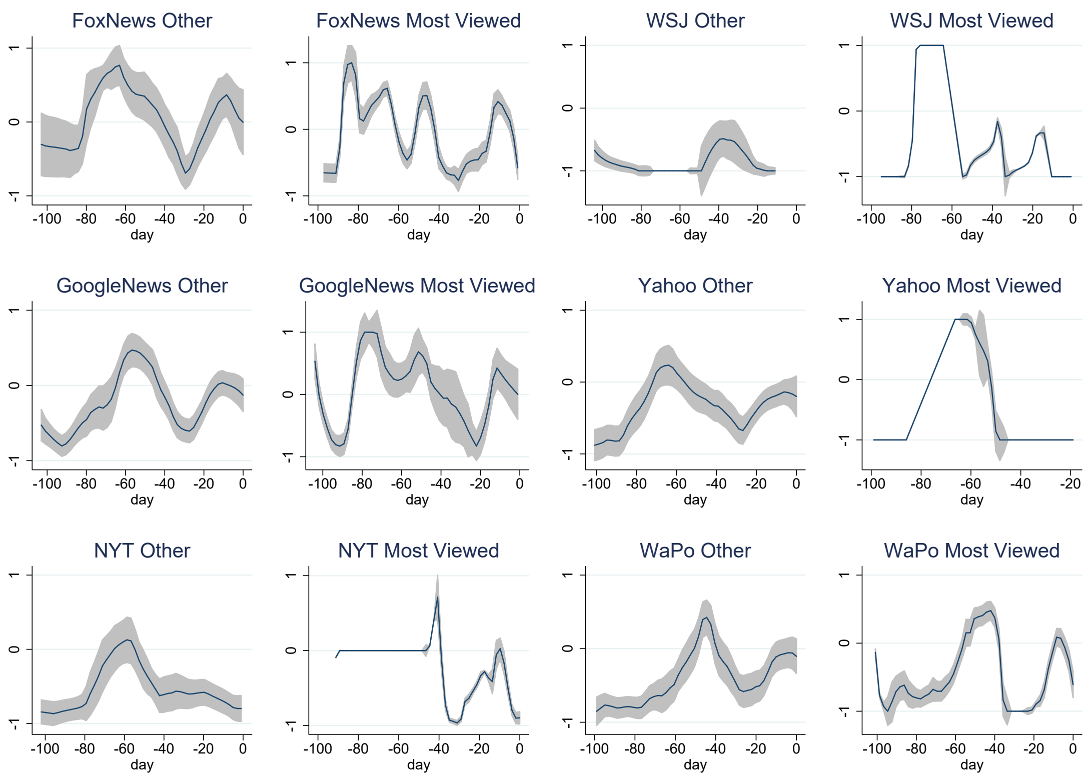
A.1 Additional figures and tables

Figure A1: Mean $Slant_1$ versus day relative to election day (day 0) by outlet in 2012



