Article-Level Slant and Polarization of News Consumption on Social Media*

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Abstract

How polarized is news consumption on social media? We fine-tune a large-language-model to assign a content-based measure of slant to the near-universe of hard-news articles published online by the top 100 U.S. outlets in 2019. We find that polarized news consumption on Facebook, defined as the difference in the average slant of articles consumed by Republicans and Democrats on the platform, is arguably high. We identify pro-attitudinal news consumption within outlets as a crucial mechanism. Analyzing the distribution of slant on the production side, we find that 67% of the article-level variation in slant is within rather than across outlets.

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1. Introduction

Over the last two decades, social media has become one of the primary ways in which people consume information and access news (Newman et al., 2023). As of 2023, around 50% of U.S. adults reported regularly consuming news through social media, with Facebook being the dominant social media platform for news access (Pew Research Center, 2023*a*; Newman et al., 2023).

The increased reliance on social media for news consumption has generated widespread concern. In particular, many worry that the high personalization of content through the political pages a user follows, the structure of the social network, and the algorithm governing users' feeds lead to the formation of "echo chambers" and "filter bubbles" that promote the consumption of pro-attitudinal news (Pariser, 2011; Sunstein, 2018).[1] The resulting limited exposure to counter-attitudinal news might hinder the formation of accurate political beliefs, and, ultimately, people's ability to constructively participate in the democratic process (Downs, 1957; Becker, 1958).

Although almost ubiquitous in the popular press, worries about pro-attitudinal news consumption online, and especially on social media, have received relatively little empirical substantiation from the academic literature (Gentzkow and Shapiro, 2011; Bakshy, Messing and Adamic, 2015; Nelson and Webster, 2017; Guess and Nyhan, 2018; Eady et al., 2019; Yang et al., 2020; Guess, 2021). Such seeming lack of evidence might partly reflect a mismatch between the level of aggregation at which political slant is commonly measured in the academic literature—namely, news outlets—and the level at which content is curated on social media platforms—namely, news articles. When measuring polarization in news consumption on social media, much of the existing literature proxies the slant of an article with that of the outlet it came from.[2] This approach does not account for the possibility that the social media curation process exposes users to ideologically congenial content even *within* outlets. If the social media ecosystem promotes the consumption of pro-attitudinal news within outlets, measuring slant at the outlet level will underestimate, perhaps severely, the degree of polarization of news consumption on social media.

This paper addresses the limitation above by means of a two-pronged approach. First, we pro-

[1] Pro-attitudinal news, also known as congenial or like-minded news, refers to news whose slant matches a person's ideology.

[2] González-Bailón et al. (2023) and Green et al. (2023) are notable exceptions. We discuss our contribution relative to them towards the end of the introduction.

pose and implement a novel content-based method to assign slant to individual news articles rather than to entire news outlets. Second, we apply our article-level slant measure to estimate the degree of polarization in news consumption on Facebook.

Our analysis relies on three main datasets. The first dataset encompasses the near universe of hard news articles (~ 1 million) published online by the top 100 U.S. outlets in terms of online visits in 2019. The second dataset is the "Facebook Privacy-Protected Full URLs Dataset," produced by a consortium of academics (Social Science One) in partnership with Facebook's parent company Meta. The dataset comprises aggregated, anonymized Facebook activity data at the URL level for all articles publicly shared on Facebook at least 100 times. The third dataset is a panel of browsing behavior for a representative sample of U.S. adults.

The cornerstone of our analysis is a content-based measure of slant at the article level obtained by fine-tuning a large language model (LLM) pre-trained on a vast corpus of text data. To generate the training data on which to fine-tune the model, we hired two expert raters (as well as a research assistant), gave them a sample of more than 4,400 articles randomly drawn from our database of hard news articles, and asked them to assign to each article a measures of slant on a scale from -3 (very left-wing) to 3 (very right-wing). Fine-tuning the LLM substantially increases its performance, from a prediction accuracy of 0.72 to a prediction accuracy of 0.83.

An array of validation exercises shows that our machine-learning-based measure of article-level slant is well-calibrated. For instance, when we aggregate our measure at the outlet level and compare it to one of the most well-established and comprehensive measures of outlet-level slant (Bakshy, Messing and Adamic, 2015), we find a Pearson correlation of 0.89. Similarly, when we compare our article-level slant measure to the slant manually assigned by media watchdog Ad-Fontes Media to a small subset of our articles, we find a Pearson correlation of 0.82.

Our first set of results focuses on the production of slant by the top 100 U.S. outlets in terms of online visits in 2019. Analyzing the landscape of slant on the production side helps contextualize our main result about polarization in news consumption and provides a useful benchmark against which to measure the distribution of slant on social media. To obtain a quantitative measure of the importance of taking into account article-level slant, we perform a variance decomposition estimating the degree to which variation in slant at the article level can be accounted for by outlet provenance.[3] We find that the vast majority ($\sim 67\%$) of the variance in slant at the article level is within outlets rather than across outlets. This finding highlights the importance of measuring slant at the article level and the potential for social media to expose users to ideologically congenial news even within outlets.

Next, we analyze the distribution of slant on the production side. Based on the near-universe of articles published by the top 100 outlets in 2019, we find that the overall slant distribution is unimodal and centered around moderate. However, there is substantial variation in slant by article type and topic. For example we find that opinion article have a bimodal distribution and that articles about welfare, gender, LGBTQ issues, gun rights, and racial relations are more slanted than articles about international conflicts, natural disasters, drugs, and trade.

Our second set of results focuses on the circulation and consumption of slanted articles on social media. For our main result, we introduce and estimate a new measure of polarization in news consumption. We define polarization in news consumption as a scaled difference between the average slant of the articles that Republicans and Democrats consume on Facebook. We find that the degree of polarization in news consumption on social media is arguably substantial: the distance on our scale between the average slant that Republicans and Democrats consume on Facebook corresponds to the distance in slant between the average article from the Washington Times and the average article from the Washington Post.[4] We also find that the news consumed through social media is substantially more polarized that the online news accessed through other means; for instance, it is 2.4 times more polarized than the news accessed through search engines.

To provide an additional benchmark for our polarization result, we calculate a version of our measure where, following the approach employed by much of the literature, we proxy the slant of each article by the slant of the outlet it came from. This way, we mechanically shut down the channel of pro-attitudinal news consumption within outlets. We find that the degree of polarization in news consumption is 50% higher when we take into account the possibility of pro-attitudinal news consumption within outlets—as per our original measure of polarization—than when we shut down that channel by proxying the slant of an article by that of the outlet it comes from.

[3] Our variance decomposition is designed to be robust to the fact that we measure slant at the article level with a degree of noise.

[4] Where the Washington Post and the Washington Times rank at the 11^{th} and 82^{nd} percentile of the overall distribution in average slant across the outlets in our dataset.

Thus, employing measures of slant at the outlet rather than the article level leads to a substantial underestimation of the degree of polarization in news consumption on social media.

We highlight three additional important drivers of polarized news consumption on social media. First, we show that extreme articles are much more likely to be shared widely on Facebook than moderate articles. As a result, the distribution of articles that are widely shared on Facebook has much thicker tails than the distribution of articles produced. Second, we examine whether polarization in news consumption is primarily driven by the articles that Democrats and Republicans are exposed to on their feeds or by the articles that they select among the articles they are exposed to. We find that 82% of our measure of polarization can be explained by the articles that Democrats and Republicans are exposed to on their feeds, thus highlighting the role of the feed-curation process in driving polarization in news consumption on social media. Third, in an attempt to further unpack the role of the feed-curation process, we explore the degree to which echo chambers—which arise from the interaction between the politically homophilous structure of the Facebook network and pro-attitudinal sharing patterns—can explain polarization in news consumption on Facebook. A back-of-the-envelope calculation finds results consistent with echo chambers being a substantial, although not exclusive, driver of polarization in news exposure on social media. Specifically, we find that if users' feeds simply reflected the articles shared by their friends, the degree of polarization in news exposure on Facebook would be around 59% of what it currently is.

This project contributes to the literature trying to measure the differential consumption of news by partisanship or ideology (Bakshy, Messing and Adamic, 2015; Flaxman, Goel and Rao, 2016; Gentzkow and Shapiro, 2011; González-Bailón et al., 2023; Green et al., 2023). To help readers navigate this crowded literature, Appendix Table A.1 provides a schematic overview of the research articles most closely related to our paper. To the best of our knowledge, this paper is the first to employ a content-based measure of article-level slant at scale to estimate the degree of polarization in news consumption on social media.

We view each component of the sentence above as conceptually important. First, we believe that our measure of *polarization* in news consumption is an essential complement to other measures employed in the literature, such as measures of segregation and favorability (Gentzkow and Shapiro, 2011; González-Bailón et al., 2023).[5] Specifically, an important hypothesis that researchers and

[5] See Appendix H for definitions of measures of segregation and favorability, and for a detailed discussion of the

policymakers are interested in assessing is whether Democrats and Republicans consume articles with different slant—as captured by our measure of polarization—as opposed to whether they simply consume different articles—which would be captured by measures of segregation or favorability.[6] The conceptual distinction between the polarization measure we introduce and measures of segregation and favorability can be readily seen in the following thought experiment. Consider a world in which: i) people only follow local politics, ii) individuals are geographically segregated by political ideology, and iii) the articles discussing local politics are all exactly moderate. In that world, our measure of polarization would equal zero, whereas measures of segregation would be at their maximum.[7]

Second, we believe that, for studying polarization of news consumption in the digital age, it is particularly important to develop a *content-based* measure of slant at the *article level*. The existing alternatives are mainly audience-based measures of slant at the article level (as in Bakshy, Messing and Adamic, 2015; González-Bailón et al., 2023; Green et al., 2023), content-based measures of slant at the outlet level (as in Groseclose and Milyo, 2005; Gentzkow and Shapiro, 2010), or audience-based measures of slant at the outlet level (as in Flaxman, Goel and Rao, 2016; Nyhan et al., 2023).[8] The importance of developing a content-based measure of slant rather than an audience-based measure of slant follows from the observation in the previous paragraph that the differential consumption and sharing patterns across Democrats and Republicans captured by audience-based measures of slant might, in principle, have little to do with slant. The importance of developing a content-based measure of slant at the article level rather than at the outlet level follows from the observation that the curation process on social media occurs at the article level and that individuals might consume pro-attitudinal articles even within outlets. A relatively small literature

difference between those measures and the one we develop and employ in this paper.

[6] Of course, whether Democrats and Republicans consume the same or different articles is itself an important, albeit separate, policy-relevant question.

[7] As another example, consider outlets that source their content from news agencies like the Associated Press (AP). Suppose the same article from a news agency is published by both a liberal and a conservative outlet. Under our content-based measure of slant, the two identical articles would, by definition, receive the same slant score regardless of the outlet of provenance. As a result, our measure of polarization would remain unchanged even if Democrats predominantly read the article in the liberal outlet and Republicans predominantly read the article in the conservative outlet. In contrast, measures of segregation would increase if Democrats accessed the article through the liberal outlet and Republicans accessed the same article through the conservative outlet. Section H.1 shows that this phenomenon does indeed occur in the data.

[8] Audience-based measures of slant are those that rely on differential consumption or sharing patterns by Democrats and Republicans.

does attempt to assign a content-based measure of slant to individual news articles (Boxell and Conway, 2022; Budak, Goel and Rao, 2016; Garz et al., 2020; Green et al., 2023; Peterson, Goel and Iyengar, 2021). Such papers, however, do not deploy their content-based article-level measure of slant at scale and/or focus on topics (e.g., the role of journalists in the production of slant) that are largely orthogonal to the ones considered in this paper.

Overall, the content-based measure of slant at the article level that we introduce in this paper allows us to make the following qualitative contributions to the literature. First, we show for the first time that most of the variance in article-level slant occurs within rather than across outlets. Second, we introduce and estimate a novel measure of polarization in news consumption on social media, which captures the degree to which Democrats and Republicans consume articles with different slant. Contrary to much of the literature, we find that polarization in news consumption on social media is arguably high.[9] Third, we provide unique evidence on the mechanisms that produce polarized news consumption on social media. Specifically, we compare the slant landscape on the production side to that of articles that circulate widely on social media, highlighting special features of the social media environment—e.g., pro-attitudinal sharing patterns and network homophily—that drive polarization in news consumption.

The rest of this paper is organized as follows: Section 2 provides some background information about the prevalence of news consumption on social media and about the curation process on social media platforms; Section 3 introduces the datasets we use for our analysis; Section 4 describes our methodology to assign slant at the article level and a battery of validation exercises; Section 5 describes the slant landscape of the news produced by the top 100 U.S. outlets in 2019; Section 6 presents our main result about polarization of news consumption on social media and describes the mechanisms driving it; Section 7 presents extensions and robustness analyses; Section 8 concludes.

2. Background

As of 2023, around 50% of U.S. adults reported consuming news on social media "often" or "sometimes" as opposed to "rarely" or "never" (Pew Research Center, 2023*a*). Furthermore, individuals

[9] This finding dovetails with the analysis in González-Bailón et al. (2023) showing that Democrats and Republicans tend to consume different outlets and, even more markedly, different articles.

aged 19 to 29 reported preferring to consume news from social media more than from any other medium and were more likely to consume news on social media compared to visiting news sites or apps (Pew Research Center, 2023*b*).

Due to a combination of its sheer size ($\sim$ 190 million monthly active users in the U.S.) and the fact that many of its users get news on the platform, the dominant platform for news consumption on social media in the U.S. is Facebook (Datareportal, 2023). According to 2023 Pew Research Center data, 30% of U.S. adults report regularly getting news from Facebook, more than from any other social media platform. As a point of comparison, only 14% and 12% of U.S. adults report regularly getting news from TikTok and Twitter (now ”X”), respectively (Pew Research Center, 2023*a*).

A striking difference between news consumption on social media and more traditional forms of news consumption such as newspapers is the degree of personalization of the news bundles that readers are exposed to. In particular, traditional newspapers distribute the same content to virtually all consumers; therefore, a person reading a newspaper top to bottom (e.g., the New York Times) is exposed to a bundle of news articles whose slant is curated by the news outlet. Conversely, the bundles of articles that social media users are exposed to are tailored to their individual tastes: news articles appear on users' feeds as a function of the pages that they follow on the platform, of the network of friends they are connected to, and of the platform's content-ranking algorithm.

The highly personalized process of news content curation on social media makes it so that the slant of an article that appears on a user's feed need not reflect the average slant of the news outlet that the article came from. For instance, a Democrat Facebook user might be more likely to encounter New York Times opinion columns by Paul Krugman (a relatively left-wing columnist according to our slant measure), whereas a Republican Facebook user might be more likely to encounter New York Times opinion columns by Bret Stephens (a relatively right-wing columnist according to our slant measure). For this reason, in order to study the slant of the bundle of news that Democrats and Republicans are exposed to and consume on social media, it is necessary to assign a measure of slant to individual news articles rather than to entire outlets.

3. Data

Our analysis relies on three main datasets: one that includes the URL, text, and meta-data of a large collection of hard news articles, one that details the number of Facebook views, clicks, and shares for a subset of those articles, and one that tracks the browsing behavior of a sample of U.S. adults.

3.1 Near Universe of Hard News Articles

The first dataset we employ in our analysis comprises the near universe of hard news articles ($\sim$ 1 million) published online in 2019 by the top 100 U.S. outlets in terms of online visits.[10] Our choice of focusing on the top 100 U.S. outlets is the result of a trade-off between covering as large a fraction of online news consumption in the U.S. as possible and data collection costs. According to Comscore data, visits to the top 100 U.S. outlets cover 93% of all online consumption from U.S. outlets focused on hard news, thus yielding a database of articles with very extensive coverage.

We automatically retrieved the English-language news articles published online in 2019 by the top 100 U.S. news outlets directly from the outlets' websites.[11] We decided not to include articles containing fewer than 250 characters since these are typically not news articles (e.g., videos, alerts, or pages linking to other articles).[12] This procedure generated a dataset of 3,268,760 articles.

In order to identify and isolate the subset of hard news from the dataset of articles described in the previous paragraph, we employed a machine learning algorithm. Following the literature, we define hard news as news typically displayed in the first section of a newspaper. Thus, our definition of hard news excludes sports, entertainment, classified advertisements, weather forecasts, etc. The reasons for restricting our focus to hard news are twofold: first, slant is not as well-defined for soft news such as celebrity gossip and sports; second, hard news is arguably more relevant in shaping people's political behaviors like voting. To classify hard news, we relied on a machine-learning

[10] We exclude popular outlets from regions other than the U.S. (e.g., the BBC), news agencies (e.g. the Associated Press), as well as outlets that do not focus on hard news (e.g., Elle).

[11] To ensure that we were only collecting news articles, we restricted data collection to English articles where the HTML 'pageType' meta field is defined as 'article'.

[12] We further excluded outlets where our automatic retrieval appeared not to capture the full article text. Such outlets were: azfamily.com, dailykos.com, dailywire.com, inforum.com, komonews.com, post-gazette.com, today.com, triblive.com, usnews.com, and WSJ.com.

algorithm trained on 2,470 labels annotated by the research team. The binary classifier achieved 90% sensitivity and 97% specificity.

Our final sample includes 1,065,217 hard-news articles. Appendix Table J.1 presents the list of outlets (column 1), as well as the number of hard news articles published in 2019 by each outlet (column 2).

Using browsing data from a representative sample of 5,115 adults described in Section 3.3, we can obtain an estimate of the degree to which our dataset is comprehensive. Specifically, we can match the URLs that appear in our dataset of hard news with the hard news URLs visited by the panelists. We find that our dataset has very high coverage. Specifically, we find that only 5.8% of all hard news articles that appear in the browsing histories of the panelists and that originate from the top-100 news outlets do not find a match in our dataset. In other words, our dataset of hard news articles comprises 94.2% of all the news articles visited at least once by at least one of the 5,115 panelists in our dataset of browsing behavior.

Article cleaning The objective of our cleaning procedure was to ensure that our machine learning algorithm assessed article slant based solely on the article text and title. To clean the articles, we first tested existing packages (Domdistiller, Readability, Trafilatura) designed to extract relevant text from HTML files. We compared the differences across these packages and selected the most effective one for each outlet. Additionally, we removed extra white space and excluded paragraphs that contained only a short line of text (up to 100 characters) without a period, as such lines were typically advertisements or captions rather than part of the article body.

3.2 URL-level Facebook Activity Dataset

The second dataset we employ is the ”Facebook Privacy-Protected Full URLs Dataset”, which results from a partnership between Social Science One (SS1), a consortium of academics hosted by Harvard's Institute for Quantitative Social Science, and Facebook's parent company Meta. The dataset, henceforth referred to as the URL-level Facebook Activity Dataset, contains information about various forms of engagement with all the URLs shared publicly on Facebook more than 100 times starting on January 1, 2017.[13] The dataset provides the number of unique users who viewed, clicked, and shared a given URL on Facebook. The engagement counts (i.e. views, clicks, shares) are broken down by calendar year-month, gender, age group, and users' political affinity (discussed in detail below).[14]

For privacy protection, Meta added Gaussian noise to each engagement data point (i.e., counts of clicks, views, and shares) according to the dictates of epsilon-delta differential privacy—a mathematical framework designed to quantify and manage the privacy risk associated with the release of statistical summaries of datasets containing individual information (Messing et al., 2023). In all our analyses based on the Facebook engagement data, we aggregate engagement counts across thousands of news articles within our article slant bins, thereby averaging out the noise present in the engagement measures at the level of individual articles. Column (3) of Appendix Table A.2 provides summary statistics for the articles in the URL-level Facebook Activity Dataset.

Political Affinity Measure The URL-level Facebook Activity Dataset contains a political affinity measure that classifies Facebook users into five ideology buckets, along with a sixth bucket for users who are not assigned a political affinity score. For most of our analysis, we consolidate the measure into three buckets: liberals, moderates, and conservatives. The political affinity measure is derived from users' interactions with political pages on Facebook, employing a methodology similar to the one in Barberá et al. (2015).[15]

The political affinity measure has several desirable features. First, Bond and Messing (2015) validate a measure based on the same model against existing measures of ideology for political

[13] For privacy protection, Meta added Laplace-5 noise to the share counts used to determine which URLs are shared publicly on Facebook more than 100 times (Messing et al., 2023).

[14] We only consider engagement that occurred in the calendar year 2019. In principle, some articles published in 2019 could experience a degree of engagement in subsequent years. In practice, almost all engagement—more precisely 0.92, 0.93 and 0.91 of views, clicks, and shares, respectively—occurs immediately, in the month in which an article first appears in the URL-level Facebook Activity Dataset. This means that using 2019 engagement data should provide relatively precise engagement measures since almost no engagement occurs in the calendar year following the year when the article first appears in the dataset.

[15] This process begins by constructing an adjacency matrix that represents monthly active U.S. users (aged 18 and over) as rows and a curated list of political pages as columns. The matrix tracks whether users "like" these pages on Facebook. Correspondence analysis is then applied to a subset of this matrix, focusing on users who "like" at least ten political pages, to estimate the political positions of pages and users on a common ideological scale. Subsequently, political page-affinity scores for all users who like at least one of the selected political pages are calculated by averaging the scores of the pages they "like." These scores are then converted to percentiles to categorize users into quintiles based on their political affinity.

actors and against the self-reported political views of users, and find Pearson correlations as high as 0.94. Second, the measure is defined on the URL-level Facebook Activity Dataset, which covers the universe of URLs shared on Facebook at least 100 times. Third, the measure can be applied to users who do not actively report their ideology or register with a party.

The political affinity measure, however, has also some drawbacks. First, it is not a canonical measure of partisanship, in the sense that it does not directly track canonical indicators such as party registration. Second, it does not have universal coverage, because it is assigned only to individuals who ”like” at least one political page on Facebook. Third, it might suffer from a circularity problem, because a small set of news outlets is included in the set of political pages used in the construction of the measure. Below, we elaborate on each drawback in turn, as well as on our proposed solutions.

The first drawback of the political affinity measure in the URL-level Facebook Activity Dataset is that it is not a canonical measure of partisanship. Specifically, if we define partisanship status as being a registered member of the Democratic or Republican party, it is not immediately clear how the political affinity measure in the URL-level Facebook Activity dataset maps to party registration. Furthermore, since we do not have access to the underlying proprietary data that Meta uses to construct the political affinity measure, we cannot create a confusion matrix to understand the relationship between political affinity scores and being a registered member of the Democratic or Republican party. Luckily, however, the construction of the political affinity score in the URL-level Facebook Activity Dataset is almost identical to the construction of the political affinity measure developed in Barberá et al. (2015) using Twitter (now ”X”) data. Since the dataset used in Barberá et al. (2015) is publicly available, we can recover the confusion matrix that describes how voter registration maps to political affinity in the Twitter dataset. Assuming the confusion matrix for the Twitter and the Facebook datasets are the same, we can leverage that confusion matrix to estimate the degree of polarization in news consumption that would prevail if, in the URL-level Facebook Activity Dataset, partisanship was defined according to party registration, as opposed to being defined according to the political affinity measure. We follow this approach in the estimation of our headline statistic about polarization in news consumption on Facebook and provide the methodological details in Appendix F.

Second, since the political affinity score is only assigned to individuals who like at least one news page on Facebook, the political affinity measure does not have universal coverage: it only covers around 25% of users (Messing et al., 2023). Despite being a minority of Facebook users, individuals who are assigned a political affinity score are responsible for the lion's share of engagement—72% to 87%, depending on the engagement measure—with hard news articles on Facebook, as shown in Table A.3. Thus, whenever we report results that rely directly on the political affinity score, we capture the vast majority of engagement. As described in the previous paragraph, our headline estimate of polarization is based on party registration as opposed to the political affinity score directly. Besides having the upside of tracking a more canonical definition of partisanship, basing our preferred polarization estimate on party registration also has the advantage of allowing us to take into account the news consumption behavior of users with a missing political affinity score as described in Appendix F.

Lastly, the political affinity score might suffer from a small degree of circularity. Specifically, among the more than 500 political pages employed in its construction, there are 18 news outlets that overlap with the ones in our list.[16] In Section 7.3, we assuage concerns about such potential circularity by providing a robustness check that drops from our analysis the set of outlets that are both in our universe and among the political pages used in the construction of the political affinity variable. Furthermore, we show that our results go through when we use an alternative ideology proxy that relies on basic demographics rather than on Facebook's political affinity measure.

Besides the proposed solutions above, the key robustness check we run to assuage potential concerns about the political affinity measure is to leverage a panel dataset of browsing behavior, described in detail below, in which individuals are assigned a measure of partisanship based directly on whether they are registered Democrats or Republicans. Specifically, by considering news visits that have Facebook as a referrer, we can calculate a measure of polarization in news consumption that is completely independent from the one calculated using the URL-level Facebook Activity Dataset. Reassuringly, as shown in Section 7.3, we find that the measures of polarization calculated on our panel of browsing behavior and on the URL-level Facebook Activity Dataset are almost identical.[17]

[16] The other political pages are members of Congress, hosts of cable news shows, political parties, candidates in presidential primary elections, and other news outlets.

[17] The advantage of measuring polarization using our panel of browsing behavior is that it relies directly on party registration records; the disadvantage is that it is estimated on a sample that is not necessarily representative of the

3.3 Panel of Browsing Behavior

For additional robustness checks and analyses, we rely on browsing panel data from a representative sample of 5,115 U.S. adults, curated by market-research firm Luth Research.[18] This dataset provides comprehensive URL-level browsing activity data on both desktop and mobile devices for all panel members during the last quarter of 2019. Within this dataset, we observe 121,703 clicks on hard news articles published by the 100 outlets included in our study. A unique feature of this dataset is that it includes party registration status for 75% of panel members—specifically, those residing in states where party registration status is publicly available. Luth procures this information from TargetSmart's voter registration database, which itself is sourced from information released by state election officials.

4. Measurement of Slant at the Article Level

The cornerstone of our analysis is a content-based measure of slant for each article in our database. We construct this measure by fine-tuning a large language model on a training dataset of more than 4,400 articles whose slant was rated by experts. We discuss the procedure in detail below.

4.1 "Ground Truth" Expert Slant Labels

To successfully fine-tune a large language model to assign a measure of political slant to news articles, it is paramount to obtain a high-quality training dataset with accurate labels. To obtain the training dataset, we employed, for about six months, two freelance workers with graduate degrees in political science and criminal justice, as well as a research assistant. Henceforth, we refer to the two freelance workers as ”expert raters”.[19]

Our two expert raters were independently asked to assign slant labels to 4,433 news articles randomly selected from our database, with the randomization stratified by week of the year. For each

Facebook population.

[18] The sample is recruited to be representative, on the first moments of various observables, of the adult U.S. population.

[19] The experts were recruited through Upwork, after careful review of their credentials, a Zoom interview, and the successful completion of a sample rating task.

article, raters received solely the cleaned text and title; we did not provide any additional information, such as the URL of the article or the outlet that it came from. Raters were asked to assess the slant of each article on a 7-point scale, where 1 corresponded to a very left-wing article and 7 corresponded to a very right-wing article. For ease of interpretation, in the rest of the paper, we recenter the scale so that negative numbers indicate left-leaning articles, positive numbers indicate right-leaning articles, and zero indicates a moderate article. The raters were told to consider primarily three criteria when assigning a measure of slant to each article: language, political position, and issue coverage. Language refers primarily to the usage of partisan terminology as in Gentzkow and Shapiro (2010). Political position refers to whether the article takes a position, if at all, that is closer to the Democratic or Republican stance on the issue. Issue coverage refers to whether the article's content disproportionately emphasized issues important to either party's base.[20] The expert raters were asked to consider all three criteria and then provide a holistic assessment for each article. The instructions we gave the expert raters can be found in Appendix B.

We decided to rely on experts, as opposed to crowd-sourced ratings (e.g., via mTurk), because we believed our experts would produce higher quality ratings than mTurk workers. In fact, previous papers that employed mTurk workers found a correlation between the labels of different raters of only 0.26 (Peterson, Goel and Iyengar, 2021). As discussed in detail below, the correlation between our labels is much higher.

We took several steps to ensure high-quality ratings. First, we ordered articles by publication date, so that, when rating articles from the same period, our experts would gain a better understanding of context. Second, we asked our experts how confident they were in their ratings and removed the less than 2% of articles where at least one of the expert raters said that they were not at all confident. Third, in the rare cases where the two experts disagreed about the direction in which an article was slanted (an event that occurred 6% of the time), we passed the article to a research assistant (RA) hired specifically for the task of providing a third independent assessment. The RA reviewed the article, provided a written rationale for why he thought the two raters might disagree about the slant of the article, replaced the rating of the expert he disagreed with with his own independent rating, and finally provided a written justification for his rating.

[20] See, for instance, the example of selective coverage in Chopra, Haaland and Roth (2024) in which the Congressional Budget Office evaluates a prospective reform along two dimensions and news articles selectively report only one of the two dimensions.

The procedure above generated two labels for each of the 4,433 articles. The correlation between the original two labels is 0.56 and increases to 0.72 after including the RA's correction. Cohen's Kappa, a commonly used measure of inter-rater reliability, is 0.68, which is generally interpreted as "substantial" agreement (the second best category out of 5).[21] The disagreement in slant across the two ratings is arguably small: the median and modal absolute difference between the two labels is 0, and the average absolute difference between them is 0.60 on our 7-point scale.

To further reduce idiosyncratic noise in the rating, we use the average slant rating of the two expert raters, after the RA correction, as the label for each article in the training data.

4.2 Machine Learning

Following recent advances in natural language processing and machine learning, we use a mixture of general-purpose and task-specific machine learning to assign a measure of slant to each news article in our universe. The general purpose component consists of the generative pre-trained transformer model GPT-4o by OpenAI. The task-specific component involves fine-tuning GPT-4o, using our expert labels as training data, for the specific task of assigning a measure of slant to a given news article based on its text. For the fine-tuning component, we provided GPT-4o with the same set of instructions as our expert raters, as well as with 2,955 articles from our training set containing the average of our two experts' labels. The remaining 1,476 labeled articles were held out for validation. We only provided GPT-4o with each article's headline and text; we did not provide any additional information, such as the URL of the article or the outlet it came from.

Fine-tuning GPT-4o yielded substantial improvements in the model's ability to predict the average of our two experts' labels. The Pearson correlation between the model's predictions and the average of our two experts' ratings in the hold-out portion of our training dataset is 0.72 when the model is not fine-tuned and 0.83 when the model is fine-tuned. Thus, the increase in precision due to fine-tuning is around 20%.

[21] Cohen's Kappa is a statistical measure used to evaluate the agreement between two raters who each classify items into mutually exclusive categories. Unlike simple percent agreement, it accounts for the possibility of the agreement occurring by chance, providing a more accurate assessment of inter-rater reliability.

4.3 Model Predictions

Our machine learning model outputted, for each article in our database, a slant prediction that ranged from -3 (indicating a very left-wing article) to 3 (indicating a very right-wing article). For all analyses other than the validation analysis below, we merge slant bucket -3 with slant bucket -2.5 and slant bucket 3 with slant bucket 2.5. This is because slant buckets -3 and 3 contained too few articles to draw meaningful conclusions, especially given the noise introduced to the URL-level Facebook Activity Dataset due to differential privacy.

For reference, Table A.2 provides some summary statistics about the mean and standard deviation of the slant of articles in our datasets, and Table A.4 lists the titles of the ten most clicked articles on Facebook in 2019 from the most extreme left-wing and right-wing slant buckets.

4.4 Validation Exercises

Our paper introduces the first large-scale content-based measure of slant at the article level built on expert labels. Since the measure is novel, it is important to carefully validate it before relying on it in our analysis. In this section, we describe the results of an array of validation exercises showing that our methodology to estimate slant at the article level produced precise and high-quality estimates.