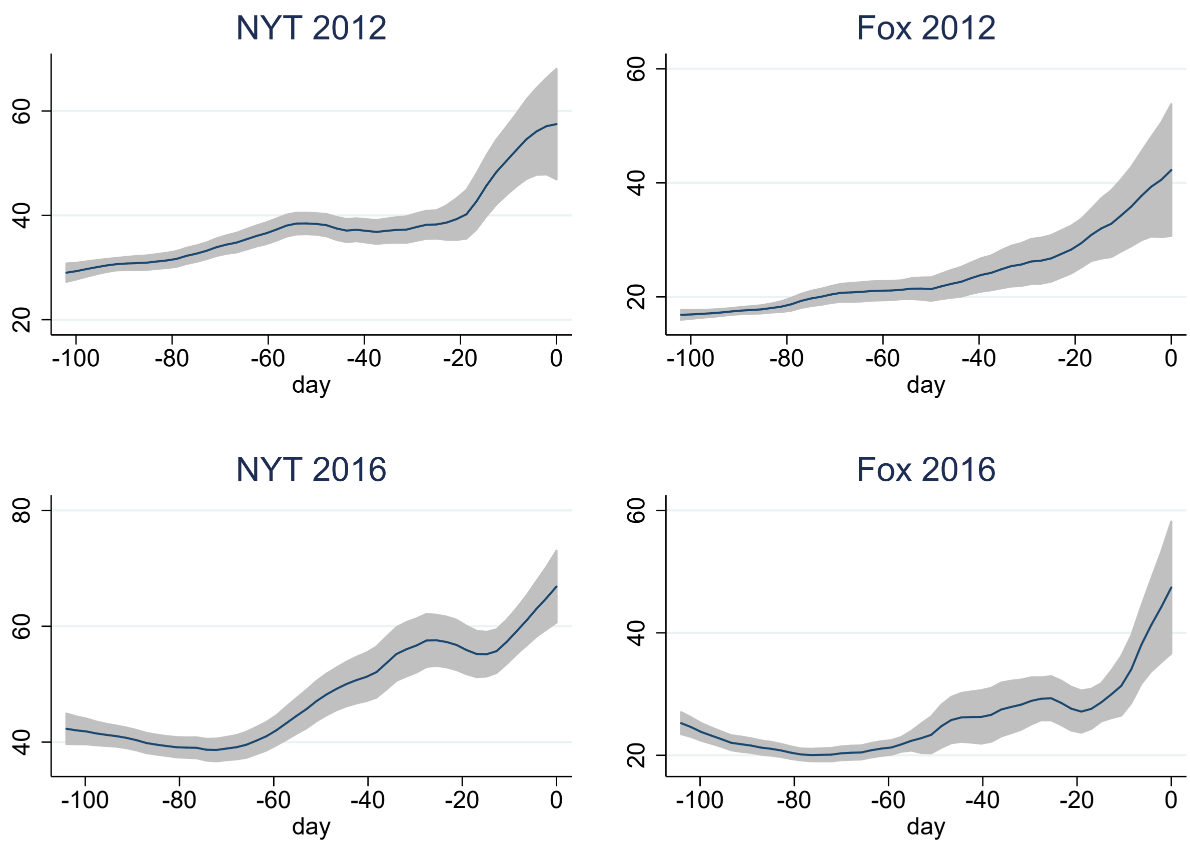
Note: Curves are kernel-weighted smoothed local polynomials with 95% confidence interval bands. Positive values of *Slant* denote better chances of winning for the Republican candidate, whereas negative values indicate better chances for the Democratic candidate.

Figure A2: Mean $Slant_1$ versus day relative to election day (day 0) by outlet in 2016



Note: Curves are kernel-weighted smoothed local polynomials with 95% confidence interval bands. Positive values of *Slant* denote better chances of winning for the Republican candidate, whereas negative values indicate better chances for the Democratic candidate.

Figure A3: Google Trends data (day 0 = election day)



Note: Curves are kernel-weighted smoothed local polynomials with 95% confidence interval bands. "NYT" = Google searches for "new york times"; "Fox" = Google searches for "fox news".

Table A1: Instructions for rating slant of horse race headlines

Category	Definition
Very good news for Clinton	"Very good news" about Clinton's chances of winning (and very bad news about Trump's chances) – that Clinton is substantially more likely to win, or that her chances have greatly improved recently
Good news for Clinton	"Good news" about Clinton's chances of winning (and bad news about Trump's chances) – that Clinton is more likely to win, or that her chances have improved recently
No change	No change in either candidate's chance
Good news for Trump	"Good news" about Trump's chances of winning (and bad news about Clinton's chances) – that Trump is more likely to win, or that his chances have improved recently
Very good news for Trump	"Very good news" about Trump's chances of winning (and very bad news about Clinton's chances) – that Trump is substantially more likely to win, or that his chances have greatly improved recently
Ambiguous or unclear	Relevant to the chances of one of the candidates winning, but unable to determine which candidate is being favored (if at all)
Not relevant	This headline does not seem to be about the candidates' chances of winning the election

Note: MTurkers were given the following instructions: "The following items are real headlines of reports of major US news outlets from July-November 2016 about the upcoming presidential election that year between Hillary Clinton and Donald Trump. Most, but not all, of these articles are about information about which candidate is more likely to win the election. How do you think a typical reader would perceive these headlines? [using the categories above] We would like for you to evaluate these 40 headlines. We will look over your evaluations and if we believe you have done them carefully and reasonably, we will invite you, by email, to do additional similar work (potentially quite a lot)." For 2012 headlines the references were to Obama and Romney.

Table A2: *Slant* values for headlines from November 7, 2016

Headline	$Slant_1$	$Slant_2$	$Slant_3$	Outlet	MV
polls trump and clinton virtually tied in key swing states	0.00	0.00		Fox	1
momentum buster? fbi's comey tells congress	-0.50			Fox	0
email review completed decision not to prosecute clinton stands					
trump supporters say they feel michigan momentum	0.67	0.67		Google	0
president obama makes closing argument if we win florida its a wrap	-0.50			Google	0
poll on eve of election day clinton maintains her edge over trump	-1.00	-1.00	-1.00	Google	0
iowa poll trump opens 7point lead over clinton	1.00	1.00	1.00	Google	0
us presidential election live countdown to the polls	0.00			Google	1
live blog last updated 7.30am aest us election live trump clinton	0.00			Google	0
in final pitch to voters latest polls					
obama if clinton wins florida she will win the election	-0.50			Google	0
our final map has clinton winning with 352 electoral votes. compare your picks with ours.	-1.00	-1.00	-1.00	Google	0
clinton has solid lead in electoral college trumps winning map is unclear	-1.00	-1.00	-1.00	NYT	1
trump and clinton tied in final upshot poll of north carolina	0.00	0.00		NYT	1
clinton cleared on new emails keeps small lead in polls	-1.00	-1.00	-1.00	NYT	0
clinton leads trump by 4 points in lates poll	-1.00	-1.00	-1.00	WSJ	1
1 hillary clinton has enough electoral votes to win the white house in final fix map	-1.00			WashPost	1
postabc tracking poll clinton 47 trump 43 on election eve	-1.00	-1.00	-1.00	WashPost	1
amid lastminute push in va. clinton holds 6point lead in latest poll	-1.00	-1.00	-1.00	WashPost	0
trump urges voters to deliver justice at polls	0.50			WashPost	0

Note: MV = most viewed.

Table A3: Probability of story making most viewed list (date polynomial instead of day fixed effects)

	$Slant_1$	$Slant_2$	$Slant_3$	$Slant_1$	$Slant_2$	$Slant_3$
Panel A: 2012						
Fox $\times Slant$	0.029	-0.015	-0.020	0.013	-0.030	-0.030
	(0.104)	(0.113)	(0.106)	(0.101)	(0.112)	(0.110)
WSJ $\times Slant$	-0.117	-0.114	-0.142	-0.125	-0.123	-0.155
	(0.203)	(0.205)	(0.174)	(0.199)	(0.199)	(0.171)
USAT $\times Slant$	-0.080	-0.009	-0.020	-0.076	-0.005	-0.016
	(0.080)	(0.099)	(0.094)	(0.081)	(0.097)	(0.092)
Yahoo $\times Slant$	-0.023	0.007	-0.001	-0.003	0.031	0.022
	(0.037)	(0.046)	(0.052)	(0.035)	(0.042)	(0.049)
NYT $\times Slant$	-0.057	-0.032	-0.039	-0.041	-0.013	-0.018
	(0.062)	(0.070)	(0.070)	(0.061)	(0.069)	(0.069)
HuffPost $\times Slant$	-0.002	0.022	0.015	0.011	0.031	0.023
	(0.035)	(0.039)	(0.044)	(0.035)	(0.040)	(0.045)
Competing headline controls?				✓	✓	✓
Adj. R^2	0.259	0.271	0.231	0.262	0.274	0.231
N	425	382	277	425	382	277
Panel B: 2016						
Fox $\times Slant$	-0.124**	-0.167***	-0.159**	-0.122**	-0.151**	-0.150**
	(0.060)	(0.060)	(0.061)	(0.060)	(0.059)	(0.061)
WSJ $\times Slant$	-0.033	-0.099	0.676***	-0.040	-0.132	0.627***
	(0.174)	(0.609)	(0.187)	(0.185)	(0.598)	(0.218)
Yahoo $\times Slant$	-0.026	0.066	0.111	-0.039	0.037	0.084
	(0.079)	(0.100)	(0.125)	(0.079)	(0.104)	(0.131)
Google $\times Slant$	0.018	-0.005	-0.005	0.037	0.014	0.014
	(0.028)	(0.031)	(0.032)	(0.026)	(0.030)	(0.032)
NYT $\times Slant$	0.212*	0.328**	0.259	0.196*	0.321**	0.248
	(0.119)	(0.146)	(0.178)	(0.118)	(0.145)	(0.175)
WashPost $\times Slant$	-0.017	0.027	0.025	-0.027	0.011	0.022
	(0.050)	(0.068)	(0.072)	(0.052)	(0.069)	(0.076)
Competing headline controls?				✓	✓	✓
Adj. R^2	0.194	0.248	0.224	0.204	0.267	0.233
N	696	501	381	696	501	381

Note: OLS estimates, using story-level data. Left-hand side variable: most viewed (yes/no). All models include the constituent terms of the interactions and a 4th order date polynomial. The 2016 models also include dummies for Yahoo stories' first date occurring during one of two time-frames in which Yahoo data collection changed. Competing headlines controls are fixed effects for number of headlines with $Slant_1$ value for the outlet on first day that story was reported. Standard errors are clustered by the first date the story was available. *, **, *** denote 10%, 5%, 1% significance.