First, for the articles in the hold-out portion of our training dataset, we correlate the prediction from our machine learning algorithm with our expert slant label (given by the average rating of our two experts). As mentioned above, we find a correlation of 0.83.[22] In Appendix E, we show that, since our "ground truth" measure of slant is itself noisy (the correlation between the two experts' labels is 0.72) we can derive, under a set of assumptions, an upper bound on the maximum achievable correlation between our model prediction and our slant labels of 0.91. In light of this upper bound, our model predictions attain 91% of the maximum achievable correlation, which we view as highly satisfactory.

Second, we compare the absolute difference between the model prediction and the expert slant labels. The mean absolute difference (MAE) is 0.36, which corresponds to only 5% of the length of

[22]The R^2 from a regression of a hold-out article's model-predicted slant on its average expert label is 0.69 and the RMSE is 0.55.

our scale. We also run this comparison separately for each expert. The absolute differences between our model and each expert label are smaller than the absolute difference between the expert labels; this is true for both the original and the RA-amended expert labels. Finally, we check how often the predicted slant and the expert slant label have the same direction of slant (among all non-neutral articles). We find an agreement rate of 95%.

Third, we aggregate our measure at the outlet level and compare it to one of the most comprehensive existing measures of outlet-level slant, namely the measure by Bakshy, Messing and Adamic (2015). Figure 1 plots the outlet-level slant rating against the outlet-level measures we obtain by averaging the slant of all the articles produced by the same outlet. We find a Pearson correlation of 0.89.

Fourth, we correlate our model predictions of slant with high-quality human slant ratings from an independent source: media watchdog Ad Fontes Media (henceforth "AFM"). AFM uses a panel of analysts from across the political spectrum to rate a representative sample of news articles every week. For the year 2019, we found a total of 512 news articles with publicly available expert slant ratings from AFM. Lending credence to our model predictions, we find a high correlation of 0.82 between the two slant measures. To illustrate the fit across the distribution, we plot the mean AFM slant rating across articles in each model-predicted slant bin in Figure A.1. We find a smooth linear relationship between the two ratings. Given that the AFM raters are chosen to evenly represent political perspectives (each article gets rated by a panel of three individuals, one from the political left, one from the political center, and one from the political right), the strong alignment between our model predictions and the AFM labels should also alleviate concerns about our two expert raters having the same political orientation.[23]

The comprehensive validation exercises above solidify our confidence in the measure of article-level slant assigned to the near universe of hard news articles analyzed in this study.

[23] Both our raters self-identify as weakly liberal.

5. News Production

In order to provide useful context and to benchmark our measure of polarization in news consumption on social media, our first set of results analyzes the production of slant by the top 100 U.S. outlets in 2019. We begin this analysis by introducing a variance decomposition aimed at obtaining a quantitative measure of the importance of taking into account article-level slant instead of relying on slant measured at the outlet level.

5.1 Variance Decomposition: The Role of Outlets

One of the key arguments in this paper is that measuring slant at the outlet level might underestimate polarization in news consumption on social media. This argument is predicated on the intuition that the social media environment can induce partisans to sort ideologically within outlets and not just across outlets. Of course, a necessary condition for meaningful partisan sorting within outlets is that there be variation in slant within outlets in the first place.

To assess the degree of variation in slant within outlets we perform a variance decomposition. The following two illustrative cases might help build intuition. At one extreme, one can imagine a world in which all articles from the same outlet have the same slant. In that world, the entirety of the variance in slant across articles would be explained by outlet provenance. At the other extreme, one can imagine a world in which all outlets have the same average slant, and articles differ in slant only within outlets. In that world, none of the variance in slant across articles would be explained by outlet provenance. Proxying the slant of an article with the average slant of the outlet it comes from is perfectly accurate in the first illustrative case and it becomes progressively less accurate the closer reality is to the second illustrative case. In other words, the smaller the fraction of variance in slant that can be accounted for by outlet provenance, the more important it is to measure slant at the article level.

We begin our analysis by illustrating the role of within- vs. across-outlet variation in slant with a case study of two of the most influential U.S. news outlets: the New York Times and Fox News. Figure 2 shows the distribution of article-level slant separately for each outlet. The two outlets clearly differ in their average slant, with the slant distribution of articles from the New York Times skewing visibly more left-wing than that of Fox News. The difference in average slant between the two outlets is 0.98 points on our scale. Despite the average difference in slant, however, there is substantial overlap in the two distributions: within each outlet, approximately 50% of articles are neutral or cross-cutting (i.e., exhibiting a slant of the opposite sign than the average slant of the outlet). Thus, the two outlets contain both liberal and conservative articles. Appendix Figure J.1 shows the distribution of slant for all outlets and demonstrates that there is substantial within-outlet variation in slant for virtually all outlets.

To obtain a quantitative measure of the extent to which, in general, the slant distributions of articles from different outlets overlap, we turn to a variance decomposition. We begin by noting that, due to measurement error in our slant measure, a "naive" variance decomposition—obtained by first regressing our model-predicted article-level slant on outlet fixed effects, and then retrieving the R^2 as a measure of the fraction of the overall variation in slant that is accounted for by fixed differences across outlets—would produce biased estimates. In particular, in the presence of measurement error in our slant measure, the naive variance decomposition above would necessarily underestimate the true amount of variation in article-level slant that can be accounted for by outlet provenance, as shown in Appendix D.

Our measure of article-level slant is affected by two separate sources of measurement error: first, the labels of our two experts exhibit a degree of noise in that they do not always agree. Second, our machine learning algorithm produces a noisy slant prediction. We deal with the latter source of noise by limiting our variance decomposition to our dataset of labeled articles, and we deal with the former source of noise by leveraging the fact that we have two independent labels per article and by employing a measurement-error-correction technique. The details of the variance decomposition are provided in Appendix D. Conceptually, our measurement-error-correction technique is similar to the standard procedure that estimates the variance of an underlying latent variable by considering the covariance of two independent but noisy draws of that variable.

Our variance decomposition shows that outlet differences account for only 33% of the variance in article-level slant. In other words, ignoring within-outlet variation in slant induces one to miss 67% of the overall variation in article-level slant —that is, all the variation that occurs *within outlets*.

Our variance decomposition has two main implications: first, it emphasizes the importance of considering slant at the article level. Second, it shows that there are ample opportunities for ideological sorting within outlets.

5.2 Overall Distribution of Slant

Figure 3 presents the overall slant distribution of the ∼1 million hard news articles published online by the 100 most-visited U.S. news outlets in 2019. The distribution of slant on the production side is unimodal and centered around moderate values. Notably, 40% of all articles have a slant of zero, classifying them as centrist. Among the remaining articles, 68% are left-leaning, meaning left-leaning articles are around twice as common as right-leaning ones.[24] When comparing slant intensity, however, right-leaning articles are on average more extreme. In fact, the share of extreme right-leaning articles, defined as articles with a slant of 2 and above, among all article in our data is 7%, while the share of extreme left-learning, defined as articles with a slant of -2 and below, is only 3%.

Figure J.1 presents the distribution of slant for each outlet and shows that there is a clear asymmetry in how news outlets produce left- and right-leaning content. Only 1 outlet produces articles among which the majority is extremely left-leaning, whereas a considerably larger number of 6 outlets predominantly generate extremely right-leaning articles. These patterns dovetail with findings from the literature that point to the presence of a small segment of the news ecosystem that caters almost exclusively to conservatives (González-Bailón et al., 2023; Guess, 2021).

5.3 Distribution of Slant by News Category and Topic

Next, we analyze how slant varies by news category and topic. This analysis compares opinion versus non-opinion pieces, local versus national versus international news, and slant differences across various topics. We use GPT-4o to extract these characteristics—see Appendix C for details.

[24]The independent ratings by AdFontes Media described in Section 4.4 support these findings. Specifically, our model's 0-centrist designation closely matches AdFontes: for articles rated 0 by our model that also have AdFontes ratings, the average AdFontes rating is -0.11 (after we re-scale their scale to -2.5 to 2.5 with 0 unchanged), indicating these articles are indeed likely to be centrist. Moreover, among articles with AdFontes ratings, both slant measures broadly agree on the fraction that are left-leaning, moderate, and right-leaning.

Opinion vs. Non-Opinion The large language model classifies 23% of articles as opinion pieces. We find that opinion pieces are significantly more slanted than non-opinion articles. Specifically, 43% of opinion articles have an absolute slant of 2 or more on our scale, compared to only 2% of non-opinion pieces. As illustrated in Figure A.2, the distribution of slant in non-opinion articles is unimodal and centered around moderate values, with relatively thin tails on both sides. In contrast, opinion pieces exhibit a strongly bimodal distribution, with peaks at both ends of the slant spectrum, indicating a tendency towards more extreme positions.

The small share of moderate opinion pieces is consistent with arguments on the decline of moderates in US politics, both among political elites and engaged citizens (Abramowitz, 2010). Moreover, our finding that opinion pieces are particularly slanted, together with results from the literature showing that news consumers often trust opinion pieces as sources of fact (Bursztyn et al., 2023), suggest that opinion pieces might be an important contributor to political polarization among the news-reading electorate.

National vs. Local vs. International News Figure A.3 presents clear differences across the three news categories of articles and shows that national news is substantially more slanted than international and local news. When we limit our analysis to national news, the media landscape no longer appears to be primarily moderate, as a majority of articles have an absolute slant of at least 1 on our scale. Furthermore, 18% of national news articles have an absolute slant of 2 or more, whereas only approximately 3% of local and international news do. Interestingly, when focusing only on national news, we still observe more left-leaning than right-leaning articles and more extreme right-leaning than extreme left-leaning articles.

The discrepancy in slant across national, local, and international news can partly be explained by the fact that national news tends to cover relatively more contentious topics. For instance, 40% of international news articles cover international conflicts. Since in 2019 the U.S. was not directly involved in many of those conflicts, articles covering them tend to feature more factual and neutral coverage, as shown below. Similarly, bipartisan topics such as drug abuse are primarily covered in local news, and such coverage once again tends to be relatively neutral.

Slant across News Topics Our last piece of analysis in this section investigates the distribution of slant across news topics. Appendix C provides a list of the news topics and descriptions thereof that we used when prompting GPT-4o to classify our articles into topics.

We begin our analysis by showing the degree to which various topics are over vs. under-represented among left-leaning articles relative to right-leaning articles.[25] We consider a topic as being over- (under-) represented among left-leaning articles if, among all left- and right-leaning articles about that topic, the proportion of left-leaning articles is higher (lower) than the proportion of left-leaning articles across our entire sample of left- and right-leaning articles. Figure 4 presents the results. Perhaps unsurprisingly, the most over-represented topic among left-leaning articles is the topic of Republican scandals, and the most under-represented topic is that of Democrat scandals. This result aligns with prior evidence at the outlet level (Puglisi and Snyder, 2011) and provides further validation for our slant measure. Besides scandals involving Republicans, the most over-represented topics among left-leaning articles include natural disasters, the environment, policing practices, housing, drugs, gender, race, and LGBTQ issues. Besides scandals involving Democrats, the most over-represented topics among right-leaning articles include technology, the economy, international conflicts, welfare, trade, national security, and innovation.

A lasso regression analysis of article slant on the unigrams and bigrams in the article titles provides evidence in line with the rest of our topic analysis. The results, depicted in Figure A.4, show that the most predictive unigrams for right-leaning articles are "dems", "aoc", "hillary", "democrats", "illegal", "socialism", "left", "china", and "beto", while those for left-leaning articles are "trump", "climate", "women", "lgbtq", "black", "globe", "pride", and "gay". These language-based signals map closely onto the topic-level findings, with right-leaning articles highlighting immigration and trade-related terms, and left-leaning articles emphasizing climate change, gender, race, and LGBTQ issues.[26]

Next, in order to obtain an indication of which topics are more contentious in terms of news coverage, we study the dispersion in slant across topics. Figure A.6, which displays the standard deviation of slant by topic, shows that cultural topics such as gender, LGBTQ issues, and race,

[25] For this analysis, we consider an article as being left-leaning if it has a slant below -0.5 and right-leaning if it has a slant above 0.5. We drop articles that are broadly moderate, namely articles with a slant between -0.5 and 0.5.

[26] To give a sense of the most slanted topics, overall, we show the mean absolute slant by topic in Figure A.5.

together with the topics of welfare, gun rights, the environment, and immigration have the most dispersion in coverage in terms of slant. Conversely, topics such as international conflicts, drugs, natural disasters, trade, and crime have the least dispersion in terms of slant.[27] Figure A.7 shows the full distribution of slant by topic.

6. News Consumption on Facebook

In the previous section, we provided a broad overview of the slant landscape of the hard news articles in our database. In this section, we first estimate the degree of polarization in news consumption on social media and then study the drivers of such polarization. The distribution of slant on the production side provides context for our polarization result and helps us describe the mechanisms driving it.

6.1 Polarization in News Consumption on Social Media

Construction of the Polarization Measure In order to study the degree to which news consumption on social media is polarized, we introduce a new measure of polarization in news consumption. Our measure, denoted by $\mathscr{P}(\overline{S_R}, \overline{S_D})$, calculates polarization based on the difference in click-weighted average slant between Republican and Democrat Facebook users, normalized to range between -1 and 1. The measure is constructed using the following formula:

$$\mathscr{P}(\overline{S_R}, \overline{S_D}) = \frac{\overline{S_R} - \overline{S_D}}{5} \tag{1}$$

where $\overline{S_j}$ represents the click-weighted average slant for users registered with party $j \in$ {D,R} and where D stands for Democratic and R for Republican party. To interpret the measure on a standardized scale from -1 to 1, we normalize it by dividing it by the maximum possible distance (five points) on our scale.[28]

[27]The topic of policing practices also has a relatively low degree of dispersion in slant. We note that our dataset pre-dates the death of George Floyd in May 2020, which sparked a series of protests about police brutality throughout the U.S.

[28]Recall that, in order to have a sufficient number of articles in each bucket to perform our analysis, we merge slant

We believe our measure has three desirable features that make it an important complement to other measures developed in the literature, such as measures of segregation and favorability. First, and foremost, our measure takes into account both the ideology of a user and the slant of the news articles that the user consumes. This allows us to study whether, indeed, Democrat users tend to consume left-leaning articles and Republican users right-leaning articles.

Second, our measure is straightforward to interpret: a value of 1 indicates extreme pro-attitudinal news consumption, a value of 0 means both groups consume news with an identical slant, and a value of -1 indicates extreme counter-attitudinal news consumption.

Third, our measure allows for an easily interpretable comparison between article-level and outlet-level polarization. Specifically, as shown in an example in Appendix H, a comparison of our polarization index calculated at the article level (henceforth, article-level polarization) and the index calculated at the outlet level (henceforth, outlet-level polarization) reveals the following intuitive results. Article-level polarization is strictly larger (smaller) than outlet-level polarization if and only if individuals engage in pro-attitudinal (counter-attitudinal) news consumption within outlets. Polarization at both levels is equal if and only if individuals select articles within outlets without regard to their political slant, as would occur if users consumed random articles from within each outlet.

Many of the standard measures in the literature (e.g., measures of segregation) lack these features. First, measures of segregation rely solely on consumption patterns; they do not feature an independent measure of the slant of the content consumed. Thus, they measure whether Democrats and Republicans consume different articles, but not whether they consume articles with a different slant. Second, the interpretation of segregation measures is arguably less intuitive. For instance, segregation measures can reach their maximum even when Democrats and Republicans consume counter-attitudinal rather than pro-attitudinal news. Lastly, segregation measures suffer from a small-sample bias, as discussed in Gentzkow, Shapiro and Taddy (2019) and as shown in the illustrative example comparing segregation at the outlet and article levels analyzed in Appendix H.[29] A more detailed analysis of the theoretical and empirical differences between our polarization mea-

bucket -3 with slant bucket -2.5 and slant bucket 3 with slant bucket 2.5. As a result, our effective scale ranges from -2.5 to 2.5.

[29]The small-sample bias is unlikely to be relevant for a dataset as large as the URL-level Facebook Activity Dataset, but it could be relevant, for instance, for datasets of browsing behavior containing a relatively small set of users.

sure and measures of segregation and favorability is presented in Appendix H.

Headline Polarization Results Using our novel article-level measure of slant, we estimate that, in 2019, the degree of polarization in news consumption on Facebook was 0.17 (see Table 1). This measure of polarization employs, as a definition of partisanship, being a registered Democrat or a registered Republican, and it is estimated as described in Appendix F.

The next few paragraphs provide a series of benchmarks showing that our preferred estimate of polarization in news consumption on Facebook is arguably high. Our first benchmark compares the difference in click-weighted average slant between Republican and Democrat users (i.e., the numerator in Equation 1) to the standard deviation in the overall database of news articles. The mean difference in the slant of articles clicked on by Republican and Democrat users is 0.84. The standard deviation in our overall database of news articles is 0.99. Therefore, the mean difference in slant for articles clicked on by Republican and Democrat users is 0.85 standard deviation units.

Another benchmark for our polarization measure compares the slant difference in articles consumed by Republicans and Democrats on Facebook to the difference between the average slant of articles from ideologically contrasting outlets. We find that the slant difference between the average news articles consumed by Republicans and Democrats on Facebook equals the distance in slant between the average article from the Washington Times and the average article from the Washington Post (where the Washington Post and The Washington Times rank at the 11th and 82nd percentile of the overall distribution in slant across our outlets, respectively).

For additional context, we can compare the slant difference in articles clicked on by Republicans and Democrats on Facebook to the average slant difference between articles written by different New York Times columnists. For instance, we find that the slant difference in news consumption on Facebook between Democrats and Republicans is comparable to the slant difference between the average article written by liberal columnist Nicholas Kristof and by moderate/conservative columnist David Brooks.

Our final benchmark compares the distance in slant between articles consumed by Republicans and Democrats on Facebook to the slant difference between articles shared by various politicians on Twitter (now ”X”). We find that the slant distance in our analysis is slightly smaller than the average distance between articles shared by Democratic Senator Chuck Schumer and those shared by Republican Senator Marco Rubio.

As discussed, our headline measure of polarization employs, as a definition of partisanship, being a registered Democrat or a registered Republican. If we were to directly use the political affinity score from the URL-level Facebook Activity Dataset as a measure of partisanship, we would obtain a measure of polarization of 0.29 (see Table A.3). The higher level of polarization obtained using the political affinity scores, as opposed to our estimates of party registration, is in line with the observation in Appendix F that the political affinity score in the URL-level Facebook Activity Dataset is likely to pick out individuals with particularly strong partisan leanings. In light of the above, our preferred estimate of polarization in news consumption is the former, namely the one employing the more standard definition of partisanship based on party registration. Section 7.3 shows that, when we estimate polarization in news consumption based on an independent dataset of browsing behavior where partisanship is defined according to party registration records, we obtain an estimate of 0.16—a number that is almost identical to our preferred estimate.

6.2 Mechanisms

What drives the high degree of polarization in news consumption on social media? In this section, we address four key mechanisms. First, we study the degree to which polarization in news consumption on Facebook is driven by the selection of ideologically congenial articles within outlets. Second, we analyze the extent to which polarization in news consumption is driven by the articles that users are exposed to on their feeds versus the articles they select conditional on the ones they are exposed to. Third, we examine how the distribution of articles that circulate widely on social media differs from the distribution of slant on the production side. Fourth, we perform a back-of-the-envelope calculation to estimate, under a host of assumptions, the degree to which echo chambers are responsible for polarized news exposure and consumption on Facebook.

6.2.1 Within vs. Across Outlets

In order to study the degree to which polarization in news consumption on Facebook is driven by the selection of ideologically congenial articles within outlets, we proceed in two steps. First, we provide direct evidence that Facebook users with a political affinity score consume pro-attitudinal news within outlets. Second, we study the extent to which shutting down the channel of pro-attitudinal news consumption within outlets affects our preferred measure of polarization.

Figure 5 focuses on the top 20 outlets in terms of online visits and shows that, even within an outlet, the average article consumed by users with a liberal political affinity score is virtually always more left-leaning than the average article consumed by users with a conservative political affinity score. Table J.1 presents statistics about the slant of the average article consumed by users with a liberal and a conservative political affinity for each outlet in our dataset. The pattern is similar: partisans tend to consume pro-attitudinal content even within outlets.

In order to study how polarization in news consumption changes when we shut down the channel of pro-attitudinal news consumption within outlets, we re-calculate our polarization index after assigning to each article a measure of slant that equals the average slant of the outlet that the article came from. This exercise mimics the results one would obtain if, in line with much of the literature, one were to carry out the analysis of polarization in news consumption on Facebook at the outlet level rather than at the article level.

When we shut down the channel of pro-attitudinal news consumption within outlets as described above, we obtain a measure of polarization in news consumption of 0.11.[30] In contrast, as shown in Section 6.1, when we allow for the selection of ideologically congenial articles within outlets, we obtain a measure of polarization of 0.17. Thus, the estimate of polarization in news consumption on Facebook increases by 55% when the channel of pro-attitudinal news consumption within outlets is taken into account. Figure A.8 shows that this gap is similar or larger when, instead of focusing on news consumed, we focus on the articles individuals viewed or shared. These results are in line with our initial intuition that the curation process on social media, which operates at the level of individual news articles, promotes substantive pro-attitudinal news consumption within outlets.

[30]As in our preferred measure of polarization from the previous section, this measure employs, as a definition of partisanship, being a registered Democrat or a registered Republican. If we were to consider a measure of polarization in news consumption based directly on the political affinity score, we would obtain a similar result in terms of the fraction by which polarization in news consumption is underestimated when the channel of pro-attitudinal news consumption within outlets is shut down.

6.2.2 Selection vs. Exposure

Our measure of polarization in news consumption on social media can be decomposed into two factors: exposure and selection conditional on exposure. Exposure refers to articles that appear on partisans' feeds; selection conditional on exposure refers to the way in which partisans select which articles to click on and read among the articles that appear on their feeds. In this section, we show that the lion's share of polarization in news consumption can be accounted for by differential *exposure* to slanted articles.[31]

We find that the polarization in news exposure on Facebook is 0.14. Thus, exposure alone can account for 82% of the degree of polarization in news consumption on Facebook. In other words, if Democrats and Republicans on Facebook clicked randomly among the articles that appear in their feeds, rather than actively selecting articles among the ones that appear in their feeds, polarization in news consumption would be only 18% smaller than it currently is.[32,33,34]

6.2.3 Production vs. Distribution

How does the distribution of slant from the top 100 U.S. outlets in 2019 translate to the social media ecosystem? The Facebook environment need not reflect the distribution of slant on the production side for three main reasons. First, the homophilous network structure on social media, together with pro-attitudinal sharing patterns by Democrats and Republicans, can generate *echo chambers* in which partisans are primarily exposed to and consume ideologically congenial news (Sunstein, 2018). Second, personalized ranking algorithms might produce *filter bubbles* that promote pro-attitudinal content (Pariser, 2011). Third, social media platforms offer ample scope for individuals to customize their feeds (Negroponte, 1995). In this section, we analyze various ways in which

[31] We measure the degree of exposure to a particular news article using the number of times the article was viewed on Facebook.

[32] As in our preferred measure of polarization from Section 6.1, this measure employs, as a definition of partisanship, being a registered Democrat or a registered Republican. If we were to consider a measure of polarization in news consumption based directly on the political affinity score, we would obtain a similar result in terms of the percent of polarization in news consumption that is explained by exposure and by selection conditional on exposure.

[33] Of course, our analysis is in "partial equilibrium." A "general equilibrium" analysis would take into account the feedback patterns that exist between exposure, consumption, and sharing behavior.

[34] Consistent with our findings for news consumption, we also find strong pro-attitudinal news exposure within outlet, as depicted in Figure A.9.

the distribution of slant in the Facebook ecosystem differs from the distribution of slant on the production side, as well as the drivers of such differences.

Slant of the Articles Circulating on Facebook We begin by analyzing, as a function of an article's slant, the probability that the article is shared publicly on Facebook more than 100 times. This definition corresponds to the criterion used by Meta for including an article in the URL-level Facebook Activity Dataset. We measure this outcome using an indicator that equals one if a given article from our database of articles appears in the URL-level Facebook Activity Dataset and zero otherwise.

Figure 6 shows the probability that an article from our database appears in the URL-level Facebook Activity Dataset as a function of the article's slant. We find a stark V-shaped pattern: the more extreme the article, the higher the probability that it gets shared on Facebook more than 100 times. The difference in the likelihood of getting shared more than 100 times across slant categories can be substantial. For instance, centrist articles with a slant of 0 have an 11% chance of being widely shared on Facebook, whereas extreme articles with an absolute slant of 2 or more have an over 39% chance of being widely shared on the platform. Thus, extreme articles are approximately 4 times more likely to be publicly shared on Facebook at least 100 times. We note that this analysis includes virtually all hard news articles published online by major outlets in 2019, thus arguably offering the most comprehensive picture to date of the relationship between slant and sharing behavior on Facebook.

In light of the sharing patterns documented above, the distribution of slant of the articles that are shared on Facebook at least 100 times is quite different from the distribution of slant on the production side. Figure A.10 overlays the two distributions and shows how the distribution of slant of the articles that are shared on Facebook at least 100 times has much thicker tails than the distribution of slant on the production side. In fact, comparing the variance of the two distributions, we see that the variance of the former is 60% higher than the variance of the latter.

Over-representation of slanted news types and topics on Facebook In Section 5, we showed that opinion pieces, national news, and articles about certain topics are particularly slanted. Here we show that articles with those characteristics are much more likely to be shared on Facebook at least 100 times.

Figure A.11 shows that contentious topics (i.e., topics with a relatively high standard deviation in slant on the production side) tend to also be over-represented among widely shared articles on Facebook. Figure A.12 shows that, compared to the production side, both national news and opinion pieces are over-represented among the articles shared on Facebook at least 100 times by a factor of at least 41%.

Pro-attitudinal sharing patterns What role do pro-attitudinal sharing patterns by liberals and conservatives play in promoting the circulation of slanted articles on Facebook? For this exercise, we limit our attention to articles in the URL-level Facebook Activity Dataset; i.e. articles publicly shared on Facebook at least 100 times. Figure 7 shows the distribution of the number of shares per article, separately for individuals with liberal and conservative political affinity scores, as a function of an article's slant. The figure depicts striking differences in sharing behavior: liberals share left-leaning content around three times more often than moderate content and almost never share right-leaning articles. Conservatives display the mirror image of this behavior: they primarily share right-leaning content, and they almost never share left-leaning articles.[35]

Appendix Figure A.15 presents the same analysis separately for articles that users clicked on before sharing and articles that users shared without first clicking on them. We do not find dramatic differences between the two figures, suggesting that reading an article does not increase or decrease the tendency to share pro-attitudinal news.

Appendix Table A.5 shows that the sharing patterns of opinion articles on Facebook are substantially more pro-attitudinal than the sharing patterns for non-opinion articles. Specifically, the sharing patterns of opinion articles on Facebook are 2.6 times more polarized than those of non-opinion articles.

[35]Appendix Figure A.13 shows the same figure after residualizing for outlet fixed effects. Compared to the unresidualized version, the distributions of shares by liberal and conservative users do move closer together, indicating that outlets play a role in explaining the differential sharing patterns among liberals and conservatives. However, even after residualizing on outlet fixed effects, the distribution of shares by liberals is markedly to the left of that by conservatives, showcasing, again, the important role of within-outlet differences in sharing behavior across the political spectrum. Figure A.14, which shows stark within-outlet differences in the mean slant of articles shared by Facebook users with conservative vs. liberal political affinity, further underscores this point.

In the next section, we show how our finding that both liberals and conservatives share pro-attitudinal articles much more frequently than counter-attitudinal ones can help us assess the degree to which polarized news exposure and consumption on social media is driven by echo chambers.

6.2.4 The Role of Echo Chambers

In order to assess the degree to which echo chambers can explain polarization in news exposure on Facebook, we perform a back-of-the-envelope calculation. Specifically, we estimate, under a set of assumptions described in Appendix G, a lower bound on the amount of polarization in news exposure on Facebook that would prevail if users' feeds were only shaped by their friend networks and by the content shared by those friends. By doing so, we mechanically shut down other channels that shape users' feeds such as the personalized content-ranking algorithm and the users' own customization decisions. We then compare the amount of polarization in news exposure obtained in the first step to the actual amount of polarization in news exposure on Facebook estimated in Section 6.2.2. For simplicity, we employ, throughout this section, the polarization measure based on political affinity scores from the Facebook URL-level Activity Dataset, rather than party registration.[36]

Echo chambers in news consumption can be thought of as arising from the interaction of two distinct features of the social media environment: i) the relatively high degree of political homophily of social media networks, and ii) pro-attitudinal sharing patterns by partisans. When both features are simultaneously present, users share pro-attitudinal content in groups of like-minded individuals, thus giving rise to echo chambers. In Section 6.2.3, we documented strong pro-attitudinal sharing patterns by Facebook users. The remaining ingredient to estimate the role of echo chambers is information about the degree of political homophily of the Facebook network.

There are various measures of network homophily (Jackson, 2008). For the purpose of our analysis, we rely on the following six statistics: the fraction of friends of liberal users who are liberal ($x_{\{lib \leftarrow lib\}}$), conservative ($x_{\{lib \leftarrow con\}}$), and moderate ($x_{\{lib \leftarrow mod\}}$), and the fraction of friends of conservative users who are liberal ($x_{\{con \leftarrow lib\}}$), conservative ($x_{\{con \leftarrow con\}}$), and moderate ($x_{\{con \leftarrow mod\}}$).

[36] Using the polarization measure based on party registration would have required to impose two sets of assumptions: one for translating polarization based on political affinity scores into polarization based on party registration as described in Appendix F, and another for estimating the role of echo chambers as described in Appendix G.

As shown in Appendix G, these statistics allow us to estimate a lower bound on the degree of polarization in news exposure that would obtain if users' feeds were only shaped by the structure of the Facebook network and by the articles shared by their friends.

Formally, we calculate:

$$\hat{\mathscr{P}}^{echo}_{exposure}(\bar{y}_{lib},\bar{y}_{con},\bar{y}_{mod},x_{\{lib\leftarrow lib\}},x_{\{lib\leftarrow con\}},x_{\{lib\leftarrow mod\}},x_{\{con\leftarrow lib\}},x_{\{con\leftarrow con\}},x_{\{con\leftarrow mod\}}) =$$

$$= \frac{1}{5}\{[\bar{y}_{lib}\cdot x_{\{con\leftarrow lib\}}+\bar{y}_{con}\cdot x_{\{con\leftarrow con\}}+\bar{y}_{mod}\cdot x_{\{con\leftarrow mod\}}]-$$

$$[\bar{y}_{lib}\cdot x_{\{lib\leftarrow lib\}}+\bar{y}_{con}\cdot x_{\{lib\leftarrow con\}}+\bar{y}_{mod}\cdot x_{\{lib\leftarrow mod\}}]\}$$

where $\bar{y}_{lib}$ denotes the average slant of articles shared by users with a liberal political affinity score, $\bar{y}_{con}$ denotes the average slant of articles shared by users with a conservative political affinity score, and $\bar{y}_{mod}$ denotes the average slant of articles shared by users with a moderate political affinity score. The first (second) part of the numerator in the expression above is a proxy for the average slant that conservative (liberal) Facebook users would be exposed to if their feed was governed solely by the sharing behaviors of their friends. Taking the difference between the first and second components and normalizing it by five yields a measure that is comparable to the actual degree of polarization in news exposure calculated using the political affinity scores as a measure of partisanship.

When calculating the expression above, we plug in the measures of $\bar{y}_{lib}$, $\bar{y}_{con}$, $\bar{y}_{mod}$ that we obtained from the sharing patterns documented in Section 6.2.3. Furthermore, we rely on data from Bakshy, Messing and Adamic (2015) in order to obtain estimates for $x_{\{a\leftarrow b\}}$ where $a,b \in \{lib,\ mod,\ con\}$.

Following this approach, we conclude that the amount of polarization in news exposure that would result from echo chambers alone is at least 59% of the actual degree of polarization in news exposure calculated using the political affinity scores as a measure of partisanship.