A.2 Survey

We design an experiment allowing us to study the effects of congeniality on within-outlet news demand, with real, timely, presidential election-related news, as follows. In the morning (between 9:00 AM and 10:00 AM) following each of the first three 2016 US presidential election debates, we conducted a survey on MTurk on interest in debate news versus other news.[15] We used debate news, rather than horse race news, for the surveys because the timing of debates is known well in advance. This allowed us to prepare to post the surveys shortly after the stories became available. Apart from that, debate news stories share several important similarities with horse race stories: 1) they both provide information on the candidates' chances of winning the election; 2) the partisan congeniality of stories on both topics is relatively clear; and 3) the partisan congeniality of stories tends to vary both across and within outlets.

The first and third debates were between the presidential nominees, and the second one was between the vice president candidates. In each survey, we asked a small number of demographic and party affiliation questions, and asked respondents to pick the article they were most interested in reading from four headline options—two articles on which candidate won the debate, one from the NYT and one from Fox, and two articles on other topics from news.yahoo.com. The headlines are provided in Table A5. We use articles from just these three outlets because of their prominence and consistent availability in our web data, and to keep the choice set simple. Both the Fox and NYT headlines that we used in the first survey stated that Clinton won the first debate, and both said that Pence won the second. They disagreed on the third debate. Fox's headline said that Trump won, while the NYT's headline did not declare a winner.

[15]See Appendix Table A4 for sample statistics for key variables. Compared to the population, survey respondents recruited on MTurk tend to be younger, better educated, and more likely to identify with the Democratic party (Berinsky et al., 2012), though sectoral breakdown of employment is similar to more representative online surveys—the sectoral differences are no more than 7% (Huff and Tingley, 2015). A broad variety of experiments done on MTurk have tended to reach similar conclusions as those done on more representative samples (e.g., Mullinix et al., 2015). The two major advantages MTurk offered over a survey firm were: 1) MTurk is much more cost effective, allowing us to obtain a larger sample and 2) MTurk gave us control over the timing of surveys, which, as we explain, is crucial for their validity.

Respondents were told that after choosing the article, they would be asked a question on the article's content. We noted that the difficulty of the question would be the same regardless of which article they picked, and that they would receive an additional payment if they answered the question correctly, so they should pick the article they are (were) truly most interested in. Respondents were paid \$0.50 per survey and a bonus of \$0.25 for answering the reading question correctly. The exact wording of the instructions can be found in the notes to Table A5.

Since respondents were presented with a choice of articles that were both timely and real, and given an incentive to actually read the article they selected, respondent choices should reflect the articles that they would be most likely to read in similar real-world situations. Perhaps the most unnatural element of our design was that respondents were presented with news choices from diverse outlets at the same time. This would be unrealistic for news consumers who, for example, go straight to the NYT website to decide which story to read, or have a Facebook feed consisting of ideologically similar sources. Thus, this element could bias observed demand for news from non-ideologically aligned outlets upwards. It is also worth noting that the respondents might have already gotten their debate news prior to the survey. We tried to minimize this possibility by conducting the surveys fairly early in the morning after the debates. Another issue was priming: In the first two surveys, we asked which candidate the respondents were planning to vote for last, after choosing and reading their article. We chose this order to avoid priming respondents about the election, which could influence article selection in an unnatural way. In survey 3, we randomly asked some respondents about their preferred candidate before presenting the article options to assess if the order mattered. Unreported tests indicate that the order did not have significant effects on article choice.

We surveyed 250 MTurkers (US residents aged 18 or older) after each debate. We discarded observations in which the respondent did not answer the reading comprehension question correctly. We also discarded 16 observations in which the respondent chose "other" in response to the partisan self-identification question, as we suspected many of these respondents were partisan, potentially influencing their article choices, but did not want to reveal this. Our final sample had 637 observations, with 345 identifying as Democrats or leaning toward Democrats, 177 identifying as Republican or leaning toward Republicans, and 115 as independent. Assuming congeniality of news remained neutral for non-partisan respondents, they constitute a quasi-control group that allows us to account for general changes in the importance of debate news over time and/or changes in the appeal of the non-debate news options.

The data and analysis do not map directly to those that we use for horse race news. We certainly cannot estimate average slant over a sample of headlines using the survey data, given the small number of headlines and debates.[16] Instead, we look primarily to see whether interest in debate news from the ideologically aligned outlet increases when it is more congenial. We also assess whether interest in debate news from the other outlet increases when it is more congenial, but as noted above, external validity of this analysis is more questionable.

A.3 Results

Figure A4 previews the econometric results. Across the three surveys, Democrats were least likely, and Republicans most likely, to pick "Other News" after the first debate, which was the only debate that both the NYT and Fox headlines said Clinton won. However, Democrats were slightly more likely to choose the NYT story after the second and third debates, as compared to the first debate. Democrats were significantly less likely to choose the Fox News story after the second and third debates compared to the first debate. Republicans' demand for NYT news was more stable across the debates, while their demand for Fox news grew as the congeniality (and congeniality relative to NYT) grew. Independents were much less likely than partisans to get political news in general, but became more likely to get political

[16]We did manually collect the number of debate-related links (both articles and videos) from web.archive.org on the Fox and NYT websites in the morning following each of the four debates of 2012 and 2016. Comparing the number of links to the verdicts for each debate allows us to informally examine slant at the extensive margin. The data (available on request) shows that the number of stories was fairly constant for both outlets in 2012. However, in 2016, there are indications of a bias towards congenial information. Fox had the most links after the third debate that year, and the fewest links after the fourth debate. The NYT had the fewest links after the second debate. Since Fox claimed Trump won the third debate, the NYT said the Republican (Pence) won the second, and Fox's headlines favored Clinton after the fourth debate (e.g., "Trump winning on points until terrible mistake"), both Fox's and the NYT's numbers of debate links are correlated with the congeniality of the debate outcome for their readers.

Table A4: Summary statistics for survey full sample

Category	Variable (all 0/1)	Mean
Party	Democratic	0.384
	Lean Dem.	0.124
	Independent (no lean)	0.158
	Lean Rep.	0.180
	Republican	0.154
Preferred candidate	Trump	0.261
	Clinton	0.512
	Not voting/other	0.228
Education	Some HS	0.006
	HS degree	0.121
	Some college	0.227
	2 yr degree	0.113
	4 yr coll. degree	0.415
	$>$ college	0.118
Gender	Female	0.458
	Male	0.542
Age	18-29	0.326
	30-39	0.382
	40-49	0.160
	50-64	0.113
	$\geq$ 65	0.019

Note: N=638 for all variables (N=226 from survey 1, 216 from survey 2, 196 from survey 3) except preferred candidate and gender (N=637). Respondents are master MTurkers who answered reading check question correctly.

news in later debates, suggesting a secular increase in interest in political news. Results are similar but somewhat sharper when respondents are split out by preferred candidate rather than party.

A multinomial model would be technically the best choice to formally analyze the survey data, since respondents chose among four unordered alternatives. Results for such a model are available upon request. In the interest of simplicity and transparency, we limit results here to those of linear probability models predicting a binary outcome equal to: 1) Y_i^{NYT} (= 1 if respondent i chose the NYT article); 2) Y_i^{Fox} (defined analogously); 3) whether either type of debate news story is chosen ($Y_i^{debatenews} = Y_i^{NYT} + Y_i^{Fox}$). We run two sets of regressions, one using party identity as a measure of the respondent's politics and one using the respondent's preferred candidate for this, each with the following structure:

Table A5: Headline options for each survey

Survey 1:	NYT: Commentators Give Hillary Clinton Edge in Debate
	Fox: Hillary won the first debate (it helps to be prepared)
	Yahoo: Long dog-gone trip: Florida pooch travels to Boston and back
	Yahoo: Houston gunman had two weapons, thousands of rounds at scene.
Survey 2:	NYT: Who Won the Debate? Commentators Give Edge to Mike Pence
	Fox: Pence triumphs in VP debate. And then there was the night's biggest loser...
	Yahoo: 2 Vermont teachers accused of vandalizing sidewalk
	Yahoo: Two young girls shot in Cleveland drive-by shooting
Survey 3:	NYT: Who Won the Debate? Donald Trump Avoids Annihilation
	Fox: Trump comes out swinging and wins second debate
	Yahoo: Three police officers shot in Palm Springs, California
	Yahoo: Record 1,201 couples renew wedding vows in Kalamazoo

Note: The instructions given to survey respondents before being asked to choose a headline were: "Choose one of the following articles to read. You should choose the article that you are more interested in – the one you would be more likely to read if you came across these links simply surfing the web, or on a social network, etc. After making your choice, you will have access to the article and a simple question on the article's content. Your payment will be $0.25 higher if you answer the question correctly. The question's difficulty is the same for each article. Thus, you might as well choose the article you are truly more interested in, as it will be more enjoyable to read, and you will be just as likely (or more likely) to get the extra payment." The median work time was approximately four minutes and so our payment, as an hourly rate, was relatively high for an MTurk task, which typically pay at rates less than $5 per hour.