7. Extensions and Robustness

7.1 Comparison of Social Media to Other Sources of Online News Consumption

This section investigates whether the news consumed via Facebook exhibits greater ideological polarization compared to news accessed through other online sources. Using detailed individual-level browsing history data on a panel of 1,637 registered Democrats and Republicans, we analyze the slant of news articles consumed by panel members, comparing instances where the referrer to the article was Facebook versus other online sources.

To conduct this analysis, we regress the slant of a news article consumed by an individual on a dummy variable indicating whether Facebook was the referrer, a dummy for party registration status (Republican vs. Democrat), and their interaction, while including individual fixed effects to isolate within-person variation. The results, shown in column 2 of Table A.6, reveal that Facebook amplifies polarization in news consumption: the gap in slant between articles consumed by Republicans and Democrats is 0.13 units larger for articles accessed through Facebook compared to those not accessed through Facebook—corresponding to an increase in the polarization index of 0.03 units, or 16% relative to the mean. Column 3 shows that this effect is not unique to Facebook and generally social media amplified polarization in news consumption. This finding suggests that the algorithmic curation and mechanisms unique to social media exacerbate ideological sorting relative to the broader online ecosystem.

We next compare polarization in news consumption across the ten most common referrer types, by augmenting the above-mentioned regression through the inclusion of referrer-type dummies, as well as their interaction with an indicator for being a registered Republican. We present the results in Figure 8. We find that polarization is smallest for news accessed via news aggregators, followed by search engines; it is largest for other social media platforms (driven by Twitter, now "X") and Facebook, further underscoring the potential importance of social media platforms in amplifying polarization in news consumption. In terms of magnitudes, we find that news accessed via social media is 2.4 times more polarized than the news accessed via search engines.

7.2 Extending Results to Additional Outlets

Our main analysis focuses on the 100 most visited U.S. outlets that cover hard news. We limited our scope to these outlets because we perceived the marginal benefit of adding more outlets to be smaller than the marginal cost of additional data collection. As discussed in section Section 3, these top 100 outlets account for 93% of all online hard-news consumption in the U.S. according to Comscore data. Thus, they provide very extensive coverage. Nonetheless, it is natural to wonder as to how our estimate of polarization in news consumption on Facebook would change if we included more outlets.

To explore this, Figure A.16 extrapolates our results by extending the analysis to the top 200 U.S. outlets by online visits. Our extrapolation works as follows. First, we rank outlets by size (using Comscore data) and calculate our polarization measure for ever-increasing subsets of these outlets.[37] Based on the trend observed, we assume a logarithmic relationship between the number of outlets included in the subset and our polarization measure. The logarithmic extrapolation suggests that expanding to 200 outlets would lead to a 7% increase over our baseline polarization measure.

7.3 Robustness: Political Affinity Measure

In this section, we present a battery of robustness checks to address the limitations of the political affinity measure in the URL-level Facebook Activity Dataset. As discussed in Section 3, the political affinity measure in the URL-level Facebook Activity Dataset has three limitations: first, it does not directly track canonical indicators of partisanship such as party registration; second, it covers only 25% of adult Facebook users from the U.S.; third, it might suffer from a circularity problem, because a small set of news outlets is included in the set of political pages used in the construction of the measure.

Our first and main robustness check addresses all three problems at once. Specifically, it calculates polarization in news consumption on Facebook using our independent dataset of individual-level browsing behavior. This dataset includes a highly accurate measure of partisanship in the

[37] We begin by only considering the most visited U.S. outlet, and then progressively expand the subset to less visited outlets.

form of administrative records on panel members' party registration status. We restrict attention to the 1,637 individuals who are registered Democrats or registered Republicans. To facilitate comparability with our baseline polarization index measure, we further restrict attention to all clicks on hard news articles that i) appear in the URL-Level Facebook Activity Dataset and ii) for which the referrer is Facebook. We report results in column 1 of Table A.6. The table shows that news articles clicked on by registered Republicans are, on average, 0.81 units more right-slanted than those clicked on by registered Democrats. This difference gives rise to a polarization index of 0.16, which is almost identical to our preferred polarization estimate from the URL-level Facebook Activity Dataset. Thus, we replicate our headline result using a completely different dataset where partisanship is defined directly based on administrative voting records.

Our second robustness check aims to address the potential circularity in the political affinity variable from the URL-level Facebook Activity Dataset. Specifically, we recalculate our preferred estimate of polarization in news consumption after excluding all articles from the 18 outlets in our database that are also used in the construction of the political affinity variable. We report the results in Table A.7 and find a pattern of results virtually identical to the one described in Section 6.1. Furthermore, when omitting those 18 outlets, our measure of polarization in news consumption is 59% higher when the analysis is carried out at the article level rather than at the outlet level (see Table A.8).

Our third robustness check involves proxying a person's political ideology using her demographic characteristics. Specifically, the URL-level Facebook Activity Dataset contains engagement numbers by age bracket and gender. Based on representative survey data from the ANES 2020-2022 Social Media Study, we can determine, for each age-gender bucket, the difference in the share of the demographic group's members who identify as or lean Republican and the share who identify as or lean Democrat. Using that difference as a proxy for the ideological leaning of individuals in each age-gender bucket, we can then relate the average ideology in an age-gender bucket to the average slant that individuals in that bucket are exposed to and consume on Facebook. The results are shown in Figure A.17. In line with the results in previous sections, we find that, as we move towards age-gender buckets with relatively higher Republican vote shares, the average slant of the articles individuals in those buckets are exposed to, consume, and share on Facebook becomes more right-leaning according to our slant measure.

7.4 Robustness: Threshold in the URL-Level Facebook Activity Dataset

As discussed in Section 3.2, a limitation of the URL-level Facebook Activity Dataset is that it only includes articles shared publicly on Facebook at least 100 times (after adding Laplace-5 noise to the share counts). The polarization measure derived in Section 6.1 is based on the articles included in the URL-level Facebook Activity Dataset. Naturally, polarization of news exposure and consumption on social media might be different if one were to consider all the articles consumed on Facebook. In this section, we use our browsing panel data to extend our measure of polarization to all articles consumed on Facebook.

Using our browsing panel data, we can simply compute polarization in news consumption (that is, the scaled difference in the average slant of hard news articles consumed by registered Republicans and registered Democrats) for *all* hard news articles that panelists got referred to via Facebook. We find a polarization index of 0.15— a value that is only 5% smaller than the original estimate that restricts to articles included in the URL-Level Facebook Activity Dataset. The numbers are so similar because articles shared widely on Facebook are consumed much more often than those shared fewer than 100 times—the former account for 79% of all hard news article clicks through Facebook—thereby rendering the restriction to widely shared articles relatively innocuous.

Appendix I presents a separate extrapolation exercise on the URL-level Facebook Activity Dataset to address the limitation of only observing articles shared publicly on Facebook at least 100 times. The extrapolation exercise confirms the results of the robustness check from the previous paragraph: the limitation of only observing articles shared on Facebook at least 100 times seems to have a very small impact on our polarization estimates.

8. Conclusion

In this paper, we introduced a novel measure of article-level slant and used it to quantify the degree of polarization in news consumption on Facebook. Our guiding hypothesis was that, due to the way in which content is curated on social media platforms, an important driver of polarization in news consumption on social media is ideological sorting within outlets. Of course, this driver of polarization can only be captured by means of a measure of slant at the article level akin to the one that we develop. Consistent with our hypothesis, we find a much higher degree of polarization when employing our fine-grained article-level slant measure than we do when employing a coarser measure of outlet-level slant that mimics the approach taken by much of the literature.

Overall, this paper provides strong evidence that the news environment on social media is more polarized than previously thought. This insight is crucial for understanding the dynamics of political polarization in the digital age and for informing both academic inquiry and policy interventions aimed at fostering a more balanced and informed public discourse. Furthermore, this paper highlights the importance of using content-based article-level slant measures when studying today's fragmented media landscape.

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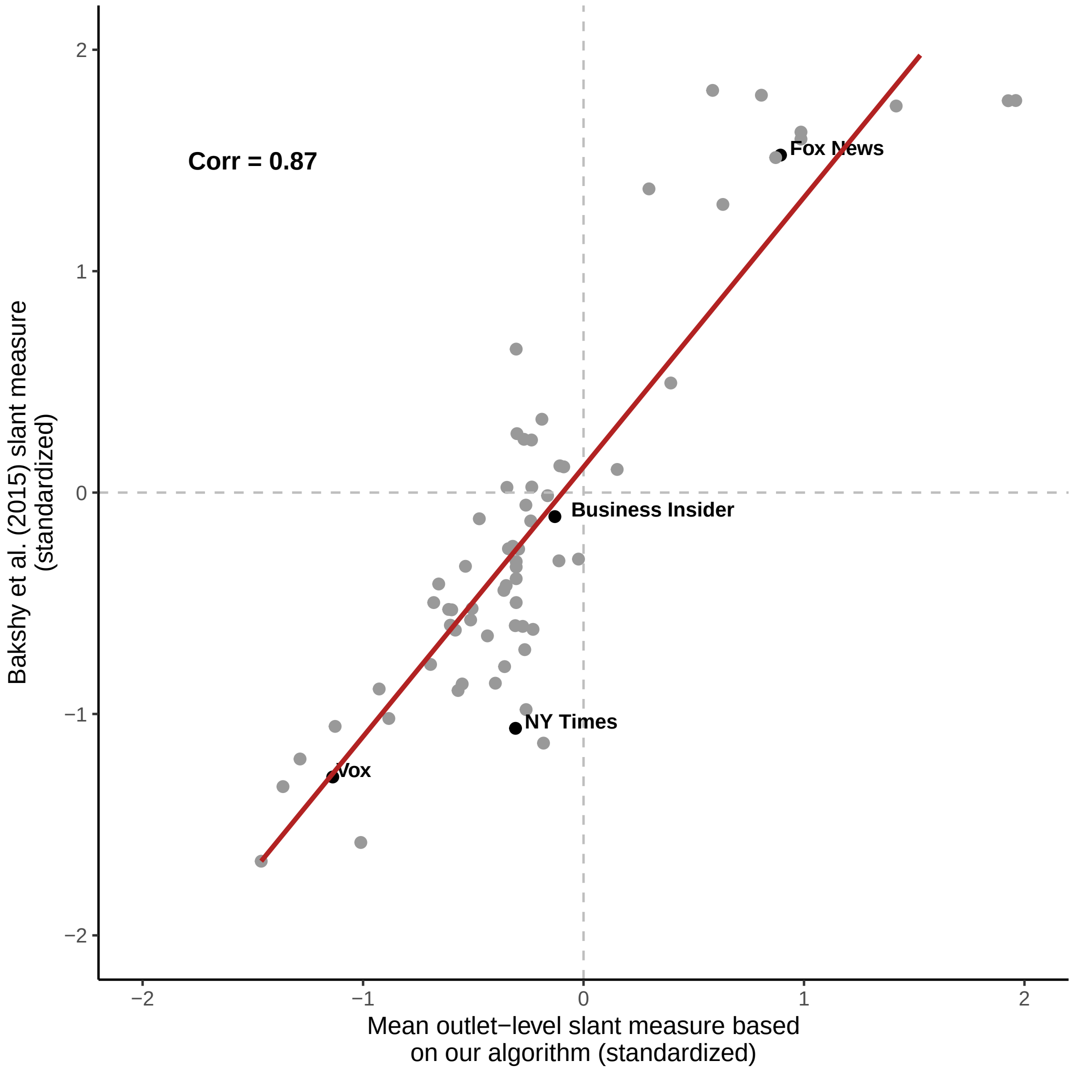
Tables and Figures

Table 1: Polarization in News Exposure, Consumption, and Circulation on Facebook

	Average Slant Reg. Democrats	Average Slant Reg. Republicans	Average Slant Difference	Polarization Index
Views	-0.57	0.13	0.69	0.14
Clicks	-0.57	0.26	0.84	0.17
Shares	-0.66	0.57	1.23	0.25

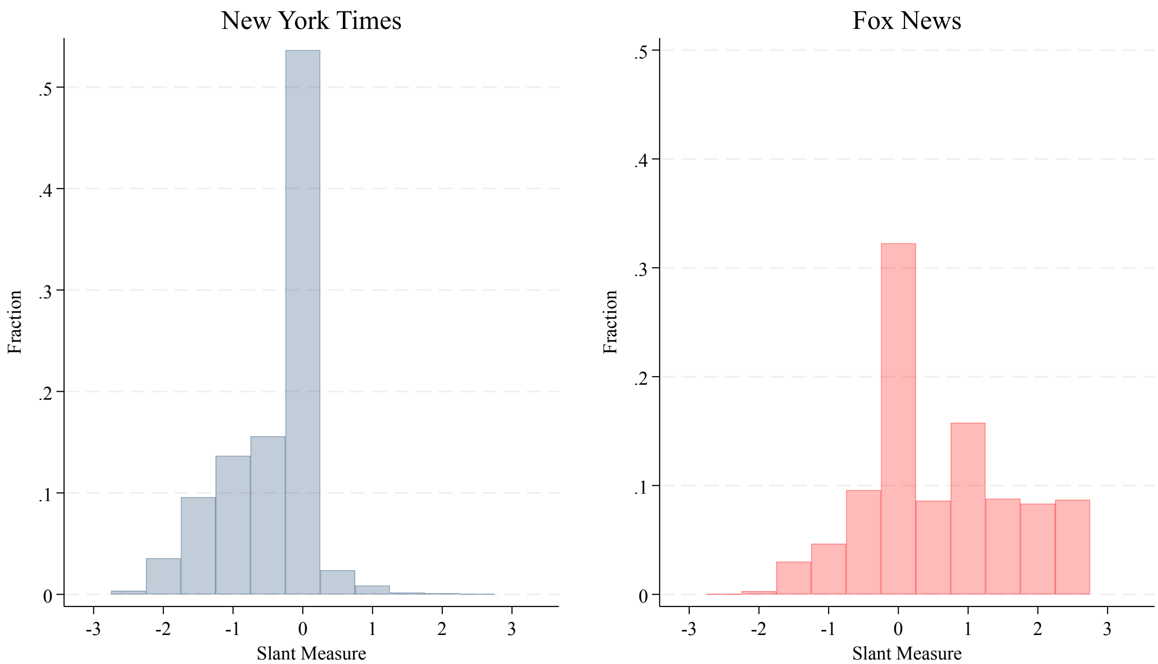
Notes: The first two columns of the table report the views/clicks/shares-weighted average slant of the news diets of registered Democrat and registered Republican Facebook users imputed according to the methodology described in Appendix F. The third column shows the difference between the first two columns. The last column normalizes the difference to be in the interval $[-1, 1]$, with -1 indicating extreme counter-attitudinal news consumption, 0 indicating no difference in average slant across the news consumed by Democrats and Republicans, and 1 indicating extreme pro-attitudinal news consumption. The news article sample includes all $N = 234,313$ hard news articles published online by the top 100 U.S. news outlets in 2019 that are in the URL-level Facebook Activity Dataset (i.e. shared at least 100 times on Facebook).

Figure 1: Comparison of Our Outlet-Level Measure with the one from Bakshy, Messing and Adamic (2015)



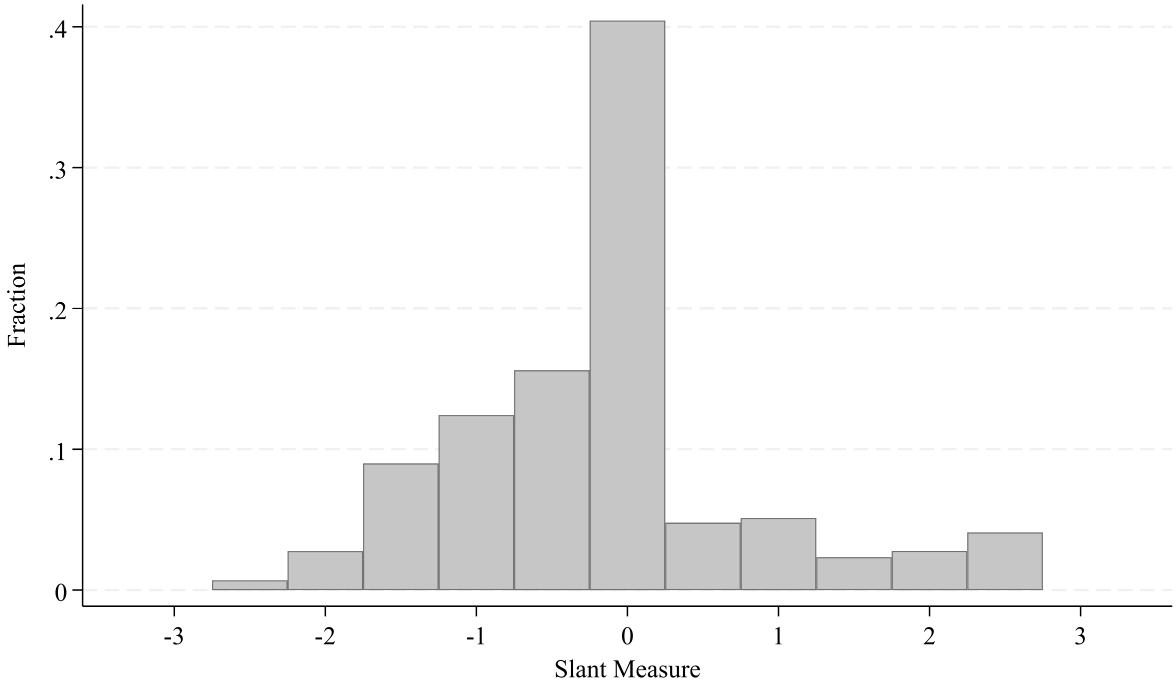
Notes: This figure presents our outlet-level slant measure on the horizontal axis, calculated as the average article-level slant across all articles published by an outlet (with article slant determined by the fine-tuned GPT-4o's predictions, as described in Section 4.2). The vertical axis represents an alternative outlet-level slant measure for the same set of outlets. Specifically, it uses the measure developed by Bakshy, Messing and Adamic (2015), which defines an outlet's slant in terms of 'alignment'—the extent to which an outlet's articles are predominantly shared by left- or right-leaning users on Facebook. The figure highlights a few well-known outlets.

Figure 2: Distribution of Slant: New York Times and Fox News



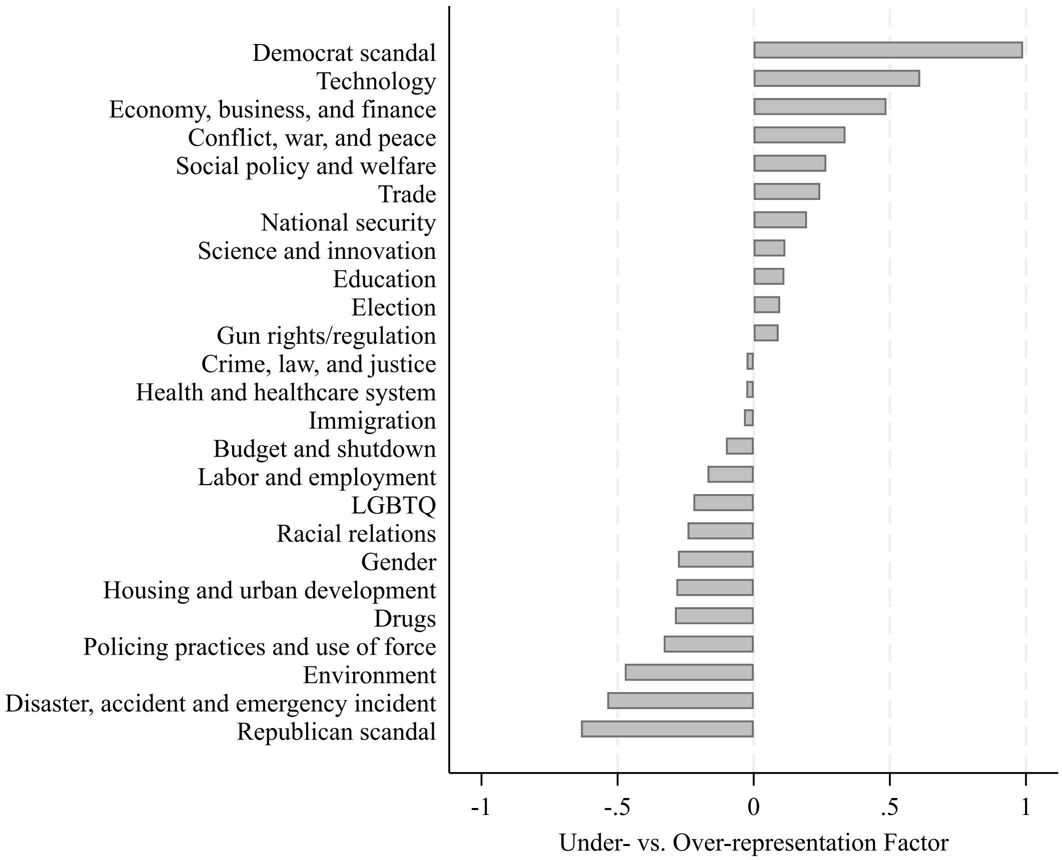
Notes: This figure shows the distribution of slant among all hard news articles ($N = 82,180$), published online by the New York Times and Fox News in 2019. Slant is given by the fine-tuned GPT-4o's prediction as described in Section 4.2. The slant scale goes from -2.5 (extremely favorable to the Democratic party) to 2.5 (extremely favorable to the Republican party).

Figure 3: Overall Distribution of Slant Across Articles



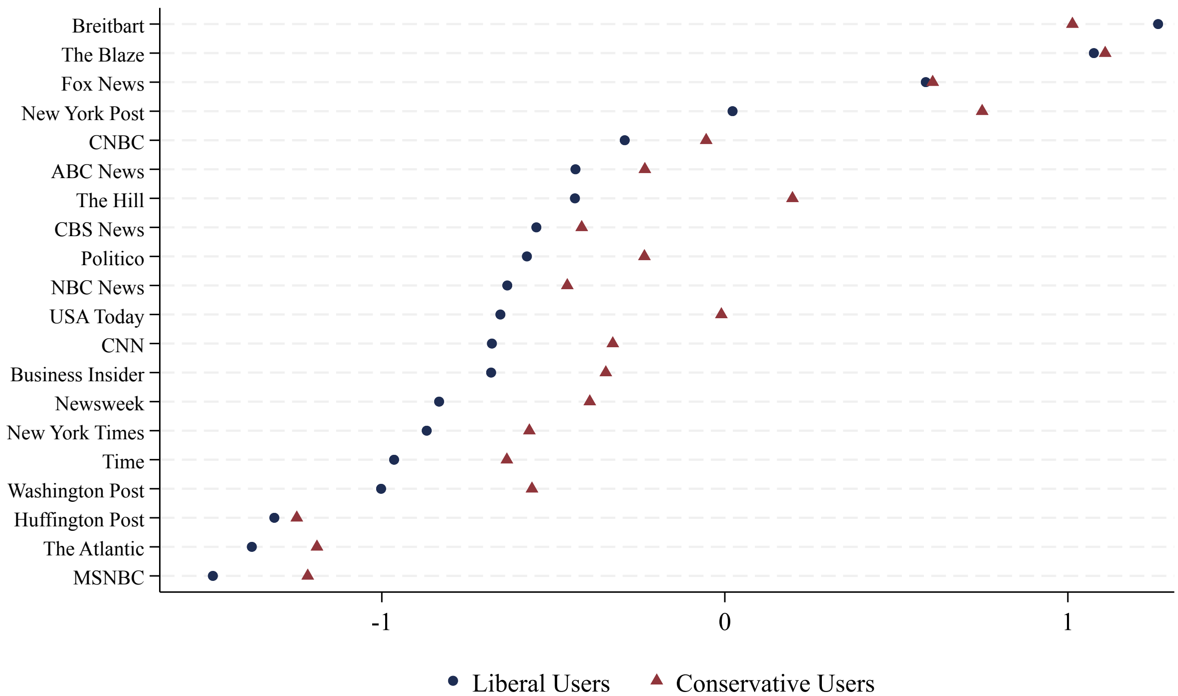
Notes: This figure shows the distribution of slant among all hard news articles ($N = 1,065,217$) published online by the top 100 U.S. news outlets in 2019. Slant is given by the fine-tuned GPT-4o's prediction as described in Section 4.2. The slant scale goes from -2.5 (extremely favorable to the Democratic party) to 2.5 (extremely favorable to the Republican party).

Figure 4: Over- vs. Under-Representation of Topics among Right-Leaning Articles



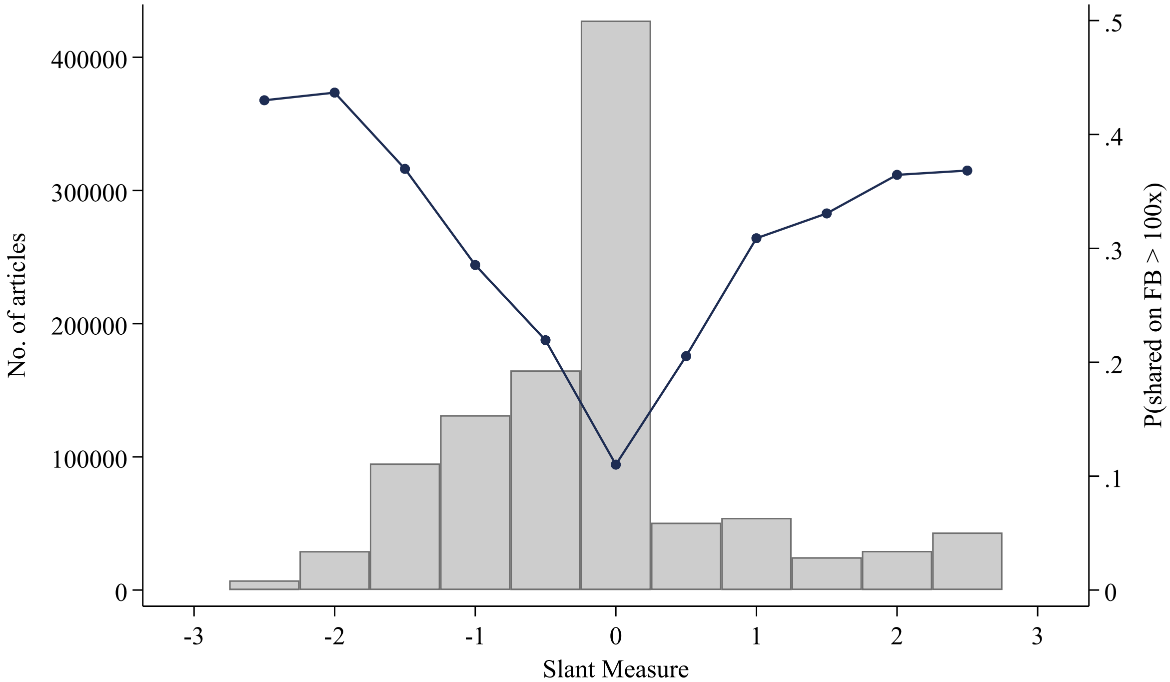
Notes: This figure shows the degree of over- vs. under-representation of topics among right-leaning articles. The figure is constructed as follows. First, all ”moderate” articles with a slant between -0.5 and 0.5 are dropped. Second, the remaining articles are defined as ”right-leaning” if they have a slant larger than 0.5 and ”left-leaning” otherwise. Third, we compute the fraction of right-leaning articles overall. Fourth, we compute the fraction of right-leaning articles for each topic. Fifth, we divide the fraction of right-leaning articles within a topic by the overall fraction of right-leaning articles and subtract one. The number we obtain—and that is plotted in the figure—is an estimate of the degree to which a particular topic is over- vs. under-represented among right-leaning articles.

Figure 5: Average Slant of Articles Clicked on Facebook by Outlet and User Political Affinity



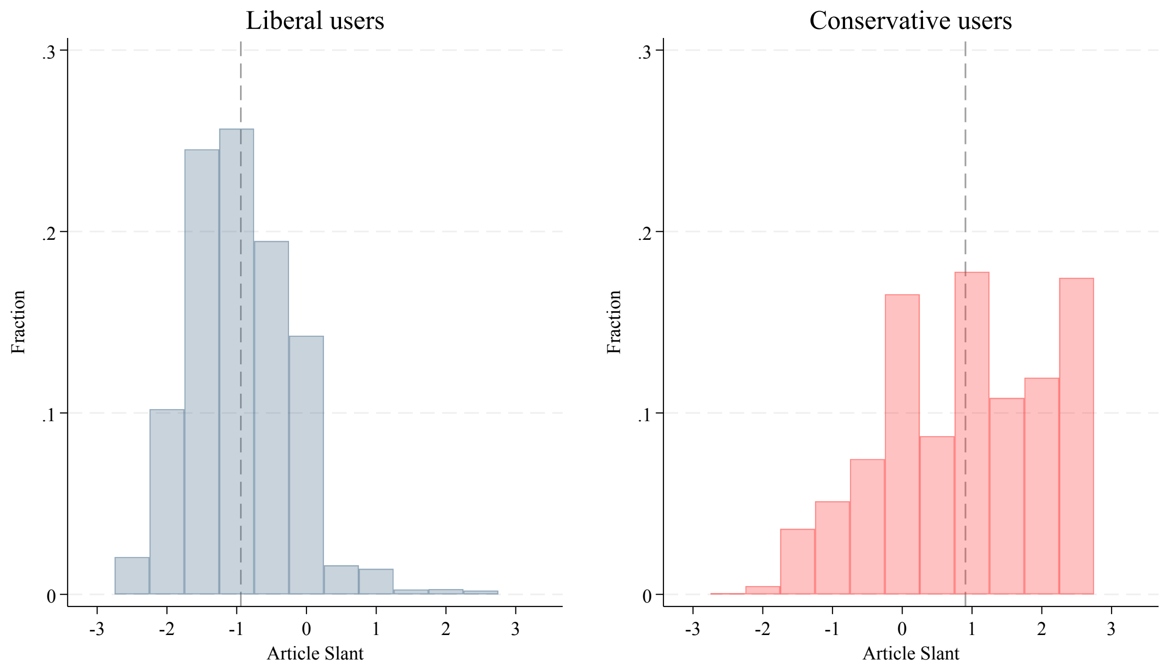
Notes: This figure shows the clicks-weighted average slant of articles by Facebook users' political affinity and outlet. The sample includes all hard news articles published online by the top 20 U.S. news outlets in 2019 that are in the URL-level Facebook Activity Dataset (i.e., articles shared at least 100 times on Facebook). Slant is given by the fine-tuned GPT-4o's prediction as described in Section 4.2. The slant scale goes from -2.5 (extremely favorable to the Democratic party) to 2.5 (extremely favorable to the Republican party).