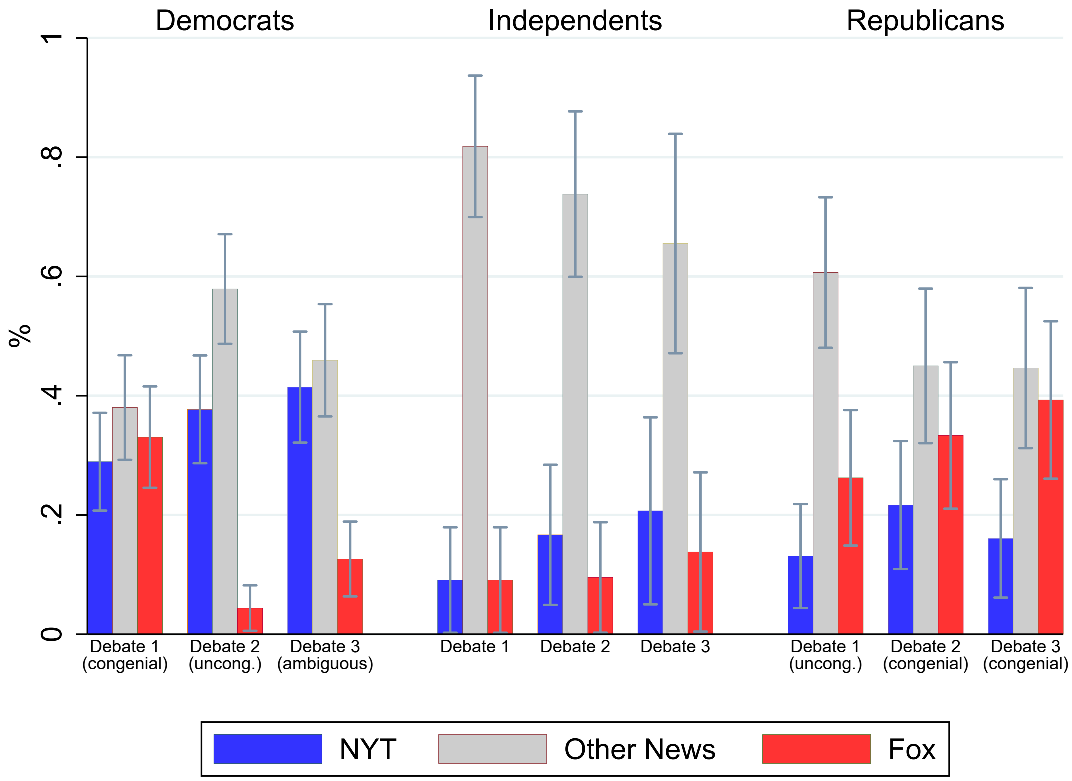
$$Y_i = \alpha + \beta_L D_i^L + \beta_R D_i^R + \beta_{S^2} S_i^2 + \beta_{S^3} S_i^3 + \beta_{L,2} D_i^L S_i^2 + \beta_{L,3} D_i^L S_i^3 + \beta_{R,2} D_i^R S_i^2 + \beta_{R,3} D_i^R S_i^3 + \beta_X X_i + \epsilon_i. \quad (4)$$

D_i^L is a dummy for respondent i being "type L" (a Democrat in one set of regressions, or Clinton-voter in the other set) and D_i^R is analogous (independents are the omitted group); S_i^t is a dummy for respondent i taking survey t (the survey 1 dummy is omitted); X_i is a vector of demographic and other controls. Some respondents took more than one survey, but including fixed effects for these respondents has very little effect on the results.[17]

The parameters of interest are the politics-survey interactions: $\beta_{L,2}$ and $\beta_{L,3}$ can be interpreted as mean changes in type L demand for surveys 2 and 3, respectively, as compared to

[17] Our main goal was to obtain the desired sample size as quickly as possible after posting the survey so that the news would be as timely as possible and did not encourage respondents to take multiple surveys or restrict them from doing this.