Figure 6: Likelihood of Shared on Facebook > 100 Times by Article Slant



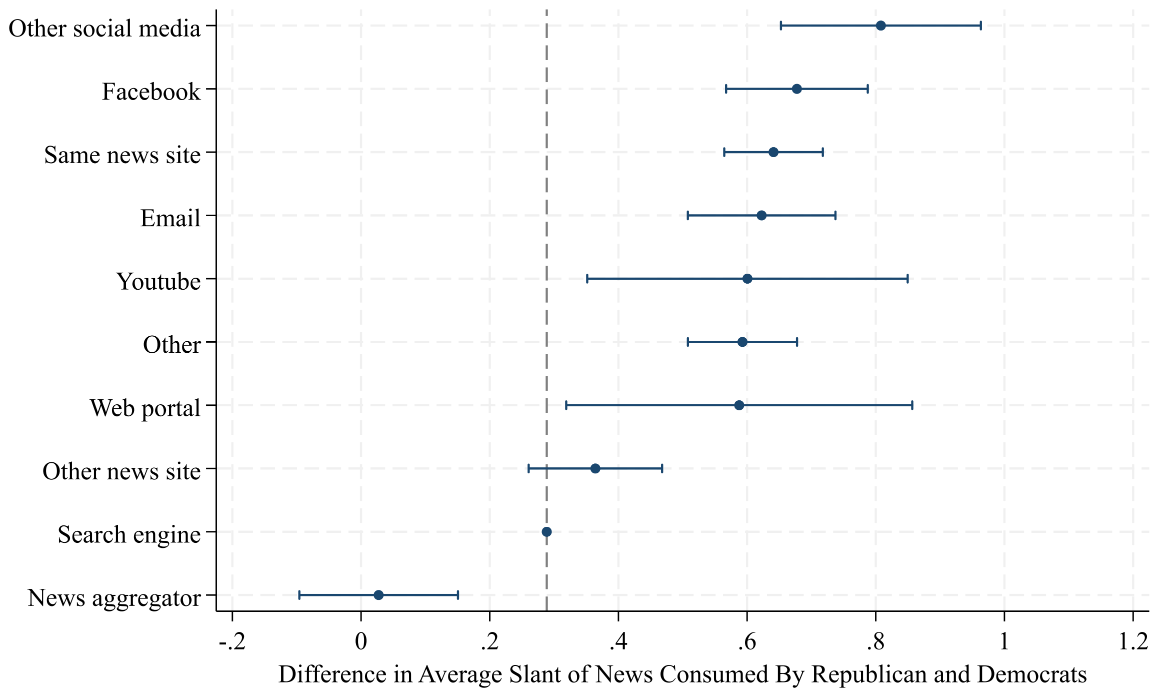
Notes: The gray bars in this figure show the distribution of slant among all hard news articles ($N = 1{,}065{,}217$) published online by the top 100 U.S. news outlets in 2019 (left y-axis). The blue line shows the fraction of articles in each bin that were shared at least 100 times on Facebook (right y-axis), as measured by whether they appear in the URL-level Facebook Activity Dataset. The sample includes all hard news articles ($N = 1{,}065{,}217$) published online by the top 100 U.S. news outlets in 2019. Slant is given by the fine-tuned GPT-4o's prediction as described in Section 4.2. The slant scale goes from -2.5 (extremely favorable to the Democratic party) to 2.5 (extremely favorable to the Republican party).

Figure 7: Empirical PDF of Facebook Shares by User Political Affinity and Article Slant



Notes: This figure shows the fraction of all shares by a given Facebook user political affinity group (liberal and conservative, respectively) that accrue to articles in a given slant bin. The dashed vertical line represents the mean of the distribution. The sample includes all $N = 234,313$ hard news articles published online by the top 100 U.S. news outlets in 2019 that are in the URL-level Facebook Activity Dataset (i.e., articles shared at least 100 times on Facebook). Slant is given by the fine-tuned GPT-4o's prediction as described in Section 4.2. The slant scale goes from -2.5 (extremely favorable to the Democratic party) to 2.5 (extremely favorable to the Republican party).

Figure 8: Differences in the Average Slant of News Diets by Party Registration Status and Referrer Type



Notes: This figure shows the results from a regression of the slant (on a scale from -2.5 to +2.5) of an individual article consumed by a browsing panelist on panelist fixed effects, as well as on dummies for different referrer origins, and their interaction with a dummy that equals one if the panelist is a registered Republican. The figure plots the estimates of the interaction coefficients, to which we add the mean difference in slant observed among registered Republicans and Democrats in the left-out category (search engine referrals). "Other social media" includes referrals from Twitter, Instagram, Pinterest, TikTok, LinkedIn, Snapchat, Reddit, Nextdoor, BeReal, and Tumblr. "Web portal" includes referrals from yahoo.com, msn.com and aol.com. "News aggregator" includes referrals from google news, yahoo news, drudgereport.com, newsbreakapp.com, smartnews.com, newser.com, and fark.com. 95% confidence bars are also plotted. The sample is restricted to all hard news article visits by registered Democrats and Republicans (1,637 individuals and 48,388 observations).

Appendix For Online Publication

Table of Contents

A. Additional Tables and Figures

Table A.1: Papers Estimating the Extent of Pro-attitudinal News Engagement

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Paper	Primary Estimand	Slant Measure	Primary Level of Analysis	Browsing Data	Social Media Data	Type of Social Media Content	Number of Articles or Outlets
Bakshy, Messing and Adamic (2015)	Ratio of clicks on counter-attitudinal vs. pro-attitudinal content	Audience-based	Outlet		U.S. Facebook users who self-report their ideology	Clicks, views, shares	500 news outlets
Flaxman, Goel and Rao (2016)	Standard deviation of average slant consumed across individuals	Audience-based	Outlet	Bing Toolbar sample	Bing Toolbar sample (only clicks referred from Facebook and Twitter)	Clicks	100 outlets
Gentzkow and Shapiro (2011)	Segregation	Audience-based	Outlet	Comscore sample		Clicks	1,379 outlets
González-Bailón et al. (2023)	Segregation	Audience-based	Article (social media) and outlet (browsing and social media)	U.S. 2020 Facebook and Instagram Election Study sample	Near universe of US Facebook users	Clicks, views, shares	$\sim$640,000 URLs
Green et al. (2023)	Correlation between predicted ideology and slant	Content-based	Article		Subset of Twitter's 10% Decahose sample	Shares	1000 URLs
Guess (2021)	Degree of overlap in the distributions of domains visited	Audience-based	Outlet	YouGov Pulse sample		Clicks	$\sim$500 news outlets
Levy (2021)	Segregation and standard deviation of average slant consumed across individuals	Audience-based	Outlet	Extension sample & Comscore sample	Extension sample	Clicks, views, shares	$\sim$500 news outlets
Nelson and Webster (2017)	Segregation	Audience-based	Outlet	Comscore sample		Clicks	72 outlets
Peterson, Goel and Iyengar (2021)	Segregation and standard deviation of average slant consumed across individuals	Audience-based	Outlet	Wakoopa Toolbar sample		Clicks	355 domains
Braghieri et al. (2025) [this paper]	Polarization (difference in mean slant consumed by Republicans and Democrats)	Content-based	Article	Luth sample	Universe of US Facebook users	Clicks, views, shares	$\sim$1 million hard-news articles of which $\sim$230,000 appear in the social media data

Notes: Column (2) describes the primary estimand used to determine the extent of pro-attitudinal news engagement (e.g., polarization, segregation). Column (3) describes how the slant of articles or domains is determined. Column (4) describes whether the analysis of pro-attitudinal engagement is measured at the outlet or the article level. Columns (5) and (6) describe the sources of data on browsing and social media behavior, respectively. Column (7) describes whether social media engagement is analyzed at the clicks, views, or shares level. Finally, column (8) presents the number of articles or domains used to compute the primary estimand. We define polarization as the difference in the mean slant consumed by registered Republicans and Democrats and define segregation as the difference between the share of Republican visits that go to outlets (or articles) predominantly visited by Republicans and the share of Republican visits that go to outlets (or articles) predominantly visited by Democrats (see Appendix F). Note that different papers in the literature refer to different measures by the same name and to the same measure by different names. For instance, although Flaxman, Goel and Rao (2016) refer to their measure as segregation, for the purposes of this paper we refer to it as standard deviation in consumption. We reserve the term segregation for the measure described in Appendix F. Similarly, Gentzkow and Shapiro (2011) refer to their measure as the isolation index, but González-Bailón et al. (2023) refer to it as the segregation index. In this paper, we refer to both as the segregation because they match the construction in F. The table only refers to measures and data used for the primary estimates (e.g., segregation or polarization). For example, Green et al. (2023) also study an audience-based measure of slant and analyze Facebook data, but this measure and data are not used to compute the principal estimand and, therefore, are not mentioned in the table. Similarly, Peterson, Goel and Iyengar (2021) also have a crowd-sourced content-based measure of slant but do not use this measure to compute the primary estimand.

Table A.2: Summary Statistics

	(1) All mean/sd	(2) Not in SS1 mean/sd	(3) In SS1 mean/sd
Opinion piece (binary)	0.23	0.21	0.30
	(0.42)	(0.41)	(0.46)
Slant	-0.14	-0.13	-0.20
	(0.99)	(0.90)	(1.25)
FB views (1000s)			219.33
			(767.08)
FB clicks (1000s)			9.32
			(33.17)
FB shares (1000s)			1.82
			(7.86)
N	1065217	830904	234313

Notes: This table reports summary statistics for all hard news articles published by the top 100 U.S. news outlets in column (1). See Appendix Figure J.1 for the full list of outlets. Column (2) shows summary statistics for the subset of articles not found in the URL-level Facebook Activity Dataset; column (3) shows summary statistics for the articles that do appear in the URL-level Facebook Activity Dataset (the dataset only includes articles shared publicly at least 100 times). The table reports means, as well as standard deviations in parentheses.

Table A.3: Engagement and Polarization in News Exposure, Consumption, and Circulation on Facebook by Political Affinity

Panel A: Engagement Based on Political Affinity

	Views		Clicks		Shares	
Political Affinity	Share(%)	Mean Slant	Share(%)	Mean Slant	Share(%)	Mean Slant
Liberal	36%	-0.81	38%	-0.85	47%	-0.94
Moderate	11%	-0.45	8%	-0.39	9%	-0.42
Conservative	25%	0.46	28%	0.59	32%	0.91
Unassigned	28%	-0.35	26%	-0.30	13%	-0.25

Panel B: Polarization Based on Political Affinity

	Views	Clicks	Shares
Average Slant Difference	1.27	1.45	1.85
Polarization Index	0.25	0.29	0.37

Notes: This table shows the summary statistics of all views, clicks, and shares in the Social Science One data based on users' political affinity. The table is based on the sample of $N = 234,313$ hard news articles published online by the top 100 U.S. news outlets in 2019 that are in the URL-level Facebook Activity Dataset (i.e. publicly shared on Facebook at least 100 times). Panel A presents two statistics for each user political affinity group and engagement type (views, clicks, shares): the share (%) of all hard news article engagements of a given engagement type that is accounted for by a given political affinity group (accordingly, columns sum to 100%), and the views-, clicks-, and shares-weighted average slant ("Mean Slant") of hard news article views, clicks, and shares, respectively, by user political affinity. Liberal, moderate and conservative users are defined as those with a political affinity score below 0, equal to 0 and above 0, respectively; those with missing political affinity scores are grouped into the category "Unassigned". Panel B reports, for each engagement type, the difference between the mean slant of news diets by liberal and conservative users on Facebook in the first row. The last row normalizes the difference by dividing it by 5, so that -1 indicates extreme counter-attitudinal news consumption, 0 indicates no difference in average slant across the news consumed by liberals and conservatives, and 1 indicates extreme pro-attitudinal news consumption. Slant is given by the fine-tuned GPT-4o's prediction as described in Section 4.2. The slant scale goes from -2.5 (extremely favorable to the Democratic party) to 2.5 (extremely favorable to the Republican party).

Table A.4: Most Clicked Liberal and Conservative Articles

Liberal	**Conservative**
I Wish I'd Had A 'Late-Term Abortion' Instead Of Having My Daughter*	When the villain is Obama, not Trump, news suddenly becomes not worth reporting*
Trump Is Not Well*	Mueller's report looks bad for Obama*
12 Times Ellen DeGeneres Perfectly Called People Out*	Obama Built The 'Cages' for Illegals, Not Trump, Says Obama ICE Chief
Georgia's abortion law imprisons women with miscarriages*	The speech they're trying to hide: President Trump's stellar UN speech*
25 Times White Actors Played People Of Color And No One Really Gave A S**t*	Hollywood Film Depicts Trump Supporters Being Hunted for Sport by Liberals*
A Stain on the Honor of the Navy*	CNN's Jim Acosta mocked for accidentally proving that border walls work
Should 11-year-old girls have to bear their rapists' babies? Ohio says yes.*	Trump's shutdown trap?*
I've Talked With Teenage Boys About Sexual Assault for 20 Years. This Is What They Still Don't Know	Donald Trump was elected to break the elite. Of course they want to impeach him*
15 Reasons Why Vaccinating Your Kids Is The Worst Thing You Can Do For Them	Rural Americans would be serfs if we abolished the Electoral College*
We should all be appalled by Donald Trump's tweet about Greta Thunberg*	Read Trump's Letter to Pelosi Protesting Impeachment*

Notes: This table lists the titles of the most clicked liberal and conservative articles with absolute slant of 2 or more, where we include up to two liberal and two conservative articles from each outlet. Articles marked with an asterisk (*) are opinion pieces. The sample covers all $N = 234,313$ hard news articles published online by the top-100 U.S. news outlets in 2019 that are in the URL-level Facebook Activity Dataset. Slant is given by the fine-tuned GPT-4o's prediction as described in Section 4.2. For clarification, the article titled "15 Reasons Why Vaccinating Your Kids is The Worst Thing You Can Do For Them" and listed in the "Liberal" column takes a fervent pro-vaccine stance and strongly relies on the rhetorical device of irony.

Table A.5: Polarization in News Exposure, Consumption, and Circulation on Facebook: Opinion vs. Non-Opinion Articles

	Average Slant Reg. Democrats	Average Slant Reg. Republicans	Average Slant Difference	Polarization Index
Panel A: Opinion pieces				
Views	-0.77	0.75	1.52	0.30
Clicks	-0.79	0.85	1.64	0.33
Shares	-0.93	1.39	2.33	0.47
Panel B: Non-opinion pieces				
Views	-0.52	-0.01	0.51	0.10
Clicks	-0.52	0.11	0.63	0.13
Shares	-0.60	0.29	0.89	0.18

Notes: This table shows the same statistics as in Table 1 for all opinion news articles ($N = 64,364$) published online in the top-100 most-read U.S. news outlets in 2019 that are in the URL-level Facebook Activity Dataset (i.e. shared at least 100 times on Facebook) in Panel A, and their non-opinion counterparts in Panel B. The classification into opinion articles is described in Appendix C.

Table A.6: Differences in the Slant of News Diets by Party Registration Status Among Browsing Panelists

	(1) Article Slant	(2) Article Slant	(3) Article Slant
Registered Republican	0.81***		
	(0.06)		
from Facebook		-0.05*	
		(0.03)	
Republican × from Facebook		0.13***	
		(0.05)	
from Social Media			-0.03
			(0.02)
Republican × from Social Media			0.16***
			(0.04)
Individual FE	No	Yes	Yes
Observations	2,052	46,467	46,467

Notes: This table shows results from a regression of the slant (on a scale from -2.5 to +2.5) of an individual article consumed by a browsing panel member on a dummy for Republican party registration in column 1; column 2 includes a dummy for whether the panelist got referred to a given article via Facebook, as well as its interaction with the Republican dummy, and individual fixed effects; column 3 includes a dummy for referral via social media (including Facebook, Twitter, Instagram, Pinterest, TikTok, LinkedIn, Snapchat, Reddit, Nextdoor, BeReal, and Tumblr) in our referrer origins, as well as its interaction with the Republican dummy, and individual fixed effect. Column 1 restricts to article clicks that i) were referred from Facebook and that ii) pertain to articles included in the URL-level Facebook Activity Dataset, while no such restrictions apply in column 2 and 3. The sample is restricted to individuals who are either registered Democrats or registered Republicans. The table is based on individual-level browsing panel data from a representative sample of individuals as described in Section 3.3. An observation is an individual click on a hard news article by a browsing panelist. Robust standard errors are provided in parentheses.

Table A.7: Polarization in News Exposure, Consumption, and Circulation on Facebook: Excluding Outlets that Feed Into Facebook's Political Affinity Measure

	Average Slant Reg. Democrats	Average Slant Reg. Republicans	Average Slant Difference	Polarization Index
Views	-0.44	0.25	0.69	0.14
Clicks	-0.47	0.33	0.81	0.16
Shares	-0.55	0.75	1.31	0.26

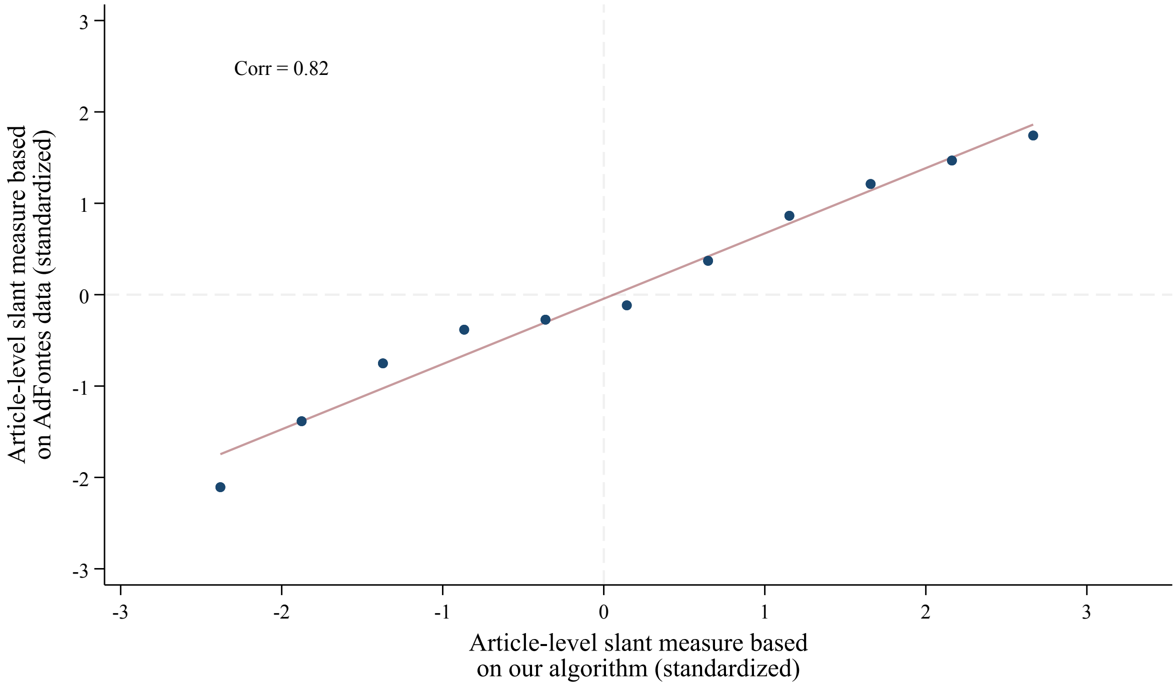
Notes: This table shows the same statistics as in Table 1, only that when constructing the statistics, we omit all articles from the 18 outlets that feature in the computation of Facebook users' political affinity scores in the URL-level Facebook Activity Dataset (see Section 3.2 for details).

Table A.8: Polarization in News Exposure, Consumption, and Circulation on Facebook when Slant is Measured at Outlet-Level: Excluding Outlets that Feed Into SS1's Political Affinity Measure

	Average Slant Reg. Democrats	Average Slant Reg. Republicans	Average Slant Difference	Polarization Index
Views	-0.26	0.12	0.39	0.08
Clicks	-0.31	0.19	0.51	0.10
Shares	-0.30	0.38	0.68	0.14

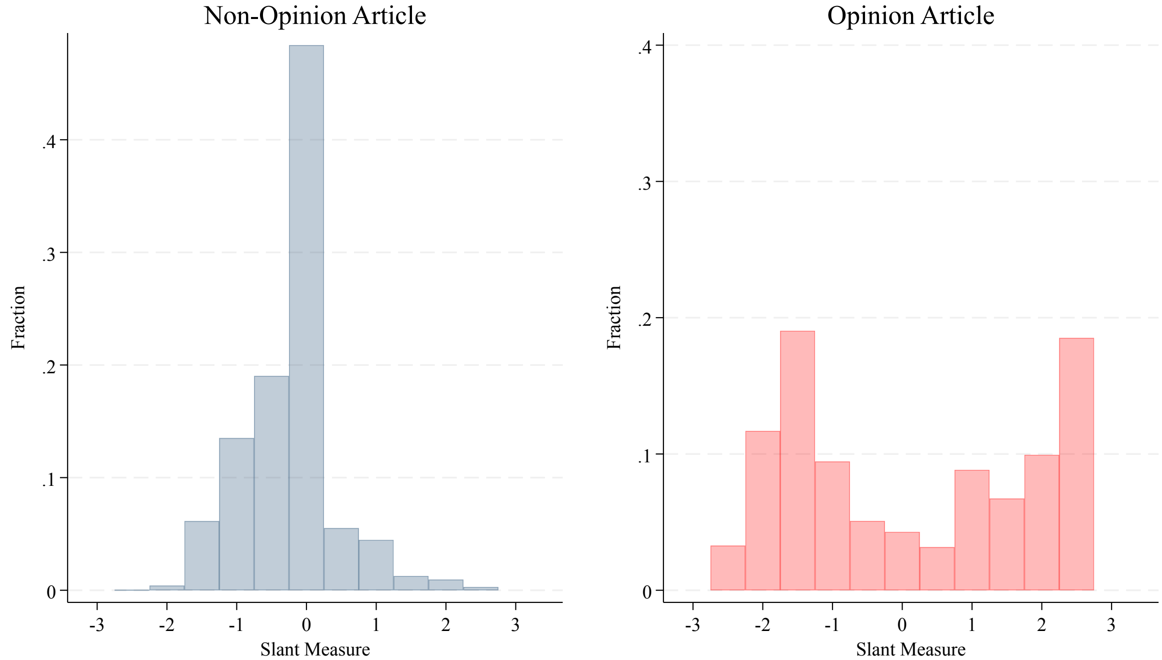
Notes: This table shows the same statistics as in Table 1 with two differences. First, when constructing the statistics, we omit all articles from the 18 outlets that feature in the computation of Facebook users' political affinity scores in the URL-level Facebook Activity Dataset (see Section 3.2 for details). Second, we calculate slant at the outlet level (i.e. we assign each article the average slant across all articles published by the outlet).

Figure A.1: Correlation between Model-Predicted Slant and Third-Party Expert Slant Ratings



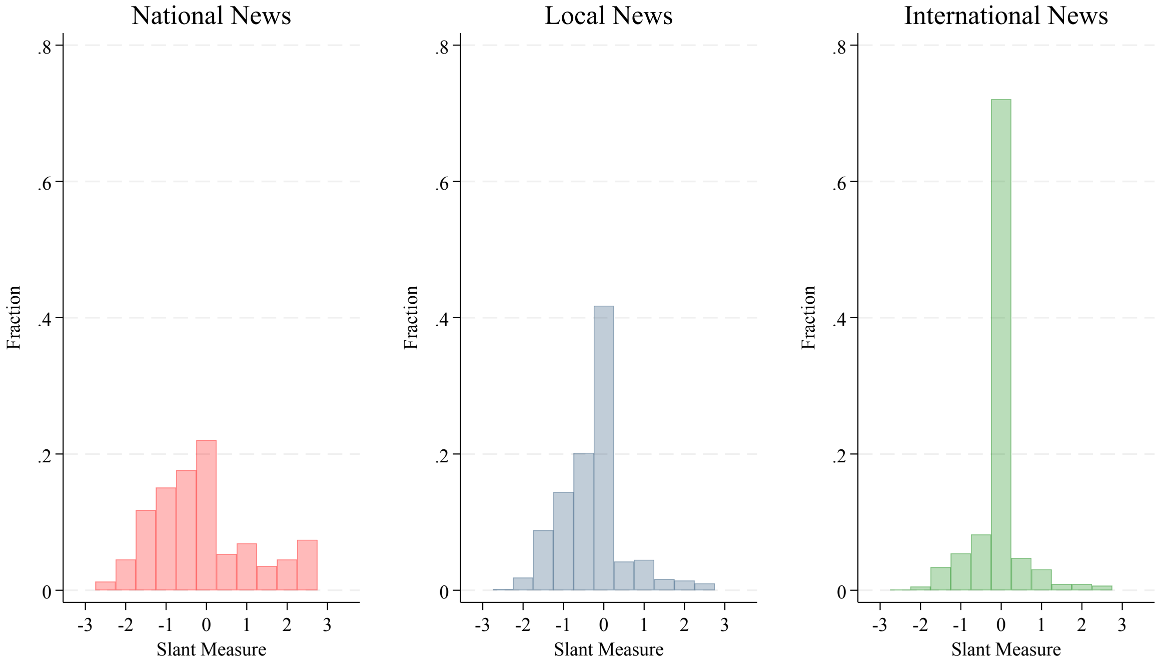
Notes: This figure shows, for each model-predicted slant bin (horizontal axis), the average third-party slant ratings (by an expert panel curated by Ad Fontes Media) across all articles in that bin. For a total of $N = 487$ articles from 2019 for which Ad Fontes Media ratings could be retrieved. To render the two scales comparable, each type of slant measure is standardized to mean 0 and standard deviation 1.

Figure A.2: Distribution of Slant: Opinion vs. Non-Opinion Articles



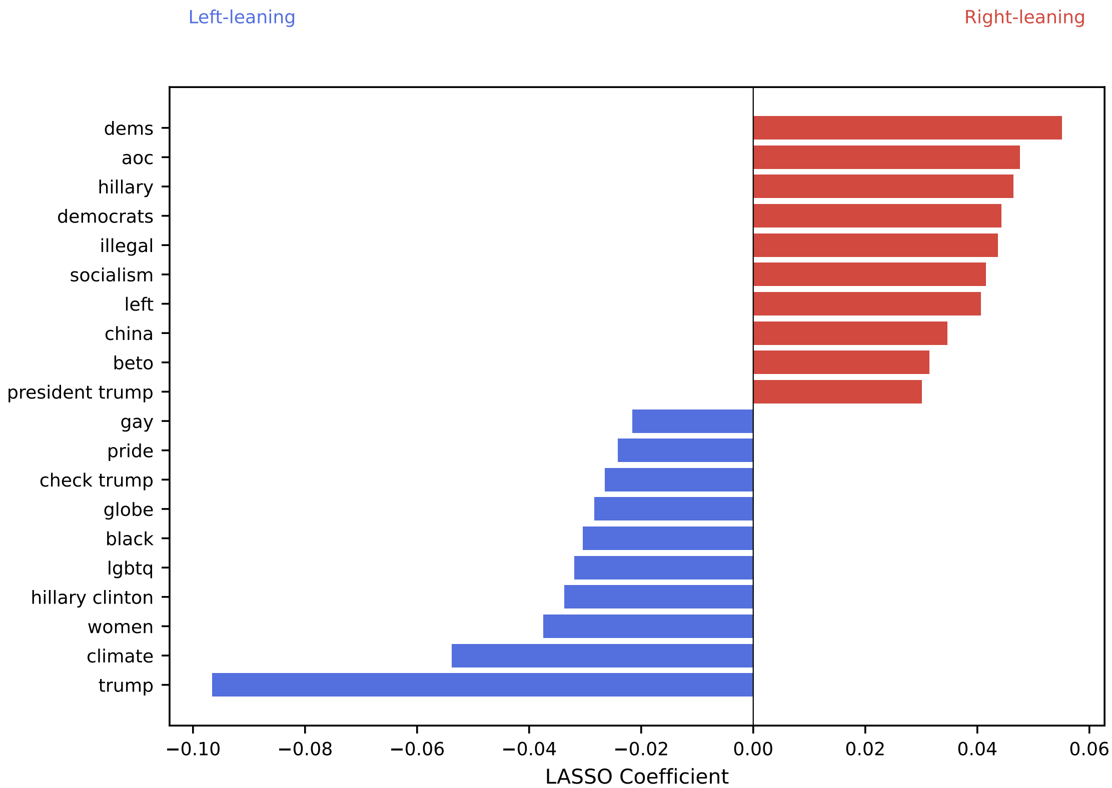
Notes: This figure shows the distribution of slant among all opinion news articles ($N = 216,323$) published online in the top-100 most-read U.S. news outlets in 2019 (right panel), and their non-opinion counterparts (left panel). Slant is given by the fine-tuned GPT-4o's prediction as described in Section 4.2. The slant scale goes from -2.5 (extremely favorable to the Democratic party) to 2.5 (extremely favorable to the Republican party). The classification into opinion articles is described in Appendix C.

Figure A.3: Distribution of Slant: National, Local, and International News



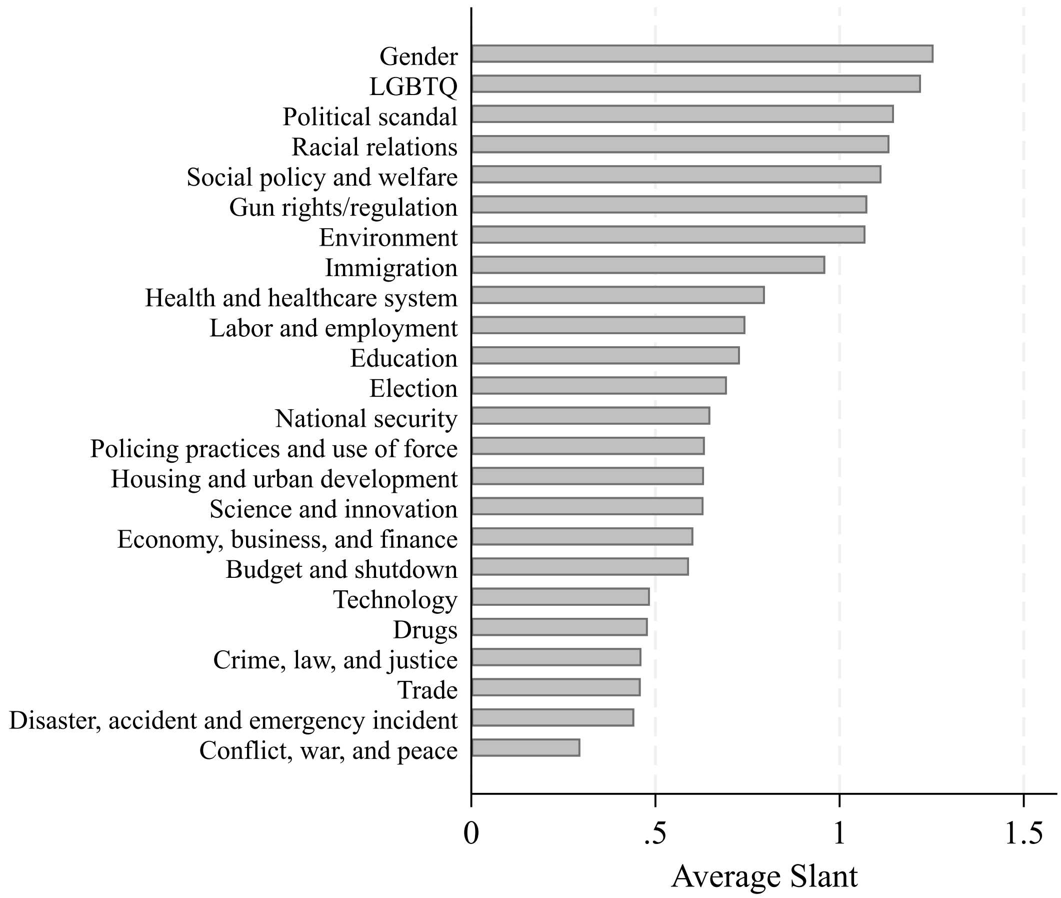
Notes: This figure shows the distribution of slant among all news articles covering national news (left panel), local news (middle panel), and international news (right panel). Slant is given by the fine-tuned GPT-4o's prediction as described in Section 4.2. The slant scale goes from -2.5 (extremely favorable to the Democratic party) to 2.5 (extremely favorable to the Republican party). The classification into national/local/international news is described in Appendix C.