Figure A4: News choices by debate and party



Note: 1) Both NYT and Fox survey 1 headlines said Clinton (Democrat) won first debate, 2) Both NYT and Fox survey 2 headlines said Pence (Republican, Trump's VP) won the second debate, and 3) Fox survey 3 headline said Trump won third debate while NYT survey 3 headline was ambiguous. The error bars denote 95% confidence intervals.

survey 1, and $\beta_{R,2}$ and $\beta_{R,3}$, have analogous interpretations for type R respondents. Recall that the NYT's first headline was most (least) congenial, and the second headline least (most) congenial, to L (R) types. Fox's first headline was most (least) congenial to L (R) types.

Table A6 reports the results. Congeniality drives Democrat and Clinton supporter demand for Fox, but not for NYT news. Democrats were 20-30 percentage points less likely to get Fox news when it was uncongenial than when it was congenial ($\beta_{L,2} = -0.293$ and $\beta_{L,3} = -0.221$ for Y_i^{Fox}). There are no significant effects for Y_i^{NYT} for either Democrats or Clinton supporters, or for any dependent variable for Republicans. For Trump supporters, there is also evidence of a congeniality effect but it is primarily for Fox: Trump supporters were around 20 percentage points more likely to get Fox news in survey 2 as compared to survey 1 ($\beta_{R,2} = 0.194$).

Thus, Democrats were just as willing to get news from the NYT when it was uncongenial, and Republicans were unwilling to get NYT news even when it was congenial, supporting the interpretation of the NYT most viewed data being primarily driven by regular NYT readers. Since Democrats were willing to click on congenial Fox news, and Trump voters somewhat less willing to click uncongenial Fox news, the interpretation of the Fox most viewed data is less clear. However, clicking on an "uncongenial outlet" is perhaps much more likely in the survey context than in reality since in the survey users were directly presented with headlines from that outlet (which users might avoid in reality). Moreover, substantial fractions of Trump supporters (24%) and Republicans (28%) were willing to click on the uncongenial Fox story.

Table A6: Likelihood of picking NYT and Fox debate winner article

	Y^{NYT}	Y^{Fox}	$Y^{NYT} + Y^{Fox}$
Panel A (Party Identity)			
Debate 2 × Democrat ($\beta_{L,2}$, uncongenial)	0.004	-0.293***	-0.289***
	(0.095)	(0.079)	(0.111)
Debate 3 × Democrat ($\beta_{L,3}$, uncongenial for Fox only)	-0.023	-0.221**	-0.243*
	(0.110)	(0.100)	(0.126)
Debate 2 × Republican ($\beta_{R,2}$, congenial)	0.009	0.071	0.079
	(0.101)	(0.104)	(0.128)
Debate 3 × Republican ($\beta_{R,3}$, congenial)	-0.095	0.112	0.016
	(0.113)	(0.121)	(0.140)
Adj. R^2	0.059	0.085	0.062
N	637	637	637
Panel B (Candidate supported)			
Debate 2 × Clinton supporter ($\beta_{L,2}$, uncongenial)	0.039	-0.274***	-0.235**
	(0.093)	(0.075)	(0.106)
Debate 3 × Clinton supporter ($\beta_{L,3}$, uncongenial Fox only)	0.122	-0.270***	-0.148
	(0.098)	(0.094)	(0.116)
Debate 2 × Trump supporter ($\beta_{R,2}$, congenial)	0.056	0.194*	0.250**
	(0.100)	(0.103)	(0.122)
Debate 3 × Trump supporter ($\beta_{R,3}$, congenial)	-0.069	0.186	0.117
	(0.099)	(0.117)	(0.132)
Adj. R^2	0.078	0.123	0.091
N	637	637	637

Note: All models are estimated using OLS with robust standard errors and include survey, education, gender, age, and party identity (Democrat, lean Democrat, Republican, lean Republican, independent) fixed effects. The reference category is debate 1. The reports on this debate were congenial for Democrats/Clinton supporters and uncongenial for Republicans/Trump supporters. *, **, *** denote 10%, 5%, 1% significance.

A.4 Model

We present a slightly modified, and simplified, version of the model of Mullainathan and Shleifer (2005), using their notation to the extent possible. The model is intended to just illustrate and clarify a few important aspects of consumer choice in our setting, and does not capture all relevant factors.

There is a single news outlet that repeatedly reports stories on the horse race. Individual news story i, n_i, is the sum of three components: $n_i = d_i + s + \epsilon_i$. d_i denotes "true" news (data) on the horse race, s is a constant that is strategically chosen by the outlet (slant) and applies to all of the outlet's stories, and ϵ_i is exogenous mean-zero story-specific noise. Each component has support $[-b, b]$ for some $b > 0$. We henceforth suppress the i subscript.

There is one representative consumer whose utility from reading n is

$$U_r = \bar{u} - \chi(s + \epsilon)^2 + \phi n, \tag{5}$$

with $\bar{u} > 0$, $\chi \geq 0$, and $\phi \geq 0$. The consumer cares about truth and loses utility from the story's slant and noise $(s + \epsilon)$ if $\chi > 0$. If $\phi > 0$, then the consumer gains utility from n being larger because this is more congenial (n is news about the preferred candidate's chances in the election). It is natural to assume both strict inequalities hold.

Before reading the story, the consumer must click on it. It is natural to define news demand as probability of a click (equivalent to expected number of clicks for a larger population of consumers). The consumer decides whether to click by first reading the story's headline, h, after privately observing her private opportunity cost of the story, $c \sim U[0, \bar{c})$. She thus clicks on the story to read it if $E(U_r|h) = \bar{u} - \chi E\left((\hat{s} + \epsilon)^2|h\right) + \phi\left(E(d|h) + \hat{s} + E(\epsilon|h)\right) \geq c$, and thus $G_c(E(U_r|h))$ is news demand conditional on h, with $G_c()$ being the CDF of c, if $E(U_r|h) \geq 0$. We assume that both of the consumer's conditional expectations $E(d|h)$ and $E(\epsilon|h)$ are strictly increasing in h.

The outlet maximizes demand by choosing s to maximize the consumer's expectation of $-\chi(s+\epsilon)^2 + \phi n = -\chi(s+\epsilon)^2 + \phi(d+s+\epsilon)$ across stories, which is done with $s^* = \phi/2\chi$ for an interior solution. The ratio ϕ/χ measures the consumer's preference for congeniality relative to truthful reporting. If $\phi = 0$ and $\chi > 0$, then the consumer only cares about minimizing slant and does not care about congeniality; if $\chi = 0$ and $\phi > 0$, then the consumer only cares about congeniality, and $s^* = b$. Let $\hat{s}$ denote the outlet's choice of s, though we do not assume the outlet necessarily makes this choice.[18]

The marginal effect of h on news demand is equal to:

$$\frac{\partial}{\partial h} G_c(E(U_r|h)) = g_c(E(U_r|h)) \left(-\chi \frac{\partial}{\partial h} E\left((\hat{s}+\epsilon)^2|h\right) + \phi \frac{\partial}{\partial h} \left(E(d|h) + E(\epsilon|h)\right) \right).$$

This expression is decreasing in $\hat{s}$, given $\chi > 0$.[19] Thus, a larger mean slant, $\hat{s}$, moderates a positive relationship between congeniality of headline slant and demand, or could even flip the sign (from positive to negative) of this relationship. Intuitively, when $\hat{s}$ is very large, readers are getting too much slant on average, so they are more likely to click headlines for stories that seem relatively unslanted. When $\hat{s}$ is not so large, demand is increasing in h because this is a signal of larger d.

Note that the changes to Mullainathan and Shleifer (2005)'s model are as follows. One is very minor, setting price to zero. Another is also minor: Rather than the reader preferring news to be as close as possible to a particular scalar (b in their notation), we assume that "more is better" for the congeniality of content. This assumption has no effect on results and simply feels more natural in our context. The addition of an unobserved noise term, ϵ, to news content, and the addition of the headline being seen before a story is clicked on, are more substantive, but do not affect the key qualitative result about there being a trade-off between congenial slant and accuracy.

[18]The model could be extended so that in equilibrium the outlet does not necessarily maximize clicks (e.g., the outlet could balance clicks with a desire to influence consumers, or the outlet could simply have incorrect beliefs about consumer parameters). We avoid such extensions in the interest of simplicity and since they are unnecessary for our purposes.

[19]Note $g_c(.)$ is a constant, and $-\chi \frac{\partial}{\partial h} E\left((\hat{s}+\epsilon)^2|h\right) = -\chi \frac{\partial}{\partial h} E\left(\hat{s}^2 + 2\hat{s}\epsilon + \epsilon^2|h\right) = -\chi \frac{\partial}{\partial h} E\left(2\hat{s}\epsilon + \epsilon^2)|h\right)$, so the derivative of this expression with respect to $\hat{s}$ is $-2\chi \frac{\partial}{\partial h} E\left(\epsilon|h\right)$, which is strictly negative since $\frac{\partial}{\partial h} E(\epsilon|h) > 0$.