Figure A.4: Terms Most Predictive of Article Slant



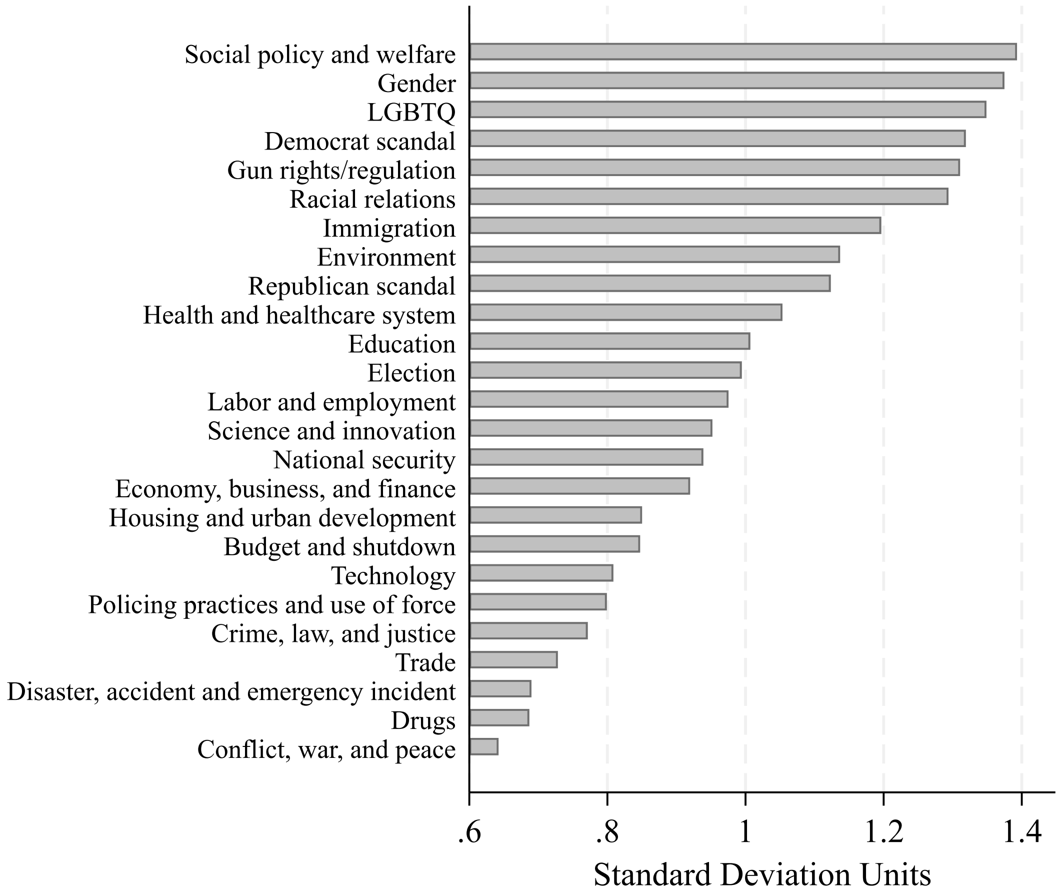
Notes: This figure presents the top ten n-grams, including both unigrams and bigrams, identified through LASSO regression as predictive of slant in news articles, based on our slant measure. These terms were extracted from article titles, with a minimum occurrence threshold of 1,000. The horizontal bar plot displays the Lasso coefficients of these n-grams, with positive values indicating a right-leaning slant and negative values indicating a left-leaning slant.

Figure A.5: Average Absolute Slant by Topic



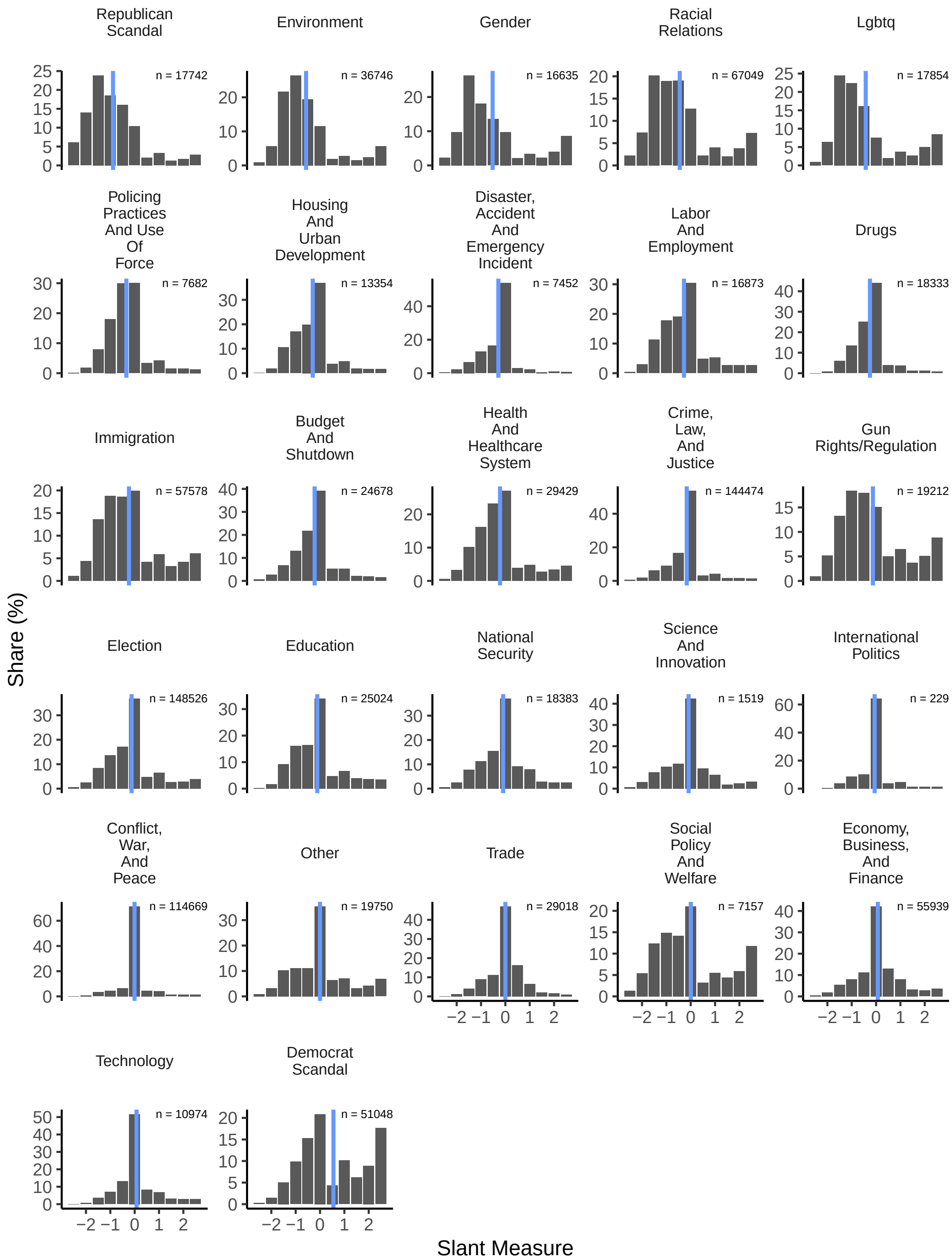
Notes: This figure shows the average absolute slant of the articles falling in each topic category listed on the vertical axis. Slant is given by the fine-tuned GPT-4o's prediction as described in Section 4.2. The slant scale goes from −2.5 (extremely favorable to the Democratic party) to 2.5 (extremely favorable to the Republican party). The absolute value of the slant scale goes from 0 (a centrist article) to 2.5 (a very extreme article). The classification into topics is described in detail in Appendix C.

Figure A.6: Standard Deviation of Slant by Topic



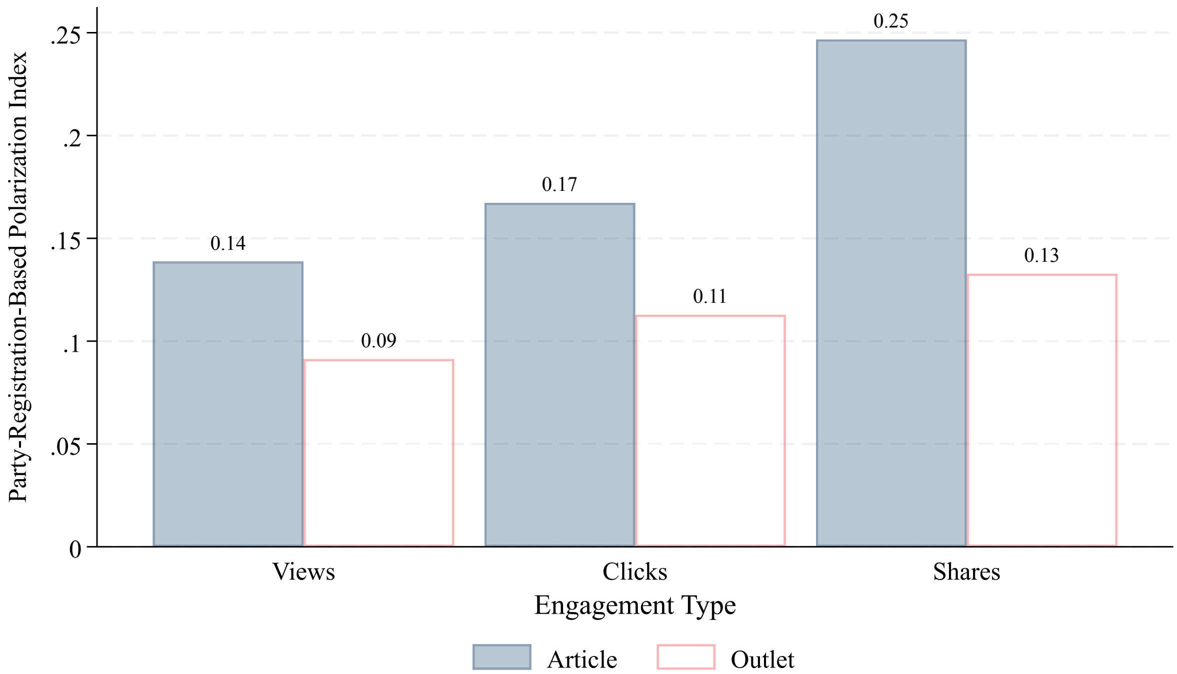
Notes: This figure shows the standard deviation of the slant of the articles falling in each topic category listed on the vertical axis. Slant is given by the fine-tuned GPT-4o's prediction as described in Section 4.2. The slant scale goes from -2.5 (extremely favorable to the Democratic party) to 2.5 (extremely favorable to the Republican party). The classification into topics is described in detail in Appendix C.

Figure A.7: Slant Distribution within Topics



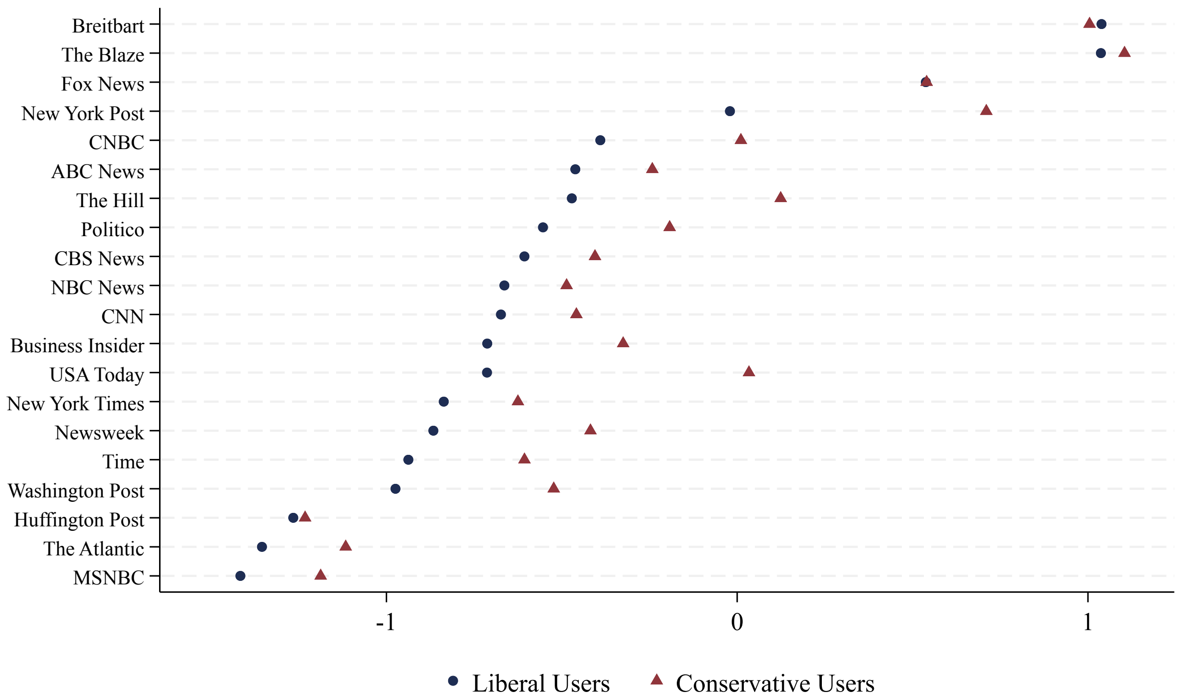
Notes: This figure shows the distribution of slant within news topics. The vertical blue line indicates the mean slant for the given topic. Slant is given by the fine-tuned GPT-4o's prediction as described in Section 4.2. The slant scale goes from -2.5 (extremely favorable to the Democratic party) to 2.5 (extremely favorable to the Republican party). The classification into topics is described in detail in Appendix C.

Figure A.8: Polarization in News Exposure, Consumption, and Circulation on Facebook Measured at Article and Outlet Level



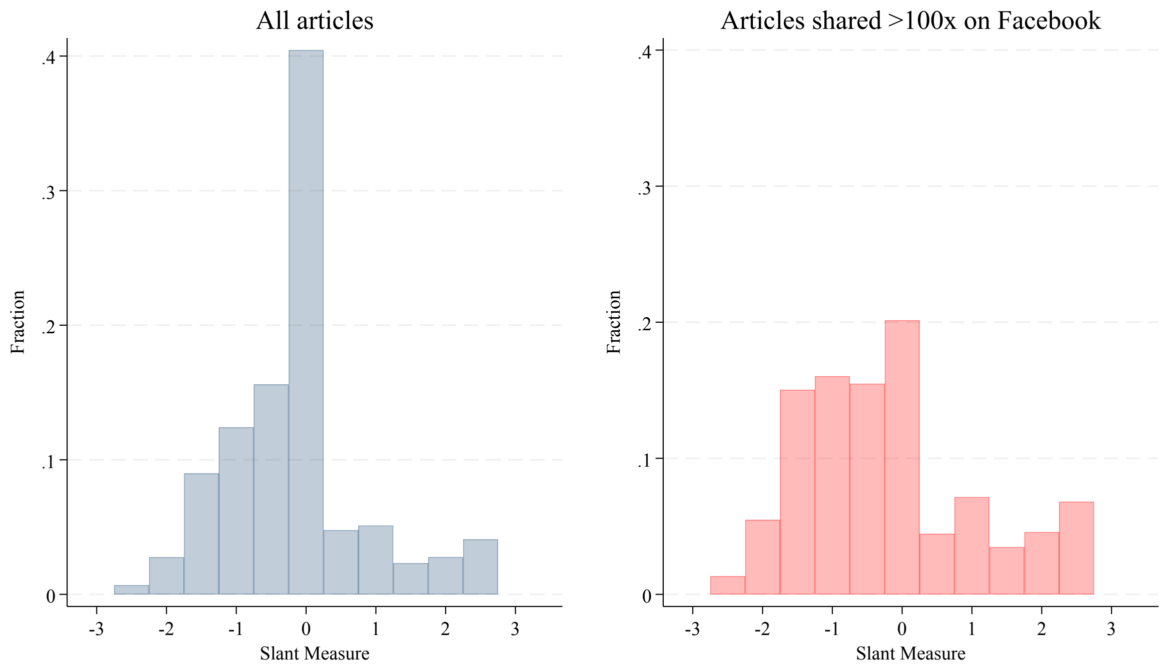
Notes: This figure shows the views-/clicks-/shares-weighted average difference in the slant of news diets by registered Republican and Democrat users on Facebook divided by 5, so that -1 indicates extreme counter-attitudinal news consumption, 0 indicates no difference in average slant across the news consumed by Democrats and Republicans, and 1 indicates extreme pro-attitudinal news consumption. The blue bars on the left show the polarization measure when slant is calculated using our main article-level slant measure (as in Table 1). The white bars on the right show the polarization measure when we assign each article its outlet-level slant measure (constructed as the average slant across all articles published by the outlet). The news article sample includes all $N = 234,313$ hard news articles published online by the top 100 U.S. news outlets in 2019 that are in the URL-level Facebook Activity Dataset.

Figure A.9: Average Slant of Articles Viewed on Facebook by Outlet and User Political Affinity



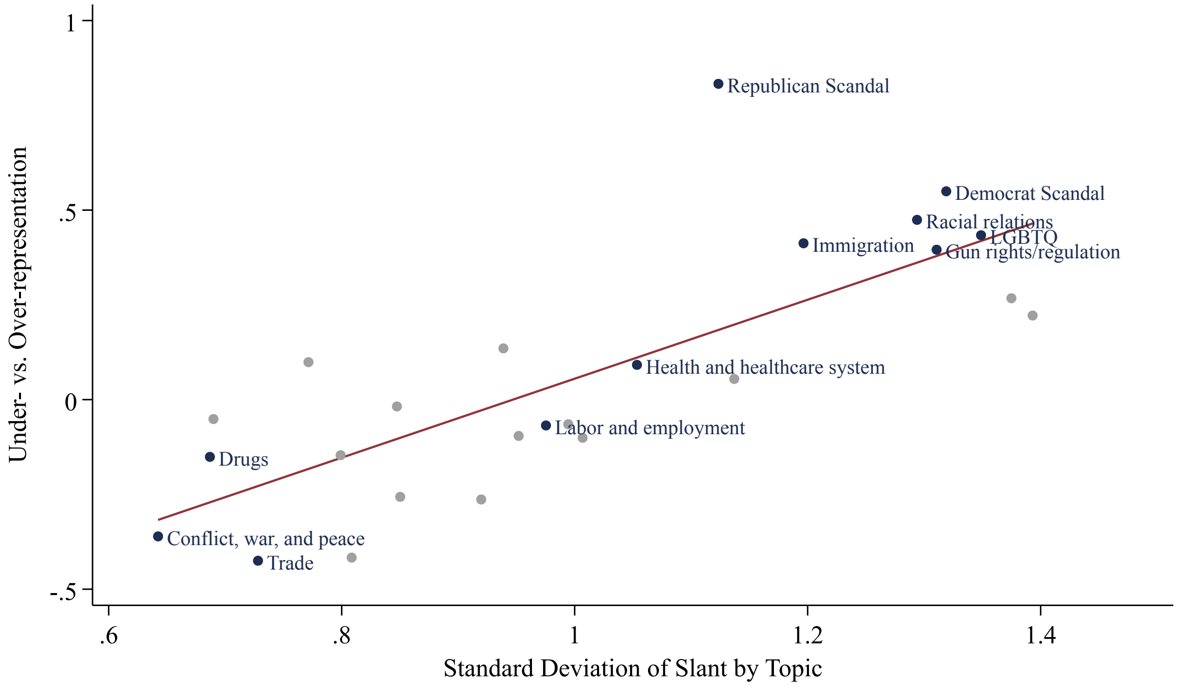
Notes: This figure shows the views-weighted average slant of articles by Facebook users' political affinity and outlet. The sample includes all hard news articles published online by the top 20 U.S. news outlets in 2019 that are in the URL-level Facebook Activity Dataset (i.e. shared at least 100 times on Facebook). Slant is given by the fine-tuned GPT-4o's prediction as described in Section 4.2. The slant scale goes from -2.5 (extremely favorable to the Democratic party) to 2.5 (extremely favorable to the Republican party).

Figure A.10: Empirical PDF of Article Slant in Full Sample vs. SS1 Sample



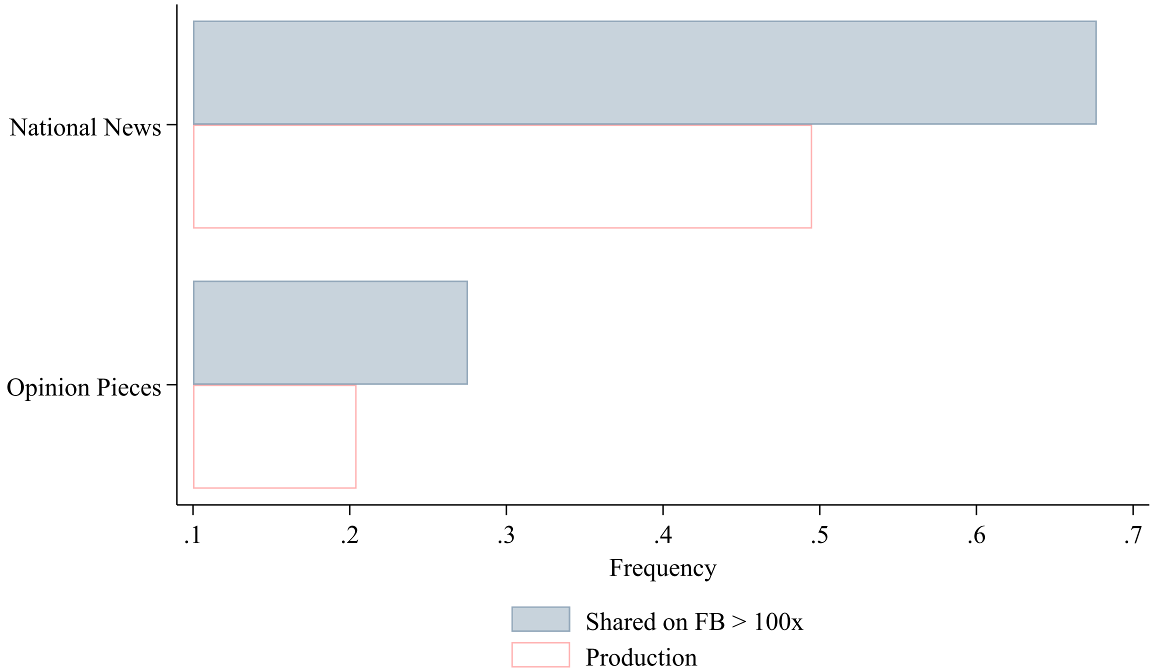
Notes: This figure shows the distribution of article-level slant for two samples: the full sample of all $1,065,217$ hard news articles published online by the top-100 U.S. news outlets in 2019 (left panel) and the sub-sample of all $234,313$ articles shared more than 100 times on Facebook (right panel)—i.e. the articles included in the Facebook engagement dataset (SS1). Article slant is given by the fine-tuned GPT-4o's prediction as described in Section 4.2. The slant scale goes from -2.5 (extremely favorable to the Democratic party) to 2.5 (extremely favorable to the Republican party).

Figure A.11: Under- vs. Over-representation of Topics among Articles Shared on FB more than 100x



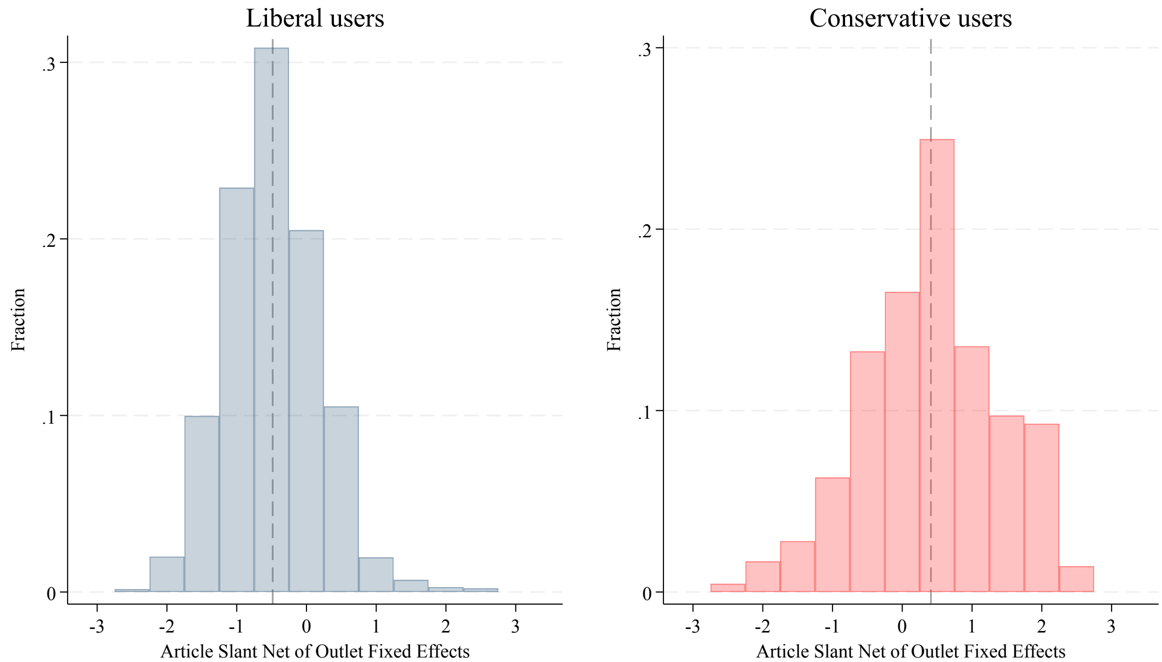
Notes: This figure shows that topics exhibiting a high standard deviation of slant tend to be over-represented in the URL-level Facebook Activity dataset. The x-axis captures the standard deviation of article-level slant for each topic. The y-axis captures the degree of under- vs over-representation. Specifically, we first compute the overall fraction of articles in each topic. Second, we compute the same fractions for articles in the URL-level Facebook Activity dataset. Third, we divide the latter number by the former and subtract one. This way, the quantity we obtain can be thought of as the degree of under- vs over-representation of articles in the URL-level Facebook Activity Dataset compared to our overall database of articles. The classification into topics is described in detail in Appendix C.

Figure A.12: Shares of Opinion Pieces and National News



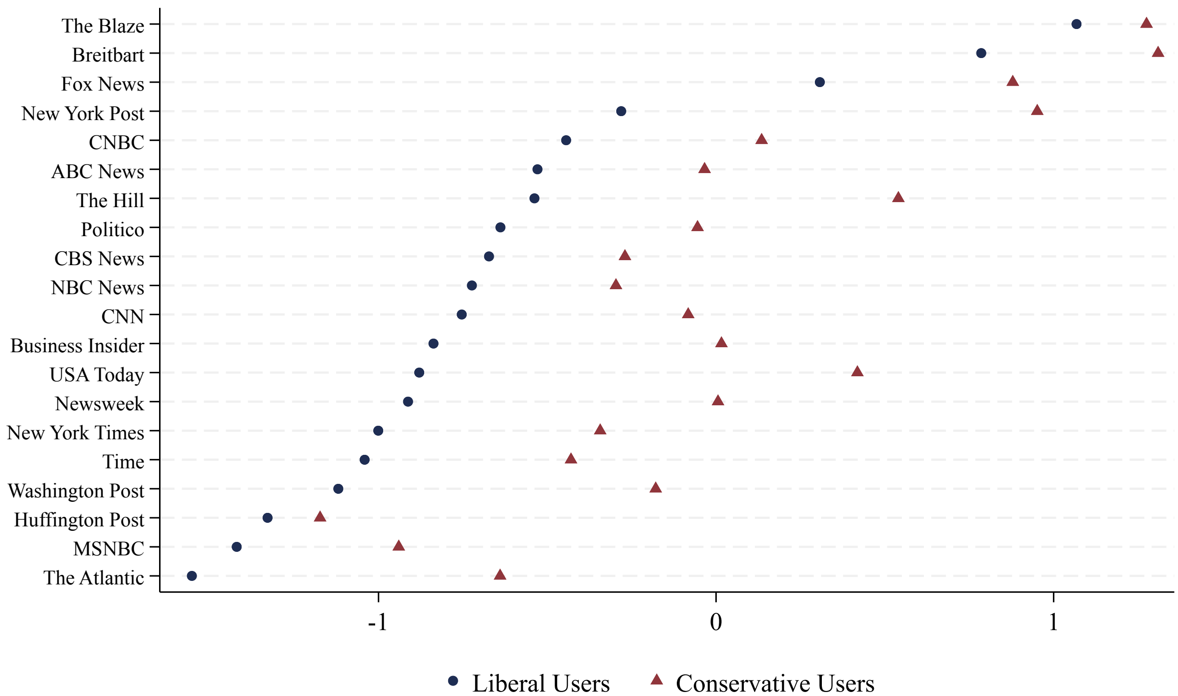
Notes: This figure presents the fraction of articles, both in our dataset ("Production") and in the URL-level Facebook Activity dataset ("Shared on FB > 100x"), classified as national news and as opinion pieces. The classification into national, international, and local news, as well as the one into opinion vs. non-opinion pieces, is described in Appendix C.

Figure A.13: Empirical PDF of Facebook Shares by Facebook User Political Affinity and Article Slant Net of Outlet Fixed Effects



Notes: This figure shows the fraction of all shares by a given Facebook user political affinity group (liberal and conservative, respectively) that accrue to articles in a given residualized slant bin. The dashed vertical line represents the mean of the distribution. The sample includes all $N = 234,313$ hard news articles published online by the top 100 U.S. news outlets in 2019 that are in the URL-level Facebook Activity Dataset (i.e. shared at least 100 times on Facebook). Residualized slant is constructed as follows: We take our article-level slant measure (given by the fine-tuned GPT-4o's prediction as described in Section 4.2), regress it on outlet fixed effects, and obtain the residuals, to which we add the unconditional mean slant across all articles from the full sample. The (residualized) slant scale goes from -2.5 (extremely favorable to the Democratic party) to 2.5 (extremely favorable to the Republican party).

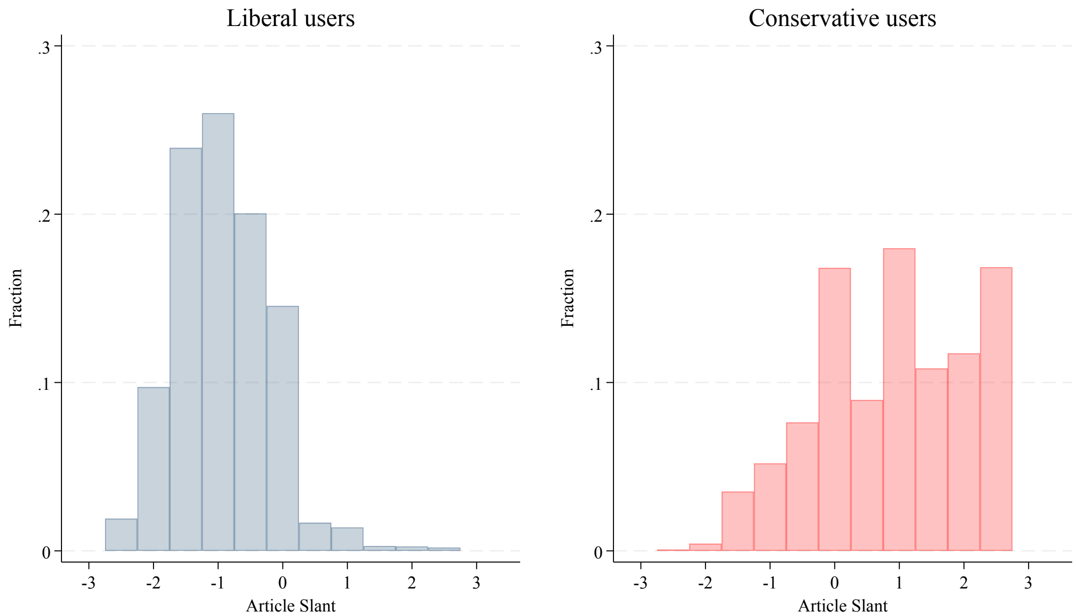
Figure A.14: Average Slant of Articles Shared on Facebook by Outlet and User Political Affinity



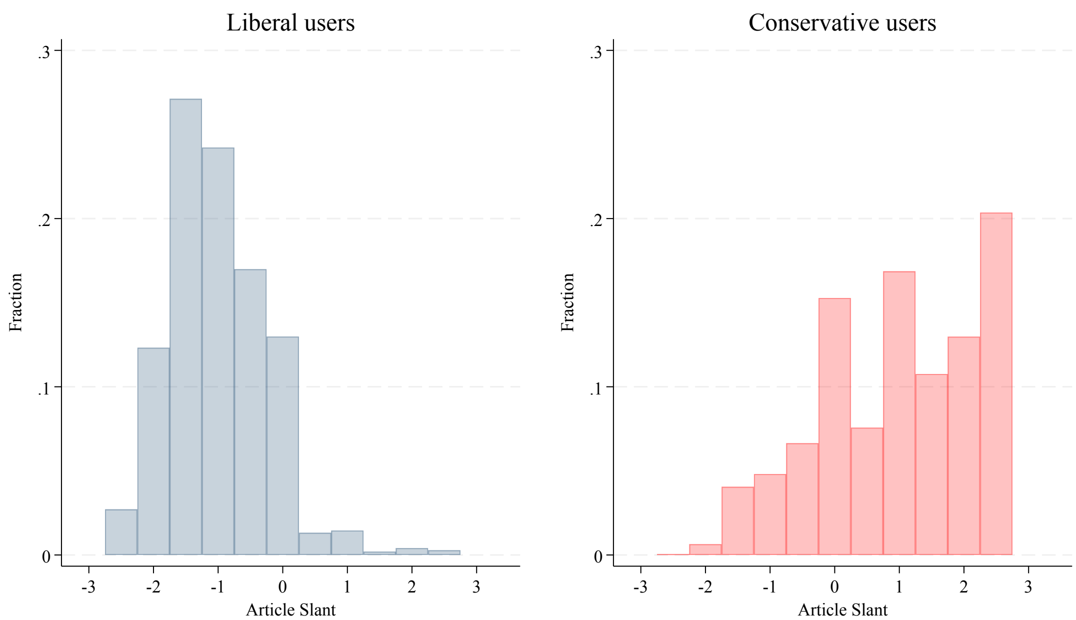
Notes: This figure shows the shares-weighted average slant of articles by Facebook users' political affinity and outlet. The sample includes all hard news articles published online by the top 20 U.S. news outlets in 2019 that are in the URL-level Facebook Activity Dataset (i.e. shared at least 100 times on Facebook). Slant is given by the fine-tuned GPT-4o's prediction as described in Section 4.2. The slant scale goes from -2.5 (extremely favorable to the Democratic party) to 2.5 (extremely favorable to the Republican party).

Figure A.15: Empirical PDF of the Slant of Articles Shared on Facebook With and Without Clicks by User Political Affinity

(a) Shares with no Clicks

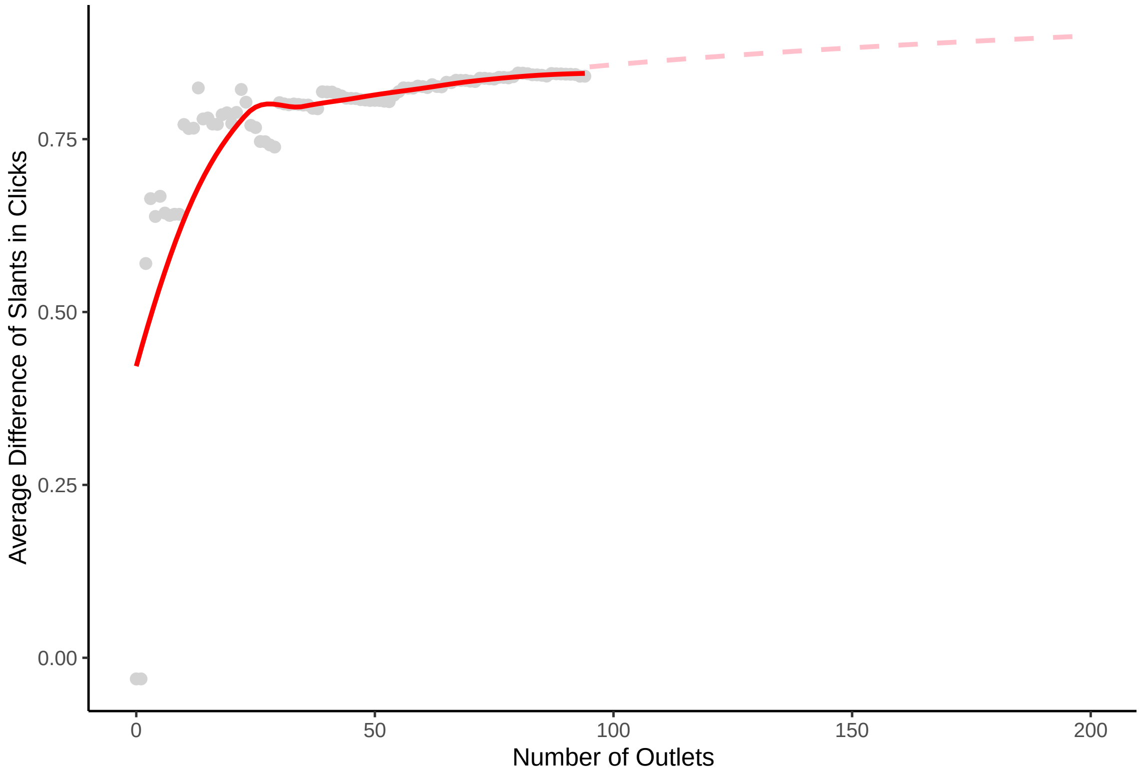


(b) Shares with Clicks



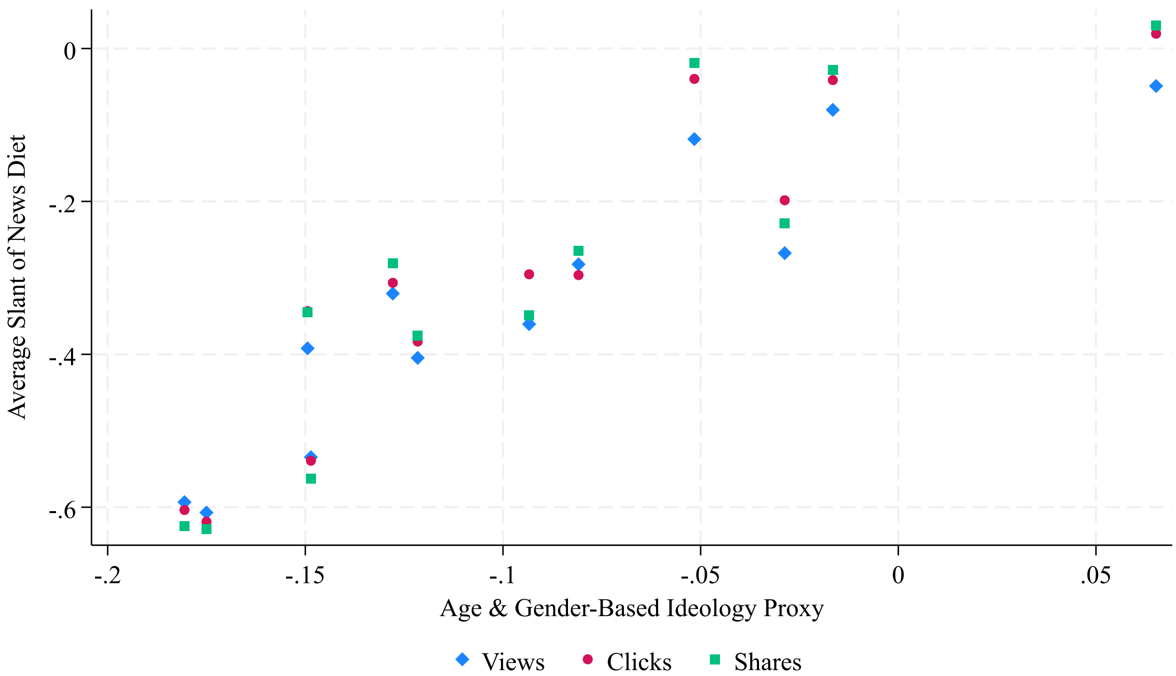
Notes: This figure shows the fraction of all shares by a given Facebook user political affinity group (liberal and conservative, respectively) that accrue to articles in a given slant bin. The figure shows the results separately for news article URLs that users clicked on before sharing on Facebook and for news article URLs that users shared without clicking. The sample includes all $N = 234,313$ hard news articles published online by the top 100 U.S. news outlets in 2019 that are in the URL-level Facebook Activity Dataset (i.e. shared at least 100 times on Facebook). The slant scale goes from -2.5 (extremely favorable to the Democratic party) to 2.5 (extremely favorable to the Republican party).

Figure A.16: Difference in the Average Slant of News Consumption by Party Registration Status, Extending Beyond Top 100 Outlets



Notes: This figure presents the clicks-weighted average difference in the slant of news diets by registered Republican and Democrat users on Facebook by extending our analysis beyond top 100 U.S. news outlets as discussed in Section 7.2. The news article sample includes all $N = 234,313$ hard news articles published online by the top 100 U.S. news outlets in 2019 that are in the URL-level Facebook Activity Dataset (i.e. shared at least 100 times on Facebook).

Figure A.17: Average Slant in News Diet By Demographic Ideology Proxy



Notes: This figure shows the mean slant of a given Facebook user group's news diet (separately for views, clicks, and shares) on the vertical axis, for 12 different user groups sorted according to the group's mean ideology proxy shown on the horizontal axis. User groups are given by gender-by-age cells, with two genders and six age groups. The ideology proxy is given by the difference in the share of the demographic group's members who identify as or lean Republican and the share who identify as or lean Democrat (such that larger numbers mean more Republican-leaning). The shares are estimated based on representative survey data from the ANES 2020-2022 Social Media Study (2020 wave), among all 3,483 respondents who reported having a Facebook account that they used in the past month.

B. Labels Construction

We provided our expert human raters with the following instructions:

Our goal is to determine how biased a newspaper article is towards a left or right-wing point of view, with the Democratic Party broadly representing the left and the Republican Party broadly representing the right. We will use a 7-point scale to measure the degree of bias, ranging from extreme left to extreme right.

There are three main factors that we consider when assessing the bias of an article: language, political position, and coverage.

(1) When we look at the language of an article, we consider whether it uses words and phrases that are typically used by members of the Republican or Democratic parties. If an article uses more Republican-like language, we consider it biased towards the right. If it uses more Democratic-like language, we consider it biased towards the left.

For example, terms like "death tax" would be considered slanted towards the right, whereas "estate tax" or "inheritance tax" would be considered slanted towards the left.

(2) Next, we look at the political position presented in the article. If the article aligns with the political views of the Republican party, we consider it biased towards the right. If it aligns with the political views of the Democratic party, we consider it biased towards the left.

As an example, an article that presents an anti-abortion stance would be viewed as having a right-leaning bias, while an article that presents a pro-abortion stance would be considered to have a left-leaning bias.

(3) Finally, we consider the issues covered in the article. If an article covers issues that are important to Republican voters and ignores issues that are important to Democratic voters, we consider it biased toward the right. If it covers issues that are important to Democratic voters and ignores issues that are important to Republican voters, we consider it biased toward the left.

For example, suppose one of the political parties proposes a minimum wage bill, and the Congressional Budget Office (CBO), Congress's official nonpartisan provider of cost and benefit estimates for legislation, publishes a report about the bill's potential impact. Suppose the CBO's report states that the bill could lift 1 million people out of poverty but could also lead to a reduction of 1.5 million jobs. If a news article only reports on the job loss without mentioning the poverty reduction, it could be considered to have a right-wing bias. Conversely, if a news article only reports on the reduction in poverty without mentioning the potential job loss, it could be considered to have a left-wing bias.

By considering these factors, we can assign a score to each article that reflects its degree of bias towards the left or right. To help you understand the slant rating scale, we've provided rankings for a few well-known politicians (we did not come up with those rankings; we took them from political scientists Keith Poole and Howard Rosenthal). You can find the rankings in the table below.

1	Very left-wing	Alexandra Ocasio-Cortez
2	Left-wing	Cory Booker
3	Somewhat left-wing	Chuck Schumer
4	Neutral	
5	Somewhat right-wing	Mitt Romney
6	Right-wing	Marco Rubio
7	Very right-wing	Ted Cruz

C. Classifying Other News Characteristics

This appendix describes how we classified news articles into opinion- vs. non-opinion pieces, into local, national, and international news, and into news topics. To do so, we used GPT-4o. We supplied the whole article text as a user message and submitted the following prompt:

"You are a helpful assistant. I have provided you with a news article above. Its title is: [title]. It was written on [date]. It was published at the following url: [URL].

We want to decide if this article is an opinion piece or not. We define opinion pieces the following way: An opinion piece is an article that mainly reflects the author's opinion about a subject.

We also want to determine the topic of the article. Each article belongs to one of the following categories:

- Budget and Shutdown: Issues related to the government's budget, including disagreements over spending priorities that can lead to temporary shutdowns of government operations and services.
- Racial Relations: Discussions around race, ethnicity, and social dynamics related to race, including perspectives on topics like systemic racism, affirmative action, identity politics, equal opportunity, law and order, discrimination, colorblind approaches, and the role of government and society in addressing racial issues.
- Crime, Law, and Justice: The establishment and/or statement of the rules of behavior in society, the enforcement of these rules, breaches of the rules, the punishment of offenders and the organizations and bodies involved in these activities.
- Conflict, War, and Peace: acts of politically motivated protest or violence, military activities, geopolitical conflicts, as well as resolution efforts.
- Democrat Scandal: Allegations or controversies involving Democratic politicians or party members, covering potential misconduct, corruption, or political missteps.
- Disaster, Accident and Emergency Incident: Coverage of natural or human-made events that result in loss of life, injury, or property damage, such as natural disasters, industrial accidents, and emergency responses.
- Drugs: All matters related to legal and illegal drug use, drug trafficking, addiction, and drug policy, including debates over legalization, regulation, and public health impacts.

- Economy, Business, and Finance: Issues related to economic trends, business practices, market dynamics, financial markets, and related policies, including analyses of economic indicators, corporate news, investment strategies, stock market updates, fiscal policies, and global economic developments
- Education: All aspects of furthering knowledge, formally or informally through schools, universities, etc.
- Election: Matters concerning elections, including campaigns, voter turnout, polling, electoral procedures, and debates among candidates for public office.
- Environment: All aspects of protection, damage, and condition of the ecosystem of the planet Earth and its surroundings, including climate change and debates over policies aimed at protecting the environment versus economic growth.
- LGBTQ: Issues related to the legal status, rights, and social acceptance of LGBTQ individuals. Includes discussions on marriage equality, anti-discrimination protections, LGBTQ and religion, transgender issues, education on gender and sexuality, and debates over the role of LGBTQ issues in public policy and cultural norms.
- Gun Rights/Regulation: Matters related to the ownership, use, and regulation of firearms, as well as debates over gun control measures, firearm regulations, gun rights and the Second Amendment, background checks, concealed carry laws, and gun-related public safety concerns.
- Health and Healthcare System: All aspects of physical and mental well-being, as well as the healthcare system, pharmaceutical companies, etc.
- Housing and Urban Development: Issues related to housing affordability, availability, urban planning, and community development. Encompasses debates over rent control, zoning laws, the role of government in addressing housing needs, market-driven solutions, homelessness, and the effects of housing policies on economic growth and social dynamics.
- Immigration: Matters concerning immigration policy, border control, treatment of immigrants and refugees, legal status, and debates over immigration and national identity, the economic impact of immigrants, and cultural integration.
- Labor and Employment: Topics related to labor rights, workplace conditions, wages, employment law, minimum wage policy, union activities, labor policy and business interests/growth, strikes, and workforce trends, including job creation and unemployment.
- National Security: Issues related to the protection of the nation's borders, counterterrorism, intelligence activities, and measures to ensure the safety of citizens.
- Policing Practices and Use of Force: Coverage of incidents involving the use of force by law enforcement and discussions around policing practices. Includes debates on police accountability, law enforcement reform, public safety, community policing, ”law and order” perspectives, and support for police officers as well as discussions on systemic challenges in policing.

- Republican Scandal: Allegations or controversies involving Republican politicians or party members, covering potential misconduct, corruption, or political missteps.
- Science and Innovation: Coverage of scientific research, discoveries, and technological advancements that are not necessarily commercial, including space exploration, health science, climate research, and general progress in knowledge and innovation.
- Social Policy and Welfare: Issues related to government social welfare programs and policies, such as food assistance, public healthcare, unemployment benefits, and debates on the social and economic impacts of welfare policies.
- Technology: All aspects pertaining to new products, commercial and non-commercial, that result from the application of recently gained scientific knowledge.
- Gender: Topics related to gender issues, including debates on women's rights, men's rights, workplace equality, reproductive rights, family policies, discrimination, and gender roles.
- Trade: Topics concerning international trade policies, tariffs, trade agreements, and economic relationships between countries, as well as their impacts on businesses and consumers.
- Other: Articles or topics that do not fit neatly into any of the predefined categories but are still of public interest or relevance to the period being analyzed.

We also want to know if the article is local, national or international politics.

- Local politics: Issues and developments related to U.S. state, county, city, or municipal government policies and political dynamics.
- National politics: Issues and developments related to U.S. federal government policies, political parties, and national leadership. Encompasses discussions on federal legislation, executive actions, Supreme Court decisions, national party debates, national public policy issues, etc.
- International politics: Matters concerning diplomatic relations and policy decisions between the U.S. and other countries, as well as political dynamics and developments in countries/regions other than the U.S.

Read the text of the article carefully and determine if it is an opinion piece (yes or no), its topic and whether it is local, national or international news.

Always add your chain of thought in the reasoning field."

D. Variance Decomposition

This appendix formalizes the variance decomposition discussed in Section 5.1.

Let $R_{i,j,k}$ denote the rating that rater $k \in \{1,2\}$ gives to article $j \in J$ coming from outlet $i \in I$. We model $R_{i,j,k}$ as

$$R_{i,j,k} = u + O_i + A_{i,j} + \varepsilon_{i,j,k}$$

where u is a constant that captures the average slant across all articles, O_i is a random variable that captures the deviation between the slant of the average article in outlet i and the average slant across all articles, $A_{i,j}$ is a random variable that captures the deviation between the slant of article j within outlet i and the slant of the average article in outlet i, and $\varepsilon_{i,j,k}$ captures the noise that comes from a rater's imperfect measurement. We assume $E\left(\varepsilon_{i,j,k}|O_i,A_{i,j}\right)=0$, $E\left(A_{i,j}|O_i\right)=0$, and $E\left(O_i\right)=0$. Note that, as a consequence, $Var\left(\varepsilon_{i,j,k}|O_i,A_{i,j}\right)=E\left(\varepsilon^2_{i,j,k}|O_i,A_{i,j}\right)$, $Var\left(A_{i,j}|O_i\right)=E\left(A^2_{i,j}|O_i\right)$, and $Var\left(O_i\right)=E\left(O_i^2\right)$.

In light of the way in which we modeled $\left(R_{i,j,k}\right)$, we can write $Var\left(R_{i,j,k}\right)$ as follows:

$$Var\left(R_{i,j,k}\right) = Var\left(O_i\right) + E\left(Var\left(A_{i,j}|O_i\right)\right) + E\left(Var\left(\varepsilon_{i,j,k}|O_i\right)\right)$$

Similarly, we can write $E\left(Var\left(R_{i,j,k}|O_i\right)\right)$ as:

$$E\left(Var\left(R_{i,j,k}|O_i\right)\right) = E\left(Var\left(A_{i,j}|O_i\right)\right) + E\left(Var\left(\varepsilon_{i,j,k}|O_i\right)\right)$$

Note that, if we were to perform a naive variance decomposition that does not take into account measurement error, we would obtain:

$$\frac{Var\left(R_{i,j,k}\right) - E\left(Var\left(R_{i,j,k}|O_i\right)\right)}{Var\left(R_{i,j,k}\right)} =$$

$$= \frac{Var\left(O_i\right)}{Var\left(O_i\right) + E\left(Var\left(A_{i,j}|O_i\right)\right) + E\left(Var\left(\varepsilon_{i,j,k}|O_i\right)\right)}$$

Thus, measurement error mechanically reduces the fraction of the variance in ratings that can be explained by different outlets differing in terms of their average slant.

To eliminate measurement error in the variance decomposition, we consider

$$Var\left(R_{i,j,1}\right) + Var\left(R_{i,j,2}\right) - E\left(\left(R_{i,j,1} - R_{i,j,2}\right)^2\right) = 2\left[Var\left(O_i\right) + E\left(Var\left(A_{i,j}|O_i\right)\right)\right]$$

Therefore, an expression that gives us the fraction of the variance in ratings (absent measurement error) that is explained by different outlets differing in terms of their average slant is:

$$\frac{\sum_{k=1}^{2}\left[Var\left(R_{i,j,k}\right) - E\left(Var\left(R_{i,j,k}|O_i\right)\right)\right]}{Var\left(R_{i,j,1}\right) + Var\left(R_{i,j,2}\right) - E\left(\left(R_{i,j,1} - R_{i,j,2}\right)^2\right)} =$$

$$= \frac{Var(O_i)}{Var(O_i) + E\left(Var\left(A_{i,j}|O_i\right)\right)}$$

E. Maximum Achievable Correlation Between Model Predictions and Expert Labels

This appendix shows how to derive an upper bound on the maximum achievable correlation between the predictions of our model and our expert labels. As shown at the end of this appendix, such upper bound underlies the claim in Section 4.4 that our model attains at least 91% of the maximum achievable correlation.

Consider the model from the Appendix D. For simplicity, let $u = 0$. This assumption is without loss of generality because one can in principle always subtract the average slant across all articles from an article-level slant measure. Furthermore, let $Z_{i,j} = O_i + A_{i,j}$, so that we don't have to separately carry around both O_i and $A_{i,j}$. Notice $E\left(Z_{i,j}\right) = E\left(O_i + A_{i,j}\right) = E\left(A_{i,j}\right) = E\left(E\left(A_{i,j}|O_i\right)\right) = 0$. Therefore,

$$R_{i,j,k} = Z_{i,j} + \varepsilon_{i,j,k}$$

We impose the additional assumption of equal variance in errors across the two raters: $Var\left(\varepsilon_{i,j,1}|Z_{i,j}\right) = Var\left(\varepsilon_{i,j,2}|Z_{i,j}\right) = Var\left(\varepsilon_{i,j}|Z_{i,j}\right)$

Let ρ_0 denote the Pearson correlation between the ratings of our two expert raters. In light of our assumptions, we can write ρ_0 as

$$\rho_0 = \frac{Var\left(Z_{i,j}\right)}{Var\left(Z_{i,j}\right) + Var\left(\varepsilon_{i,j}\right)}$$

, which, rearranging, allows us to write

$$Var\left(\varepsilon_{i,j}\right) = \frac{1-\rho_0}{\rho_0} Var\left(Z_{i,j}\right)$$

Let ρ_1 denote the Pearson correlation between our model predictions F and the average rating of the two expert raters.

We can write ρ_1 as

$$\rho_1 = \frac{Cov\left(F, \frac{R_{i,j,1}+R_{i,j,2}}{2}\right)}{\sqrt{Var(F) * Var\left(\frac{R_{i,j,1}+R_{i,j,2}}{2}\right)}}$$

where

$$Var\left(\frac{R_{i,j,1}+R_{i,j,2}}{2}\right) = Var\left(Z_{i,j}\right) + \frac{1}{2} Var\left(\varepsilon_{i,j}\right)$$

But then, using the expression for $Var\left(\varepsilon_{i,j}\right)$ obtained above, we have

$$Var\left(\frac{R_{i,j,1}+R_{i,j,2}}{2}\right) = Var\left(Z_{i,j}\right) + \frac{1}{2}\frac{1-\rho_0}{\rho_0} Var\left(Z_{i,j}\right) = \frac{1+\rho_0}{2\rho_0} Var\left(Z_{i,j}\right)$$

Furthermore, it can be shown that

$$Cov\left(F,\frac{R_{i,j,1}+R_{i,j,2}}{2}\right)=Cov\left(F,Z_{i,j}\right)$$

In light of the above, we can write ρ_1 as

$$\rho_1=\frac{Cov\left(F,Z_{i,j}\right)}{\sqrt{Var\left(F\right)*\frac{1+\rho_0}{2\rho_0}Var\left(Z_{i,j}\right)}}$$

By the Cauchy-Schwarz inequality, we have:

$$Cov\left(F,Z_{i,j}\right)\leq\sqrt{Var\left(F\right)*Var\left(Z_{i,j}\right)}$$

Therefore, we can obtain the following upper bound for ρ_1:

$$\rho_1=\frac{Cov\left(F,Z_{i,j}\right)}{\sqrt{Var\left(F\right)*\frac{1+\rho_0}{2\rho_0}Var\left(Z_{i,j}\right)}}\leq\frac{\sqrt{Var\left(F\right)*Var\left(Z_{i,j}\right)}}{\sqrt{Var\left(F\right)*\frac{1+\rho_0}{2\rho_0}Var\left(Z_{i,j}\right)}}=\sqrt{\frac{2\rho_0}{1+\rho_0}}$$

The actual Pearson correlation between the ratings of the two expert raters is $\rho_0=0.72$. Therefore, an upper bound for ρ_1 is:

$$\rho_1\leq\sqrt{\frac{2*0.72}{1+0.72}}\approx0.91$$

The actual correlation between the model prediction and our slant rating (which is simply the average of the two raters' ratings) is 0.83.

Therefore, our model achieves at least $\frac{0.83}{0.91}=0.91$, that is 91%, of the maximum achievable correlation between our model prediction and our slant labels.

F. Party-Registration-Based Polarization Estimates

This appendix describes the procedure used to estimate polarization in news consumption on Facebook when partisanship is defined by an individual's party registration status (i.e., being a registered Democrat or a registered Republican), rather than by the "political affinity" score from the Facebook URL-level Activity Dataset.

Overview of the Approach Our goal is to assign each news click in our sample to one of three party registration categories:

(i) Not Registered (NR), (ii) Registered Democrat (RD), (iii) Registered Republican (RR).

We then calculate a click-weighted average slant for RD and RR users and take the scaled difference between these two averages as our measure of polarization. However, direct party registration data are not available in the Facebook URL-level Activity Dataset, and “political affinity” (liberal, moderate, conservative) is assigned to only a subset of users. We bridge these gaps through the following steps:

1. We leverage Twitter (now ”X”) data to construct a base matrix that tabulates, for each political affinity group (liberal, moderate, conservative), how many individuals appear in each party-registration category (NR, RD, RR).
2. We account for missing affinity scores by incorporating information on the share of users who do not have a political affinity measure.
3. We allocate clicks to party registration categories using the observed or imputed distribution of users across the three party registration groups.
4. We compute the average slant for each party-registration group by weighting the known average slants of each political-affinity group.

Step 1: Constructing the Base Matrix

Let $\mathscr{G} = \{\text{liberal (L)}, \text{moderate (M)}, \text{conservative (C)}, \text{and missing } (\textit{missing})\}$ be the set of political affinity groups. Let $\mathscr{P} = \{\text{NR, RD, RR}\}$ be the party-registration categories. We start off by considering the following matrix

$$N_{g,p} \quad \text{for } g \in \{L, M, C\},\ p \in \mathscr{P},$$

where $N_{g,p}$ is the number of users whose political affinity is g and whose party registration is p.

We cannot observe this matrix directly for our Facebook sample, because the URL-level Facebook Activity dataset does not include party registration data. Instead, we rely on the matrix constructed by Barberá et al. (2015) using Twitter (now ”X”) data. The underlying methodology employed to assign a political affinity score is the same across the Twitter and Facebook datasets.[38] The Twitter dataset studied by Barberá et al. (2015) contains information about party registration for a subset of users. Assuming that the mapping between affinity and party registration $N_{g,p}$ from the Twitter data in Barberá et al. (2015) is a good approximation for our Facebook population, we take the matrix from Barberá et al. (2015) as our “base matrix.”

Summing over all g and p in this base matrix yields the total number of users in the subset who (i) have a measured political affinity and (ii) have known party-registration status:

$$N_{\text{affinity}} = \sum_{g \in \{L,M,C\}} \sum_{p \in \mathscr{P}} N_{g,p}.$$

[38] In fact, Facebook’s methodology in based on the canonical Barberá et al. (2015) paper.

By construction, $N_{\text{affinity}} \approx 25\%$ of the overall sample of Facebook users (denoted N_{total}). Hence, the number of users without a political affinity score is

$$N_{\text{missing}} \; = \; N_{\text{total}} - N_{\text{affinity}} \; \approx \; 75\% \times N_{\text{total}}.$$

We use this number in the next step of the construction.

Step 2: Imputing Party Registration for Missing Affinity Scores

For the N_{missing} users who lack a political affinity score in the URL-level Facebook Activity Dataset, we have to make an assumption about the fraction of them that would be registered Democrats, registered Republicans, or not registered with either the Democratic or Republican party. In the absence of more precise information, we assume that their distribution matches the general distribution in the population around the time period we are studying, namely 23% registered Democrats, 16% registered Republicans, and 61% not registered with either the Democratic or the Republican party.[39] Denote the imputed number of Facebook users with a missing political affinity variable who are registered Democrats, registered Republicans, or not registered with either party, respectively, by

$$\widetilde{N}_{\text{missing},p} \quad \text{for } p \in \mathscr{P}.$$

We add these $\widetilde{N}_{\text{missing},p}$ counts to the observed counts $N_{C,p}$, $N_{L,p}$, $N_{M,p}$ from the base matrix to obtain a complete matrix $\widehat{N}_{g,p}$ of user counts that covers all $g \in \mathscr{G}$ and $p \in \mathscr{P}$. Note that even though these users are missing a political affinity, they are not missing from the URL-level Facebook Activity Dataset and we can still observe their engagement counts for each URL.

Finally, we leverage the base matrix $\widehat{N}_{g,p}$ of user counts to produce a confusion matrix yielding the proportion of users with a given political affinity $g \in \mathscr{G}$ that falls into each party registration group. Specifically, we define

$$w_{g,p} \; = \; \frac{\widehat{N}_{g,p}}{\sum_{p' \in \mathscr{P}} \widehat{N}_{g,p'}}.$$

[39] These percentages are obtained from the 2020 American National Election Studies (ANES) dataset (American National Election Studies, 2020).

Table F.1: Confusion Matrix

Political Affinity	Party Registration RR	RD	NR
Liberal	0.04	0.38	0.58
Moderate	0.11	0.24	0.65
Conservative	0.52	0.06	0.41
Missing	0.16	0.23	0.61

Notes: This table shows, for each political affinity group g, the share of users who have a given party registration p (hence, each row sums up to 1). The values in the row with "Missing" political affinity are imputed using the population shares of party registration as per American National Election Studies (2020). The values in all other rows come from Barberá et al. (2015), based on Twitter (now "X") users.

Step 3: From User Counts to Click Counts

Let K_g be the total number of news clicks in our URL-level Facebook Activity Dataset attributed to political-affinity group $g \in \mathscr{G}$.

We therefore treat $\{L, M, C, missing\}$ as four mutually exclusive and exhaustive groups for the click-level analysis. In order to allocate clicks to party registration categories, we impose the following assumption. For each group $g \in \{L, M, C, missing\}$, we allocate K_g across $\{\text{NR}, \text{RD}, \text{RR}\}$ in proportion to the share of users in g who fall under each party-registration category. Specifically, we let

$$K_{g,p} = w_{g,p} \times K_g.$$

where $K_{g,p}$ denotes the number of clicks from individuals with political affinity score g imputed to individuals with party registration p.

We also define a variable that captures the total number of clicks from party-registration category p, and denote it by:

$$K_p = \sum_{g \in \{L,M,C,missing\}} K_{g,p}.$$

Step 4: Computing Average Slant by Party Registration

We observe the *average slant* of clicks for each political-affinity group $g \in \{L, M, C, missing\}$. Denote these averages by S_g.

For each party-registration category p, we compute its click-weighted average slant, S_p, as the click-weighted mean of $\{S_g\}$, using the fraction of p's clicks that come from each group g:

$$S_p = \frac{1}{K_p} \sum_{g \in \{L,M,C,missing\}} \Big(K_{g,p} \times S_g \Big).$$

Thus, if (for instance) 50 percent of the clicks assigned to RD originated from liberal users, 30 percent from moderates, 10 percent from conservatives, and 10 percent from users without a political affinity score (with respective slants $S_L, S_M, S_C, S_{missing}$), then S_{RD} would be the weighted average of the average slant for liberals, moderates, conservatives, and users without a political affinity score, using the weights 0.5, 0.3, 0.1, and 0.1 respectively.

Step 5: Obtaining the Party-Registration-Based Polarization Measure

After computing the click-weighted average slant for each party-registration category $p \in \{\mathrm{RD}, \mathrm{RR}\}$ (denoted S_p), we measure polarization as the distance between these averages, normalized by our slant scale range of 5 (from -2.5 to $+2.5$).

We refer readers to Section 6.1 of the main text for a thorough discussion of our polarization measure and its properties. There, we also report our baseline estimate of this party-registration-based polarization for Facebook news consumption in 2019 and contrast it with the estimate obtained using Facebook's "political affinity" classification directly.

As discussed in the main text, our party-registration-based measure of polarization is smaller than the measure based on Facebook's "political affinity" classification. A plausible reason is that political affinity scores of "liberal" or "conservative" disproportionately capture stronger partisans. We can see this by comparing the distribution of party registration in the overall population (23% Democrat, 16% Republican, 61% neither) with that among individuals assigned a political affinity score in Table F.1. Among those labeled as liberal, 38% are registered Democrats, 4% are registered Republicans, and 58% are not registered with either party. Among those labeled as conservative, 6% are registered Democrats, 52% are registered Republicans, and 41% are not registered. By contrast, moderates closely match the overall population distribution. These patterns show that there are more registered Democrats and Republicans among users with a political affinity score of liberal or conservative than in the general population. Thus, being assigned a liberal or conservative political affinity score is likely to be a stronger marker of ideology than party registration. This helps explain why using the political affinity measure alone yields a higher estimate of polarization in news consumption.

G. The Role of Echo Chambers

In this appendix, we describe the methodology and assumptions that allow us to obtain a (conservative) estimate of the amount of polarization in news exposure that is due to echo chambers. In other words, we measure the degree of polarization in news exposure that would prevail if users' feeds reflected only the content shared by their friends.

Formally, let s_f denote the slant of a random article that a user is exposed to due to the sharing behavior of her friends. We are interested in

$$\mathscr{P}_{exposure}^{echo} = \frac{E\left(s_f|user\ is\ conservative\right) - E\left(s_f|user\ is\ liberal\right)}{5}$$

Consider $E\left(s_f|user\ is\ i\right)$ for $i \in \{liberal, conservative\}$. Since we assume that users' feeds reflect only the content shared by their friends, we can employ the law of total expectation to obtain

$$E\left(s_f|user\ is\ i\right) = \sum_{j\in\{liberal,moderate,conservative\}} E\left(s_f|user\ is\ i, poster\ is\ j\right) P\left(poster\ is\ j|user\ is\ i\right)$$

For all $i \in \{liberal, conservative\}$ and $j \in \{liberal, moderate, conservative\}$, we obtain estimates of $P\left(poster\ is\ j|user\ is\ i\right)$ from Table S2 in Bakshy, Messing and Adamic (2015), which provides $x_{\{i\leftarrow j\}}$, the average fraction of friends of type j for a user of type i.

Thus, in order to calculate $\mathscr{P}_{exposure}^{echo}$, we only need $E\left(s_f|user\ is\ i, poster\ is\ j\right)$ for all $i \in \{liberal, conservative\}$ and $j \in \{liberal, moderate, conservative\}$. Unfortunately, we do not have access to data that allows us to estimate those probabilities. However, we can impose a plausible assumption to make progress: we assume that, for all $j \in \{liberal, moderate, conservative\}$,

$$\begin{gathered} E\left(s_f|user\ is\ liberal, poster\ is\ j\right) \leq \\ \leq E\left(s_f|poster\ is\ j\right) \leq \\ \leq E\left(s_f|user\ is\ conservative, poster\ is\ j\right) \end{gathered}$$

Specifically, we assume that: i) the news articles that posters with ideology j share with liberal users are, on average, relatively more left-leaning than the news articles that posters with ideology j share in general, and ii) the news articles that posters with ideology j share with conservative users are, on average, relatively more right-leaning than the news articles that posters with ideology j share in general.

Thus,

$$\mathscr{P}_{exposure}^{echo} = \frac{E\left(s_f|user\ is\ conservative\right) - E\left(s_f|user\ is\ liberal\right)}{5} =$$

$$= \frac{1}{5}\left\{ \sum_{j\in\{liberal,moderate,conservative\}} E\left(s_f|user\ is\ conservative, poster\ is\ j\right) P\left(poster\ is\ j|user\ is\ conservative\right) \right.$$

$$
- \sum_{j \in \{liberal, moderate, conservative\}} E\left(s_f | user\ is\ liberal, poster\ is\ j\right) P\left(poster\ is\ j | user\ is\ liberal\right) \Bigg\} \geq
$$

$$
= \frac{1}{5} \Bigg\{ \sum_{j \in \{liberal, moderate, conservative\}} E\left(s_f | poster\ is\ j\right) P\left(poster\ is\ j | user\ is\ conservative\right)
$$

$$
- \sum_{j \in \{liberal, moderate, conservative\}} E\left(s_f | poster\ is\ j\right) P\left(poster\ is\ j | user\ is\ liberal\right) \Bigg\} \equiv \underline{\mathscr{P}}^{echo}_{exposure}
$$

$\underline{\mathscr{P}}^{echo}_{exposure}$ is a lower bound on the amount of polarization in news exposure that would prevail if users' feeds reflected only the content shared by the users' friends. The key intuition is that we assume, for example, that liberal friends of liberals and liberal friends of conservatives share content with the same ideological slant. In reality, however, liberal friends of liberals may share more strongly liberal content than liberal friends of conservatives. As a result, our estimate provides a lower bound on the polarization caused by echo chambers.

Since, for $j \in \{liberal, moderate, conservative\}$, we can estimate $E\left(s_f | poster\ is\ j\right)$ as the average slant of articles shared by j-type users (denoted by $\bar{y}_j$ in Section 6.2.3), we can obtain an estimate of $\underline{\mathscr{P}}^{echo}_{exposure}$. Using directly the political affinity scores as a measure of partisanship, the estimate we obtain is 0.15. Since the overall degree of polarization in news exposure estimated using the political affinity scores is 0.25, the degree of polarization in news exposure that would result from echo chambers alone is at least 59% of the actual degree of polarization in news exposure.

H. Polarization, Segregation, and Favorability

H.1 Empirics

In the empirical part of this appendix, we substantiate the claims made in the introduction about the difference between our content-based article-level slant measure and audience-based article-level favorability scores, as well as the difference between our polarization measure and the segregation (or isolation) index.[40]

To begin with, we provide definitions of the notions of favorability score and segregation (or isolation) index. González-Bailón et al. (2023) define the favorability score of URL α as follows

$$fav_{\alpha} = \frac{C_{\alpha} - L_{\alpha}}{C_{\alpha} + L_{\alpha}}$$

where α indicates a particular URL, C_{α} indicates the number of conservative clicks on URL α, and L_{α} indicates the number of liberal clicks on URL α. Intuitively, this is an audience-based measure of the URL's leaning, where URLs with more conservative clicks getting higher score.

Gentzkow and Shapiro (2011) define the segregation (or isolation) index as:

$$S = \sum_{\alpha \in A} \left(\frac{C_{\alpha}}{\overline{C}} \times \frac{C_{\alpha}}{v_{\alpha}} \right) - \sum_{\alpha \in A} \left(\frac{L_{\alpha}}{\overline{L}} \times \frac{C_{\alpha}}{v_{\alpha}} \right)$$

where A is the set of URLs under consideration, $\overline{C} = \sum_{\alpha \in A} C_{\alpha}$ indicates the total number of conservative clicks for any URL, $\overline{L} = \sum_{\alpha \in A} L_{\alpha}$ indicates the total number of liberal clicks for any URL, and $v_{\alpha} = C_{\alpha} + L_{\alpha}$ indicates the total number of liberal and conservative clicks for URL α. Intuitively, segregation measures the difference in the share of conservatives among the audiences of outlets (or articles) visited by conservatives and the share of conservatives among the audiences of outlets (or articles) visited by liberals.

Favorability Scores We begin by analyzing the differences between our measure of slant and the favorability scores, and then segue into the differences between our measure of polarization and the segregation (or isolation) index.

In order to study the relationship between our content-based article-level slant measure and the audience-based article-level favorability scores, we proceed in two steps. First, following the procedure outlined in Buntain et al. (2023) to account for differential privacy in the URL-level Facebook Activity dataset, we restrict our attention to the set of articles shared on Facebook more than 8,962 times. This restriction ensures that the signal-to-noise ratio is sufficiently high to estimate meaningful favorability scores in spite of differential privacy. Second, we calculate the favorability scores for those articles, as described in González-Bailón et al. (2023).[41]

[40] The names segregation index and isolation index are sometimes used interchangeably in the literature. See, for instance, Gentzkow and Shapiro (2011) and González-Bailón et al. (2023).

[41] The version of the favorability score calculated in Buntain et al. (2023) and in González-Bailón et al. (2023) are

Our main empirical result when comparing the audience-based favorability scores to our content-based slant measure is that these two measures capture distinct concepts and one cannot easily be considered a proxy for the other.[42]

Figure H.1 overlays the distribution of our slant measure and the favorability scores for the set of articles clicked on Facebook more than 8,962 times. The figure shows that the favorability score exhibits a strongly bimodal distribution, whereas our slant measure exhibits a distribution that is much closer to unimodality.

The relationship between the two measures is further clarified in Figure H.2, which presents a binned scatter plot of our slant measure on the horizontal axis versus the favorability score on the vertical axis. The figure exhibits a marked S-shaped pattern, indicating that favorability scores exhibit compression among both left-leaning and right-leaning articles.

Figure H.3 plots the distribution of favorability scores, after restricting attention to the set of articles to which our slant measure assigns a value of zero. Even among articles that are considered to be neutral based on our content-based slant measure, the distribution of favorability scores is strongly bimodal. This finding echoes the concern raised in the introduction that favorability scores might assign partisan value to centrist articles published in partisan outlets simply because partisan outlets tend to have a partisan readership. In other words, an article from an outlet that is visited primarily by liberals (conservatives) is likely to be visited and shared primarily by liberals (conservatives) even when the article is moderate. Indeed, among the set of articles to which our measure of slant assigns a value of zero, we find that the correlation between the favorability score and the audience-based measure of slant at the outlet level from Bakshy, Messing and Adamic (2015) is 0.82.[43] Thus, articles that, according to our measure, are moderate appear to inherit their favorability score from the partisanship of the outlet they come from.

Finally, Figure H.4 examines articles with favorability scores near zero (between -0.5 and 0.5) and plots the distribution of their slant values. Unlike Figure H.1, this distribution is unimodal with a moderate mode. Thus, articles that our measure classifies as moderate are generally not classified as moderate by the favorability score, whereas articles that are generally classified as moderate by the favorability score are also largely classified as moderate by our slant measure.[44]

slightly different but extremely highly correlated (Pearson correlation: 0.996). The threshold we calculate to address the issues that arise due to differential privacy is based on the measure in Buntain et al. (2023). In spite of that, we calculate and discuss the favorability score from González-Bailón et al. (2023) throughout this appendix, as it is more easily interpretable and arguably more standard. Given the extremely high correlation between the two versions of the favorability scores, this decision should make little practical difference.

[42] Throughout this section, we use a click-based favorability score to ensure that the favorability score is consistent with the segregation index and our main polarization measure, which are based on clicks. The results are very similar when using a shares-based favorability score.

[43] Bakshy, Messing and Adamic (2015) determine the slant of a domain based on the ideology of individuals who shared news from the domain, similarly to a favorability score.

[44] A research assistant manually reviewed the 37 articles that our measure of slant classified as extreme (i.e., with an absolute slant measure greater than or equal to 2) and the favorability scores classified as moderate (with a favorability score between -0.5 and 0.5). The research assistant, who was informed neither about how the articles were selected nor about the purpose of the task, was simply asked to assign a measure of slant to each of the 37 articles according to the criteria specified in Appendix B. For 70% of the articles, the RA's ratings confirmed both the direction of slant and the fact that the article was extreme. For example, the following opinion piece by Brett Stephens was considered moderate by the favorability score (probably because it appeared in the New York Times), but we considered it clearly conserva-

As an extreme example of articles inheriting their favorability scores from the partisanship of the outlet they come from, let us consider a specific article written by the Associated Press, a portion of which is reported at the end of this section. This article appeared, verbatim, on the websites of ABC News, Business Insider, CBS News, NBC News, and the New York Post. The title of the article varied slightly depending on the outlet.[45] Our slant measure assigns to the article, independently of the title, a slant rating of zero. Conversely, the favorability score of the article varies substantially depending on the outlet that published it, as shown in the table below.

	Favorability Score	Content-based Outlet Slant
NBC News	-0.62	-0.61
Business Insider	-0.46	-0.62
ABC News	-0.36	-0.43
CBS News	-0.31	-0.52
The New York Post	0.27	0.44

Note that an article with the exact same text receives a liberal score when appearing in more liberal outlets (NBC News and Business Insider) and a conservative score when appearing in a more conservative outlet (The New York Post). More generally, once again, the correlation between the favorability score and the audience-based measure of slant at the outlet level from Bakshy, Messing and Adamic (2015) is high (0.84). The high degree of correlation between the favorability scores of the same AP article published by different outlets and a measure of outlet-level slant suggests that, indeed, articles can indeed inherit their favorability scores from the partisanship of the audience of the outlet they are published in.

Segregation Index The example above allows us to segue into the difference between our measure of polarization in news consumption and the segregation (or isolation) index. Specifically, in line with the discussion in the introduction, we can calculate both our polarization measure and the shares-based segregation index for the articles from the example above. We find that the polarization index equals 0, whereas the segregation index equals 0.10, which corresponds to 21% of the segregation index reported in González-Bailón et al. (2023).[46] This example shows how the segregation index can in principle be inflated in the presence of articles with a similar slant (in this case,

tive: https://www.nytimes.com/2019/01/25/opinion/venezuela-maduro-socialism-government.html. In all but two of the remaining articles, the RA confirmed the direction of slant but not the fact that the article was extreme. This exercise shows that, for articles that are considered extreme by our measure of slant and moderate by the favorability scores, the vast majority of discrepancies are adjudicated in favor of our measure of slant.

[45] ABC News titled the article ”APNewsBreak: US approved thousands of child bride requests.” Business Insider titled it ”The US government approved thousands of requests for men to bring child brides to the US.” CBS News titled it ”U.S. approved thousands of child bride requests — and that’s legal.” NBC News titled it ”U.S. approved thousands of child bride requests, lives ruined.” Lastly, the New York Post titled it ”US approved thousands of child bride requests over last 10 years.”

[46] González-Bailón et al. (2023) do not provide a click-based segregation index so we use their exposure-based index instead for this comparison. This is a conservative comparison as views are typically less segregated than clicks. When using a shares-based index, the segregation among the articles from the example above is 0.19 and corresponds to 35% of the engagement-based segregation index reported in González-Bailón et al. (2023).

identical articles) that appear in outlets with a different partisan composition of readership. By being based on a purely content-driven measure of slant at the article level, our index of polarization does not run into this problem.

To more broadly illustrate the point that the segregation index can be inflated when articles with a similar slant appear in outlets that differ in the partisanship of their readers, we carry out an additional exercise. First, we calculate the clicks-based segregation index on the overall set of articles that meet the differential privacy threshold described at the beginning of this appendix; second, we calculate the clicks-based segregation index on the subset of those articles that our content-based measure of slant classifies as moderate (i.e., articles that are assigned a slant rating of zero). We find that clicks-based segregation index on the overall set of articles is 0.63 and that, when we limit our attention to articles that are classified as moderate by our slant measure, the index takes a value of 0.47. Thus, the clicks-based segregation index on moderate articles is 75% of the clicks-based segregation index on all articles. This finding, once again, suggests that the segregation index can be driven by moderate articles published on outlets with a partisan readership.

Article ”WASHINGTON — Thousands of requests by men to bring in child and adolescent brides to live in the United States were approved over the past decade, according to government data obtained by The Associated Press. In one case, a 49-year-old man applied for admission for a 15-year-old girl.

The approvals are legal: The Immigration and Nationality Act does not set minimum age requirements. And in weighing petitions for spouses or fiancees, US Citizenship and Immigration Services goes by whether the marriage is legal in the home country and then whether the marriage would be legal in the state where the petitioner lives.

But the data raises questions about whether the immigration system may be enabling forced marriage and about how US laws may be compounding the problem despite efforts to limit child and forced marriage. Marriage between adults and minors is not uncommon in the United States and most states allow children to marry with some restrictions.

[...]”

H.2 Theory

In the theoretical part of this appendix, we introduce a very simple example to illustrate two key points. The first point is that the relationship between our measure of polarization at the outlet and at the article levels depends, in an intuitive fashion, on whether partisans consume pro- or counter-attitudinal news within outlets. Specifically, if partisans consume pro-attitudinal news within outlets, polarization in news consumption at the article level will be higher than polarization in news consumption at the outlet level; conversely, if partisans consume counter-attitudinal news within outlets, polarization in news consumption at the article level will be smaller than at the outlet level. Lastly, if partisans read randomly within outlets, polarization in news consumption will be the same at the article and at the outlet levels.

The second key point is that measures of segregation suffer from a small-sample bias. As a result, it has been argued that, in small samples, measures of segregation at finer levels of aggregation tend to be higher than measures of segregation at coarser levels of aggregation (Gentzkow, Shapiro and Taddy, 2019; Yao et al., 2019; Wong, 2003).

Formally, let M denote the set of news articles, with $M = \{1,2,3,4\}$. Let N denote the set of news outlets, with $N = \{\alpha, \beta\}$. Let articles 1 and 2 belong to outlet α and articles 3 and 4 belong to outlet β. Let there be two Democrats and two Republicans and suppose each reads a single article picked at random according to categorical distribution $Categorical(p_1^z, p_2^z, p_3^z, p_4^z)$, where the distribution is allowed to differ between Democrats and Republican (i.e., $z \in \{D,R\}$). Let $s_i \in \mathbb{R}$ denote the slant of article $i \in M$ and assume $s_1 < s_2$ and $s_3 < s_4$. Thus, each outlet has a relatively more liberal and a relatively more conservative article. Let $\mathbf{S}_a = (s_1, s_2, s_3, s_4)$ be a vector describing the slant of each article and $\mathbf{S}_o = (\frac{s_1+s_2}{2}, \frac{s_3+s_4}{2})$ be a vector describing the slant of each outlet.

Let $\mathbf{X}^z \in \mathbb{R}^4$ for $z \in \{D,R\}$ be a random vector describing the number of Democrats or Republicans who are exposed to each article $i \in M$. $\mathbf{X}^z$ has the following distribution

$$\mathbf{X}^z = \begin{cases} [1,1,0,0] & \text{w.p.} \quad 2 \cdot p_1^z \cdot p_2^z \\ [1,0,1,0] & \text{w.p.} \quad 2 \cdot p_1^z \cdot p_3^z \\ [1,0,0,1] & \text{w.p.} \quad 2 \cdot p_1^z \cdot p_4^z \\ [0,1,1,0] & \text{w.p.} \quad 2 \cdot p_2^z \cdot p_3^z \\ [0,1,0,1] & \text{w.p.} \quad 2 \cdot p_2^z \cdot p_4^z \\ [0,0,1,1] & \text{w.p.} \quad 2 \cdot p_3^z \cdot p_4^z \\ [2,0,0,0] & \text{w.p.} \quad (p_1^z)^2 \\ [0,2,0,0] & \text{w.p.} \quad (p_2^z)^2 \\ [0,0,2,0] & \text{w.p.} \quad (p_3^z)^2 \\ [0,0,0,2] & \text{w.p.} \quad (p_4^z)^2 \end{cases}$$

Thus $E[\mathbf{X}^z] = (2p_1^z, 2p_2^z, 2p_3^z, 2p_4^z)$. The average expected slant that Democrats are exposed to is, therefore, $\frac{1}{2}\{E[\mathbf{X}^D] \cdot \mathbf{S}_a'\}$; similarly, the average expected slant that Republicans are exposed to is $\frac{1}{2}\{E[\mathbf{X}^R] \cdot \mathbf{S}_a'\}$. But then, in this simple example, expected polarization at the article level can be written as

$$E[\mathscr{P}_{article}] = \frac{\frac{1}{2}\{E[\mathbf{X}^R] \cdot \mathbf{S}_a'\} - \frac{1}{2}\{E[\mathbf{X}^D] \cdot \mathbf{S}_a'\}}{5} = \frac{1}{10}\{E[\mathbf{X}^R] - E[\mathbf{X}^D]\} \cdot \mathbf{S}_a'$$

Let $\mathbf{Y}^z \in \mathbb{R}^2$ for $z \in \{D,R\}$ be a random vector describing the number of Democrats or Republicans who are exposed to each outlet $j \in N$. $\mathbf{Y}^z$ has the following distribution

$$\mathbf{Y}^z = \begin{cases} [1,1] & \text{w.p.} \quad 2(p_1^z \cdot p_3^z + p_1^z \cdot p_4^z + p_2^z \cdot p_3^z + p_2^z \cdot p_4^z) \\ [2,0] & \text{w.p.} \quad 2(p_1^z \cdot p_2^z) + (p_1^z)^2 + (p_2^z)^2 \\ [0,2] & \text{w.p.} \quad 2(p_3^z \cdot p_4^z) + (p_3^z)^2 + (p_4^z)^2 \end{cases}$$

Thus:

$$E[\mathbf{Y}^z] = [2(p_1^z \cdot p_3^z + p_1^z \cdot p_4^z + p_2^z \cdot p_3^z + p_2^z \cdot p_4^z) + 4(p_1^z \cdot p_2^z) + 2(p_1^z)^2 + 2(p_2^z)^2, \\ 2(p_1^z \cdot p_3^z + p_1^z \cdot p_4^z + p_2^z \cdot p_3^z + p_2^z \cdot p_4^z) + 4(p_3^z \cdot p_4^z) + 2(p_3^z)^2 + 2(p_4^z)^2] \tag{2}$$

The average expected slant that Democrats are exposed to is, therefore, $\frac{1}{2}\{E[\mathbf{Y}^D] \cdot \mathbf{S}_o'\}$; similarly, the average expected slant that Republicans are exposed to is $\frac{1}{2}\{E[\mathbf{Y}^R] \cdot \mathbf{S}_o'\}$. But then, in this simple example, expected polarization at the outlet level can be written as

$$E[\mathscr{P}_{outlet}] = \frac{\frac{1}{2}\{E[\mathbf{Y}^R] \cdot \mathbf{S}_o'\} - \frac{1}{2}\{E[\mathbf{Y}^D] \cdot \mathbf{S}_o'\}}{5} = \frac{1}{10}\{E[\mathbf{Y}^R] - E[\mathbf{Y}^D]\} \cdot \mathbf{S}_o'$$

As a result,

$$E[\mathscr{P}_{article} - \mathscr{P}_{outlet}] = \frac{1}{10}\{E[\mathbf{X}^R] - E[\mathbf{X}^D]\} \cdot \mathbf{S}_a' - \frac{1}{10}\{E[\mathbf{Y}^R] - E[\mathbf{Y}^D]\} \cdot \mathbf{S}_o'$$

The expression above can be simplified to:

$$E[\mathscr{P}_{article} - \mathscr{P}_{outlet}] = \\ \frac{1}{10}\left[\underbrace{(s_2 - s_1)}_{>0}\left[\left(p_1^D - p_2^D\right) - \left(p_1^R - p_2^R\right)\right] + \underbrace{(s_4 - s_3)}_{>0}\left[\left(p_3^D - p_4^D\right) - \left(p_3^R - p_4^R\right)\right]\right]$$

To illustrate how the relationship between our measure of polarization at the outlet and at the article levels depends on whether partisans consume pro- or counter-attitudinal news within outlet, we consider three cases:

1. Pro-attitudinal news consumption within outlets, which corresponds to the following assumption: $p_1^D > p_2^D$, $p_3^D > p_4^D$, $p_1^R < p_2^R$, $p_3^R < p_4^R$
2. Neutral news consumption within outlets, which corresponds to the following assumption: $p_1^D = p_2^D, p_3^D = p_4^D, p_1^R = p_2^R, p_3^R = p_4^R$
3. Counter-attitudinal news consumption within outlets, which corresponds to the following assumption: $p_1^D < p_2^D, p_3^D < p_4^D, p_1^R > p_2^R, p_3^R > p_4^R$

It is easy to show that, for pro-attitudinal news consumption within outlets $\mathscr{P}_{article} - \mathscr{P}_{outlet} > 0$, for neutral news consumption within outlets $\mathscr{P}_{article} - \mathscr{P}_{outlet} = 0$, and for counter-attitudinal news consumption within outlets $\mathscr{P}_{article} - \mathscr{P}_{outlet} < 0$. Thus, the relationship between our measure of polarization at the outlet and at the article levels depends, in an intuitive fashion, on whether partisans consume pro- or counter-attitudinal news within outlets. This illustrates the first point.

The second point that this appendix aims to illustrate is that, in our very simple example, segregation at the article level is weakly higher than segregation at the outlet level and, generically, strictly higher. This result reflects a general concern in the spatial segregation literature, namely that, in small samples, measures of segregation at finer levels of aggregation tend to be higher than measures of segregation at coarser levels of aggregation (Yao et al., 2019). Thus, in small samples, it is hard to obtain an apple-to-apple comparison of segregation at the outlet and at the article level.

Consider, once again, the environment set up at the beginning of this appendix. The segregation index at the article level can be written as

$$\mathscr{S}_{article} = \frac{1}{2}\sum_{m\in M}\left(\frac{R_m^2}{v_m}\right) - \frac{1}{2}\sum_{m\in M}\left(\frac{D_m \cdot R_m}{v_m}\right)$$

where R_m is the m^{th} component of $\mathbf{X}^R$, D_m is the m^{th} component of $\mathbf{X}^D$, and $v_m = R_m + D_m$. Thus, the expected segregation index at the article level can be written as

$$E[\mathscr{S}_{article}] = \sum_{m\in M}\left[p_m^R - 2\cdot p_m^R \cdot p_m^D + \frac{2}{3}\cdot p_m^R \cdot (p_m^D)^2 + \frac{2}{3}\cdot (p_m^R)^2 \cdot p_m^D - \frac{1}{3}\cdot (p_m^R \cdot p_m^D)^2\right]$$

The segregation index at the outlet level can be written as

$$\mathscr{S}_{outlet} = \frac{1}{2}\sum_{n\in N}\left(\frac{R_n^2}{v_n}\right) - \frac{1}{2}\sum_{n\in N}\left(\frac{D_n \cdot R_n}{v_n}\right)$$

where R_n is the n^{th} component of $\mathbf{Y}^R$, D_n is the n^{th} component of $\mathbf{Y}^D$, and $v_n = R_n + D_n$. Thus, the expected segregation index at the outlet level can be written as

$$\begin{aligned} E[\mathscr{S}_{outlet}] = &\frac{2}{3}(p_1^R + p_2^R) + \frac{2}{3}(p_1^D + p_2^D) + \frac{1}{3}(p_1^R + p_2^R)^2 + \frac{1}{3}(p_1^D + p_2^D)^2 \\ &- \frac{8}{3}(p_1^R + p_2^R)\cdot(p_1^D + p_2^D) + \frac{2}{3}(p_1^R + p_2^R)\cdot(p_1^D + p_2^D)^2 \\ &+ \frac{2}{3}(p_1^R + p_2^R)^2\cdot(p_1^D + p_2^D) - \frac{2}{3}(p_1^R + p_2^R)^2\cdot(p_1^D + p_2^D)^2 \end{aligned}$$

The following proposition holds.

Proposition: $E[\mathscr{S}_{article}] - E[\mathscr{S}_{outlet}] \geq 0$. Furthermore, $E[\mathscr{S}_{article}] - E[\mathscr{S}_{outlet}] = 0$ if and only if $p_1^R p_2^D = p_2^R p_1^D = p_4^D p_3^R = p_4^R p_3^D = 0$.

Proof

It is possible to simplify the expression for $E[\mathscr{S}_{article}] - E[\mathscr{S}_{outlet}]$ as follows:

$$E[\mathscr{S}_{article}] - E[\mathscr{S}_{outlet}] = \frac{1}{3}(G_1 + G_2)$$

, where

$$
\begin{aligned}
G_1 = & ((p_1^D)^2 + (p_2^D)^2) p_1^R p_2^R \\
& + p_1^R p_2^D (p_3^D + p_4^D + 1 - p_1^D) p_3^R \\
& + p_1^R p_2^D (p_3^D + p_4^D + 1 - p_1^D) p_4^R \\
& + p_1^R p_2^D (p_3^D + p_4^D + 1 - p_1^D) \\
& + p_2^R p_1^D (p_3^D + p_4^D + 1 - p_2^D) p_3^R \\
& + p_2^R p_1^D (p_3^D + p_4^D + 1 - p_2^D) p_4^R \\
& + p_2^R p_1^D (p_3^D + p_4^D + 1 - p_2^D) \\
& + 2 p_1^R p_2^D (1 - p_2^R) + 2 p_2^R p_1^D (1 - p_1^R)
\end{aligned}
$$

and

$$
\begin{aligned}
G_2 = & ((p_3^D)^2 + (p_4^D)^2) p_3^R p_4^R \\
& + p_3^R p_4^D (p_1^D + p_2^D + 1 - p_3^D) p_1^R \\
& + p_3^R p_4^D (p_1^D + p_2^D + 1 - p_3^D) p_2^R \\
& + p_3^R p_4^D (p_1^D + p_2^D + 1 - p_3^D) \\
& + p_4^R p_3^D (p_1^D + p_2^D + 1 - p_4^D) p_1^R \\
& + p_4^R p_3^D (p_1^D + p_2^D + 1 - p_4^D) p_2^R \\
& + p_4^R p_3^D (p_1^D + p_2^D + 1 - p_4^D) \\
& + 2 p_3^R p_4^D (1 - p_4^R) + 2 p_4^R p_3^D (1 - p_3^R)
\end{aligned}
$$

Since all of the terms in G_1 and G_2 are non-negative, $G_1 \geq 0$, $G_2 \geq 0$, and, thus, $E[\mathscr{S}_{article}] - E[\mathscr{S}_{outlet}] \geq 0$

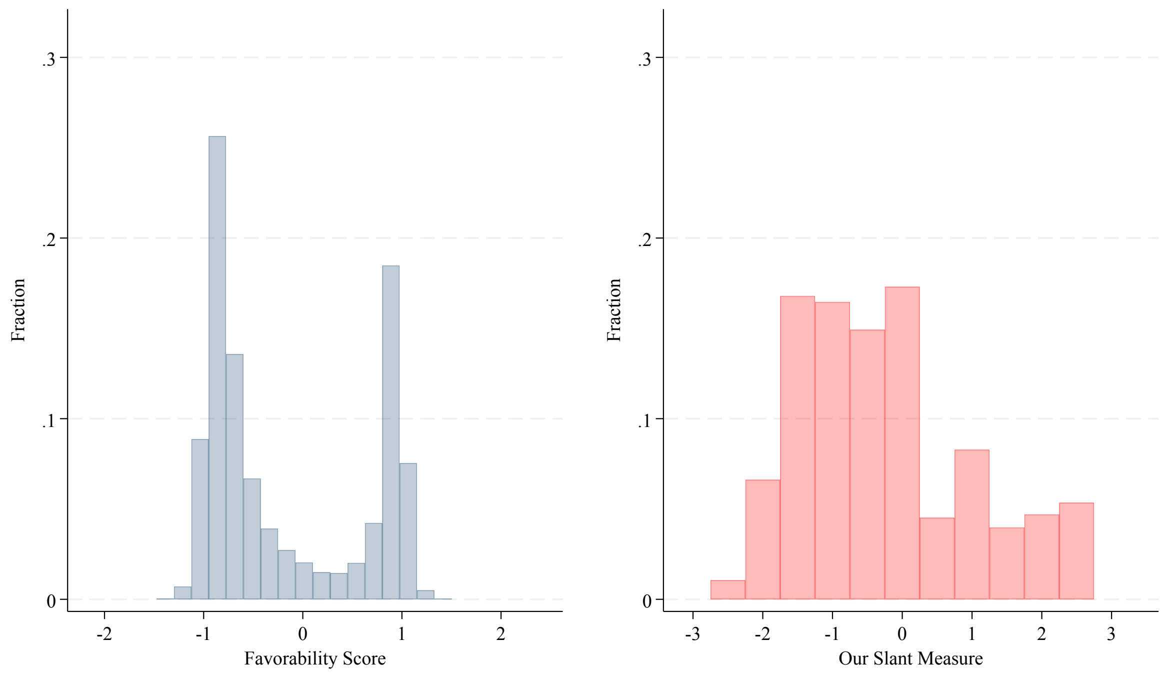
Furthermore, it is easy to see that $G_1 = 0$ if and only if $p_1^R p_2^D = p_2^R p_1^D = 0$. Similarly, it it easy to see that $G_2 = 0$ if and only if $p_4^D p_3^R = p_4^R p_3^D = 0$. Therefore, $E[\mathscr{S}_{article}] - E[\mathscr{S}_{outlet}] = 0$ if and only if $p_1^R p_2^D = p_2^R p_1^D = p_4^D p_3^R = p_4^R p_3^D = 0$. $\square$

This shows that, in the simple example above, the segregation index at the article level is always at least as large as the segregation index at the outlet level. In fact, generically, the segregation index at the article level is always strictly larger than the segregation index at the outlet level.[47]

Furthermore, the proposition shows that a necessary condition for segregation at the outlet level to equal segregation at the article level is that partisans read some articles with zero probability—a knife-edge case. Conversely, the difference between our polarization index at the article and at the outlet level equals zero precisely when partisans read randomly within outlets and, thus, consume the average slant of the outlet.

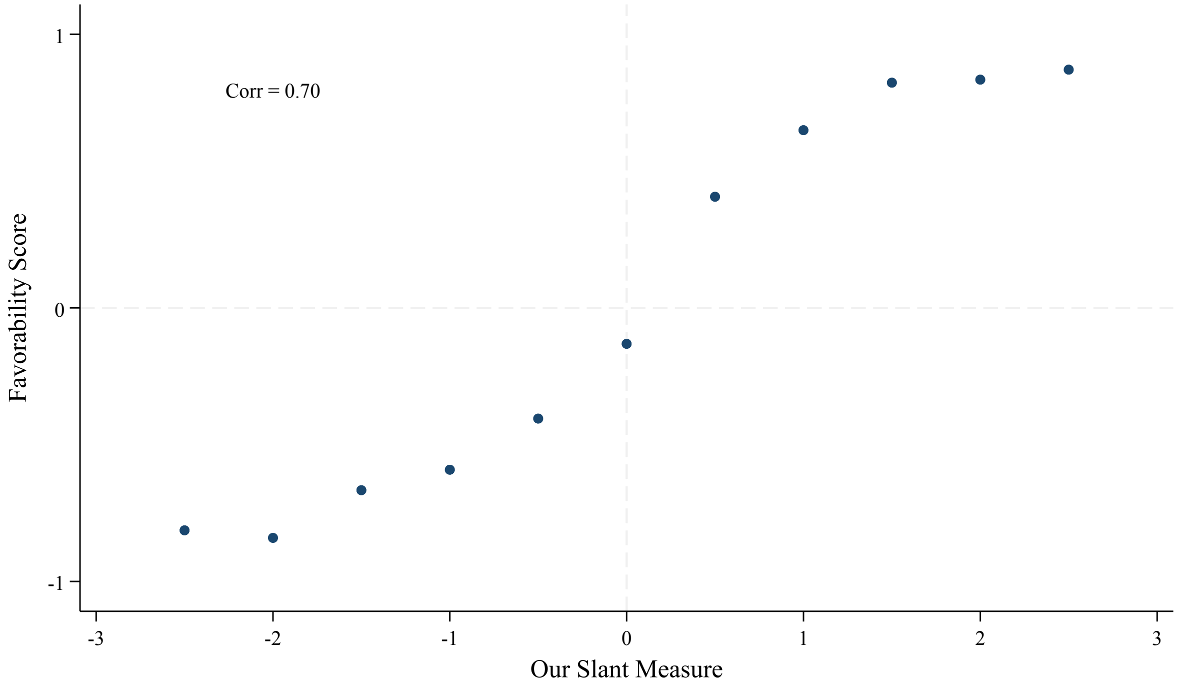
[47] The result holds generically, in the sense that the set of probability distributions $(p_1^z, p_2^z, p_3^z, p_4^z)$ for $z \in \{D, R\}$ where the result does not hold has measure zero when seen as a subset of $\mathbb{R}^8$.

Figure H.1: Distribution of Favorability Scores and Slant



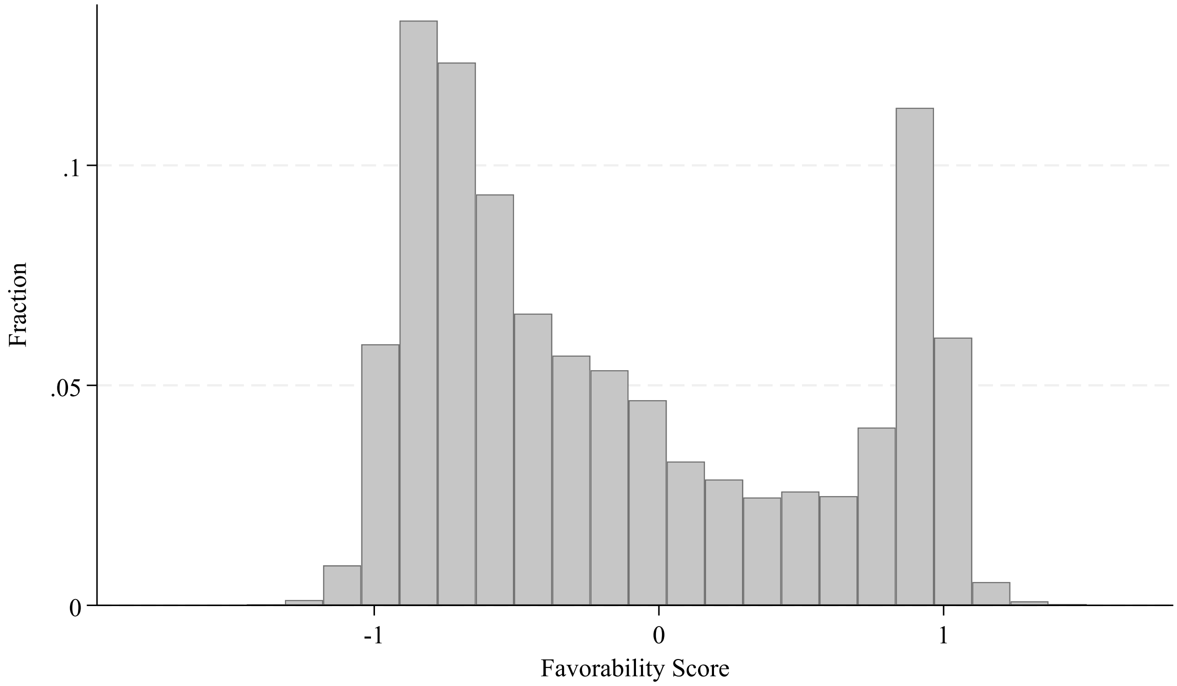
Notes: This figure shows the distribution of favorability scores (left panel) and slant (right panel) among hard news articles clicked on Facebook more than 8,962 times ($N = 38,178$) and published online by the top 100 U.S. news outlets in 2019. Our measure of slant is given by the fine-tuned GPT-4o's prediction as described in Section 4.2. The slant scale goes from -2.5 (extremely favorable to the Democratic party) to 2.5 (extremely favorable to the Republican party). The construction of the favorability scores is described in detail in Appendix H.

Figure H.2: Correlation between Favorability Scores and Slant



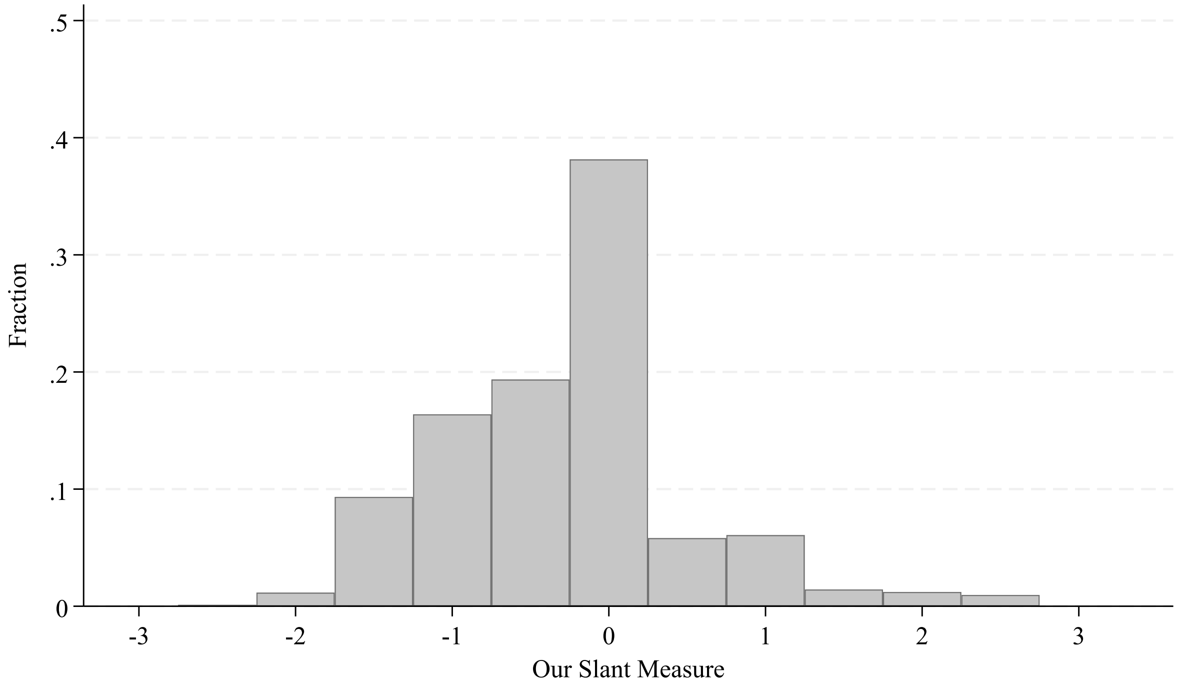
Notes: This figure shows, for each slant bin according to our slant measure (horizontal axis), the average favorability score across all articles in that bin. Our measure of slant is given by the fine-tuned GPT-4o's prediction as described in Section 4.2. The slant scale goes from -2.5 (extremely favorable to the Democratic party) to 2.5 (extremely favorable to the Republican party). The construction of the favorability scores is described in detail in Appendix H. The sample includes all hard news articles shared on Facebook more than 8,962 times ($N = 38,178$) and published online by the top 100 U.S. news outlets in 2019.

Figure H.3: Distribution of Favorability Scores: Moderate Slant



Notes: This figure shows the distribution of favorability scores among hard news articles that are classified as moderate (i.e., assigned a value of zero) according to our measure of slant. Our measure of slant is given by the fine-tuned GPT-4o's prediction as described in Section 4.2. The construction of the favorability scores is described in detail in Appendix H. The sample includes all hard news articles shared on Facebook more than 8,962 times ($N = 38,178$) and published online by the top 100 U.S. news outlets in 2019.

Figure H.4: Distribution of Slant: Moderate Favorability Score



Notes: This figure shows the distribution of our measure of slant among hard news articles that are classified as moderate (i.e., assigned a value between -0.5 and 0.5) according to their favorability score. Our measure of slant is given by the fine-tuned GPT-4o's prediction as described in Section 4.2. The slant scale goes from -2.5 (extremely favorable to the Democratic party) to 2.5 (extremely favorable to the Republican party). The construction of the favorability scores is described in detail in Appendix H. The sample includes all hard news articles shared on Facebook more than 8,962 times ($N = 38,178$) and published online by the top 100 U.S. news outlets in 2019.

I. Extrapolation Exercise

In order to further assuage concerns about the fact that the URL-level Facebook Activity Dataset only contains information about articles shared on Facebook at least 100 times, we perform an extrapolation exercise. Specifically, we use the Facebook Activity Dataset and impose assumptions that allow us to extend our measure of polarization to all articles shared on Facebook at least once. We proceed as follows.

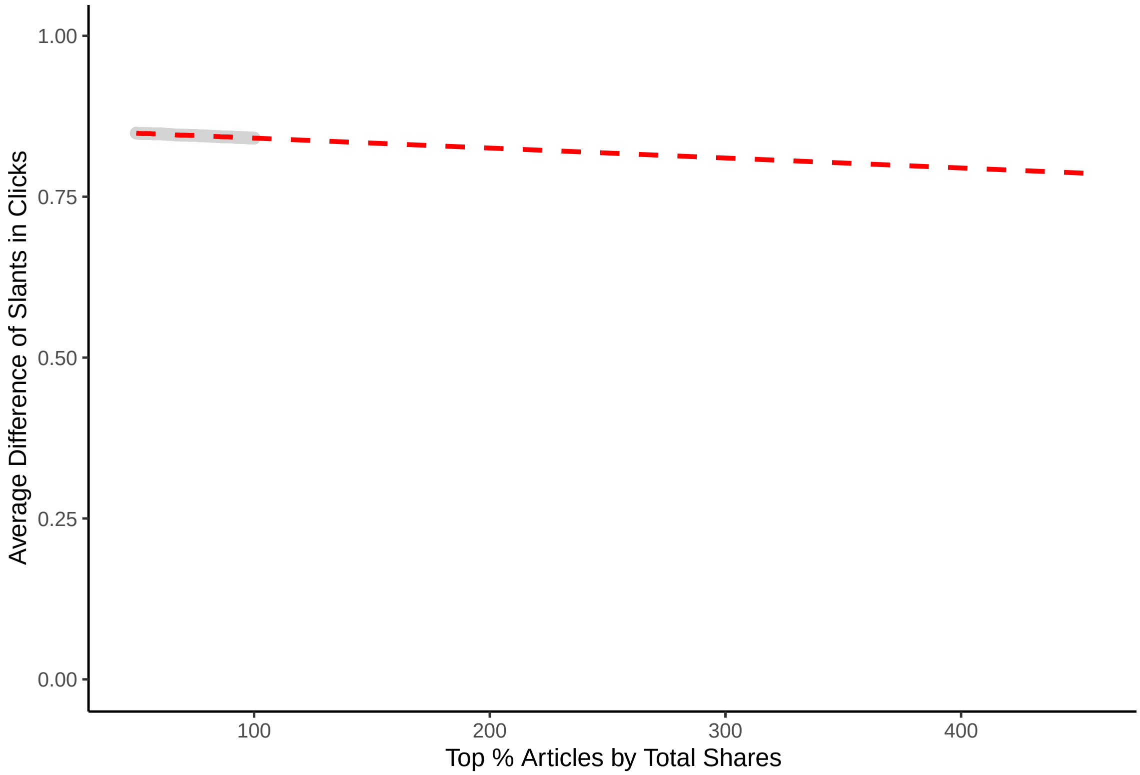
First, we examine how our polarization measure changes as we progressively add the least shared articles in the URL-level Facebook Activity Dataset. Specifically, we first calculate our polarization measure after removing articles in the bottom 50% of the URL-level Facebook Activity Dataset in terms of total shares. Next, we calculate our polarization measure after excluding articles in the bottom 49% in terms of total shares. We continue in this way until we calculate our polarization measure without excluding any articles from the URL-level Facebook Activity Dataset. Figure I.1 below presents the results. The figure shows that the polarization measure calculated on articles that are shared relatively more often is generally relatively higher. However, the increase is small in magnitude. For example, excluding articles in the bottom 20% in terms of total shares increases our polarization measure by only 0.003.

In the next step, we impose assumptions that allow us to extrapolate the pattern described above and obtain an estimate of how our polarization measure would change if we included additional articles. We assume that: i) every article in our database of articles is shared on Facebook at least once, and ii) starting from the 50% percentile in Figure I.1, the relationship between % of articles by total shares and our polarization measure is linear. The first assumption allows us to obtain a conservative estimate of the share of articles that are shared on Facebook less than 100 times; the second allows us to perform the extrapolation.

When we merge our articles dataset to the URL-level Facebook Activity Dataset, we find a match rate of 22%. Thus, we know that 22% of the articles in our database are shared on Facebook at least 100 times (subject to Laplace-5 noise). We assume that the remaining articles in our database are shared on Facebook at least once, but less than 100 times. In light of the match rate, we know that 100% in Figure I.1 corresponds to only 22% of articles shared on Facebook at least once. Therefore, we would like to extend the figure to 455% (1/0.22) to extrapolate results to all the articles shared on Facebook at least once. Employing the linear extrapolation described above, we find that polarization in news consumption would decrease to 0.16 if the SS1 included all articles shared at least once and not only articles shared at least 100 times. This is in the same ballpark as our main result from Section 6.1 (a 6% decrease).

Polarization in news consumption does not change dramatically when including many additional articles because people are exposed much less often to articles shared fewer than 100 times. Indeed, in a separate analysis, we study the relationship between the ranking of articles based on their shares and the number of views they receive. Using an extrapolation method similar to the one described above, we find that including all the articles shared on Facebook at least once would increase the total number of views by only 26.8%.

Figure I.1: Difference in the Average Slant of News Consumption by Party Registration Status, Extending to Articles Shared less than 100x



Notes: This figure shows the clicks-weighted average difference in slant of news diets by registered Republican and Democrat users on Facebook by total shares as discussed in Section 7.4. The news article sample includes all $N = 234,313$ hard news articles published online by the top 100 U.S. news outlets in 2019 that are in the URL-level Facebook Activity Dataset (i.e. shared at least 100 times on Facebook).

J. Slant distribution for each outlet in the top 100

In this appendix, we present summary statistics and histograms of the within-outlet slant distribution for each of the top 100 U.S. outlets in terms of online visits in 2019.

Table J.1: Summary Statistics within Outlets

	Obs.		Mean SS1 Slant			Sd.	% Lib
Outlet	All	SS1	All	Lib	Cons	Slant	Visits
6abc	3,609	229	-0.32	-0.32	-0.27	0.53	46.92
9news	3,169	65	-0.25	-0.44	-0.07	0.57	59.38
ABC News	21,013	2,159	-0.37	-0.46	-0.24	0.54	61.54
Abc13	3,550	299	-0.31	-0.32	-0.30	0.52	41.02
Abc7	4,729	427	-0.33	-0.34	-0.27	0.55	59.17
Ajc	11,596	868	-0.57	-0.71	-0.36	0.69	61.17
Al	3,999	1,078	-0.38	-0.54	-0.22	0.89	47.77
American Thinker	7,043	2,581	2.36	2.34	2.37	0.45	10.09
Azcentral	4,084	654	-0.69	-0.83	-0.48	0.92	63.98
Baynews9	12,628	85	-0.33	-0.33	-0.21	0.61	49.62
Bloomberg	6,334	1,408	-0.50	-0.63	-0.21	0.70	75.57
Boston	5,686	134	-0.74	-0.80	-0.73	0.67	80.91
Boston Globe	17,327	802	-0.96	-1.05	-0.80	0.86	87.58
Breitbart	41,030	15,541	1.04	1.04	1.00	1.21	2.31
Buffalonews	2,777	185	-0.37	-0.57	0.05	0.83	61.02
Business Insider	21,459	4,468	-0.57	-0.73	-0.34	0.66	68.92
Buzzfeed	1,328	409	-1.52	-1.49	-1.44	0.73	75.43
CBS News	10,502	5,207	-0.52	-0.61	-0.41	0.56	64.74
CNBC	15,055	3,617	-0.24	-0.39	0.01	0.64	63.31
CNN	24,758	14,843	-0.62	-0.67	-0.46	0.66	82.19
Cbslocal	3,819	2,451	-0.32	-0.46	-0.14	0.58	52.90
Chicago Tribune	20,577	1,578	-0.73	-0.95	-0.26	1.02	71.93
Cincinnati	2,034	262	-0.29	-0.41	0.03	0.84	60.36
Cleveland	7,980	467	-0.56	-0.70	-0.36	0.72	69.87
Click2Huston	9,615	292	-0.22	-0.31	-0.20	0.47	35.50
Clickondetroit	11,606	405	-0.32	-0.37	-0.29	0.46	55.91
Dallasnews	4,787	775	-0.46	-0.76	0.05	0.91	64.54
Detroitnews	11,010	828	-0.02	-0.42	0.64	0.97	55.10
Forbes	2,651	1,040	-0.59	-0.89	0.01	1.08	66.67
Fox News	34,900	15,502	0.57	0.54	0.54	1.10	4.93
Foxbusiness	7,828	1,302	0.61	0.61	0.60	0.88	5.98
Freep	2,728	839	-0.62	-0.64	-0.60	0.71	72.91

Table J.1: Summary Statistics within Outlets (Continued)

	Obs.		Mean SS1 Slant			Sd.	% Lib
Outlet	All	SS1	All	Lib	Cons	Slant	Visits
Heavy	2,389	187	-0.71	-1.24	0.22	0.89	73.76
Hot Air	20,175	1,304	1.62	1.59	1.58	1.00	4.67
Houston Chronicle	29,715	249	-0.49	-0.65	-0.20	0.67	70.60
Huffington Post	13,969	9,782	-1.27	-1.27	-1.23	0.64	91.10
Indystar	1,572	275	-0.40	-0.61	0.11	0.71	57.81
Inquirer	5,848	617	-0.91	-1.12	-0.26	0.83	74.46
Jsonline	2,047	438	-0.48	-0.55	-0.31	0.64	71.45
Khou	3,078	123	-0.23	-0.30	-0.11	0.59	45.52
Ksl	11,403	91	-0.11	-0.27	0.04	0.66	47.77
Ktla	6,025	899	-0.45	-0.47	-0.43	0.56	57.03
LA Times	14,744	3,308	-0.99	-1.12	-0.53	0.80	81.91
MSNBC	8,375	3,988	-1.38	-1.43	-1.19	0.61	94.06
Masslive	5,249	254	-0.49	-0.63	-0.33	0.59	61.74
Mediaite	8,459	708	-0.49	-0.70	-0.30	1.13	56.45
Mlive	4,675	1,029	-0.43	-0.48	-0.32	0.62	58.27
NBC News	12,159	7,670	-0.62	-0.66	-0.49	0.65	78.88
National Review	5,930	1,584	1.47	0.99	1.51	1.12	14.79
New York Post	15,706	4,861	0.38	-0.02	0.71	1.11	31.57
New York Times	47,280	14,314	-0.82	-0.84	-0.63	0.75	90.87
Newsday	9,757	157	-0.40	-0.50	-0.33	0.79	49.48
Newser	3,627	10	-1.20	-1.18	-0.80	0.75	67.31
Newsmax	10,763	227	1.49	0.99	1.51	0.99	12.15
Newsweek	7,336	4,890	-0.83	-0.94	-0.45	0.87	81.08
Nj	6,874	899	-0.45	-0.61	-0.36	0.81	57.71
Nola	3,182	378	-0.70	-0.87	-0.55	0.74	56.39
Nydailynews	12,473	2,728	-0.72	-0.84	-0.36	0.88	78.68
Omaha	3,796	72	-0.44	-0.59	0.02	0.77	58.82
Oregonlive	5,125	858	-0.54	-0.64	-0.40	0.74	67.67
Palmerreport	4,927	2,408	-2.15	-2.13	-2.40	0.41	88.20
Patch Media	23,586	1,545	-0.37	-0.41	-0.36	0.65	54.14
Pennlive	4,992	424	-0.28	-0.59	0.28	0.82	40.47
Pjmedia	5,490	2,493	2.06	1.99	2.03	0.89	8.09
Politico	12,139	5,429	-0.50	-0.55	-0.19	0.72	82.92
Raw Story	19,907	7,815	-1.27	-1.30	-0.97	0.67	93.10
Realclearpolitics	1,469	248	2.18	0.31	2.33	1.15	7.21
San Francisco Gate	35,016	280	-0.44	-0.60	0.02	0.64	75.32
Seattle Times	16,069	695	-0.77	-0.91	-0.08	0.78	85.13
Slate	4,658	1,821	-1.44	-1.47	-1.32	0.78	95.06

Table J.1: Summary Statistics within Outlets (Continued)

	Obs.		Mean SS1 Slant			Sd.	% Lib
Outlet	All	SS1	All	Lib	Cons	Slant	Visits
Star Tribune	26,291	480	-0.45	-0.70	0.03	0.80	62.04
Staradvertiser	2,339	128	-0.48	-0.48	-0.21	0.59	81.08
Stltoday	8,863	419	-0.54	-0.61	-0.37	0.77	68.26
Syracuse	4,558	223	-0.25	-0.38	0.02	0.67	43.80
The Atlantic	3,869	2,173	-1.34	-1.36	-1.12	0.89	90.45
The Blaze	7,469	4,418	1.10	1.04	1.10	1.09	3.72
The Epoch Times	14,572	4,007	0.75	0.65	0.89	0.85	17.54
The Hill	43,962	14,911	-0.36	-0.47	0.12	0.85	79.48
Thedailybeast	4,295	1,939	-1.05	-1.09	-0.80	0.87	91.39
Thefederalist	3,391	1,408	2.05	1.72	2.09	0.72	8.96
Time	6,565	2,214	-0.91	-0.99	-0.64	0.70	80.62
Townhall	12,389	4,353	1.75	1.67	1.74	0.95	2.59
Twitchy	9,334	703	2.20	0.03	2.29	0.57	2.91
USA Today	13,457	5,405	-0.44	-0.71	0.03	0.88	61.60
Voanews	13,214	160	-0.72	-0.71	-0.36	0.60	69.75
Vox	5,487	2,988	-1.27	-1.29	-1.11	0.64	92.13
WND	14,249	1,953	1.87	1.91	1.88	0.83	3.70
WRAL	13,537	289	-0.33	-0.45	-0.15	0.63	43.74
WTOP	19,574	164	-0.60	-0.66	-0.34	0.54	69.84
Washington Examiner	17,718	3,997	0.89	0.37	0.94	1.03	7.85
Washington Post	38,405	14,629	-0.92	-0.97	-0.52	0.87	87.79
Washington Times	20,188	1,382	0.92	0.75	0.95	1.03	9.12
Wfaa	2,944	112	-0.17	-0.29	-0.11	0.67	46.95

Notes: This table shows the number of articles, the clicks-weighted average slant by all users, by users with a liberal political affinity score, and by user with a conservative political affinity score, the standard deviation of slant, and the percentage of liberal visits defined as the percentage of visits by liberal users divided by the sum of the percentage of visits by liberal and conservative users within the outlets included in our analysis. "SS1" denotes the URL-level Facebook Activity Dataset (which is curated by Social Science One). The slant scale goes from -2.5 (extremely favorable to the Democratic party) to 2.5 (extremely favorable to the Republican party).

Figure J.1: Slant Distribution within Outlets

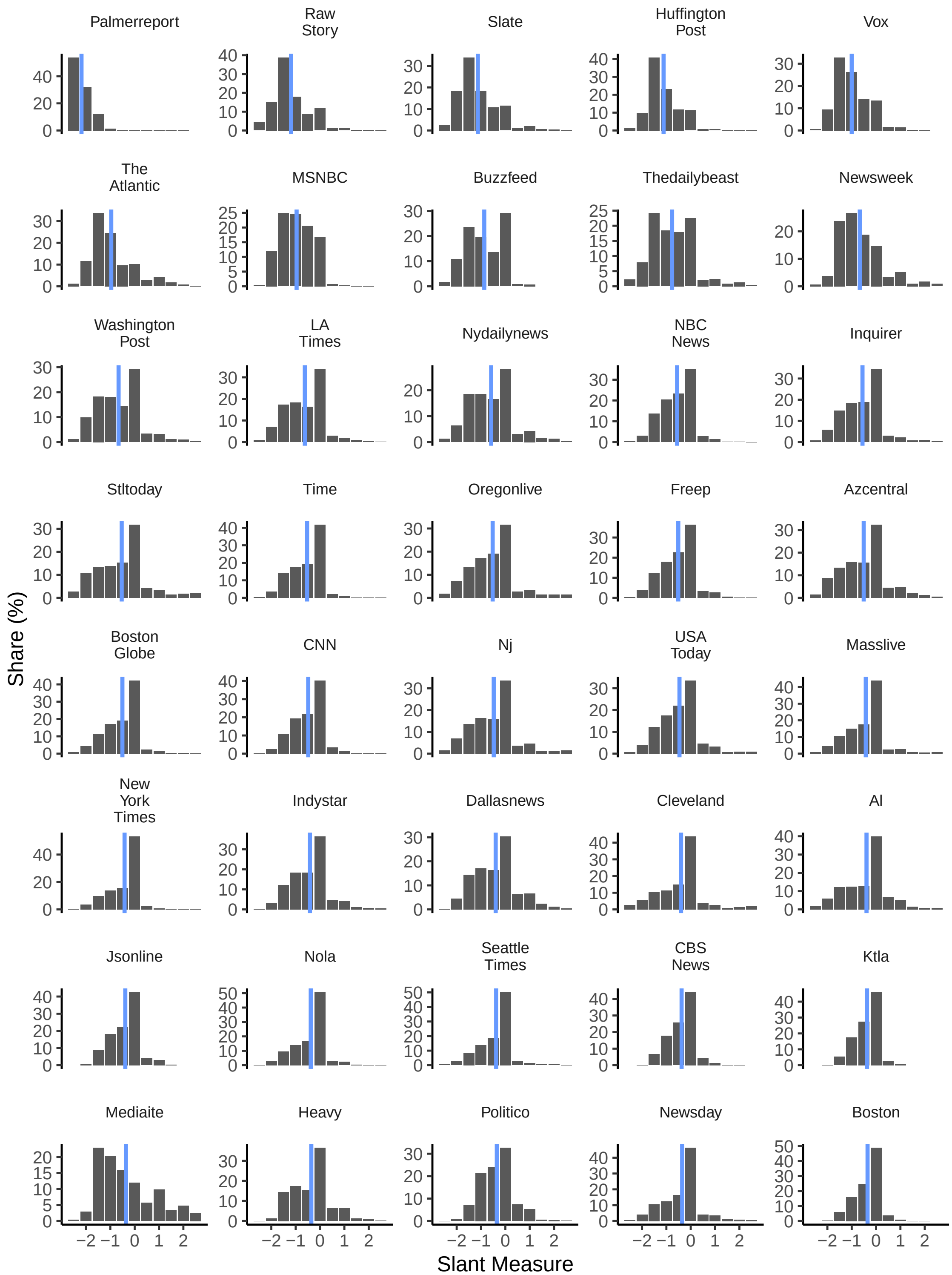


Figure J.1: Slant Distribution within Outlets (Continued)

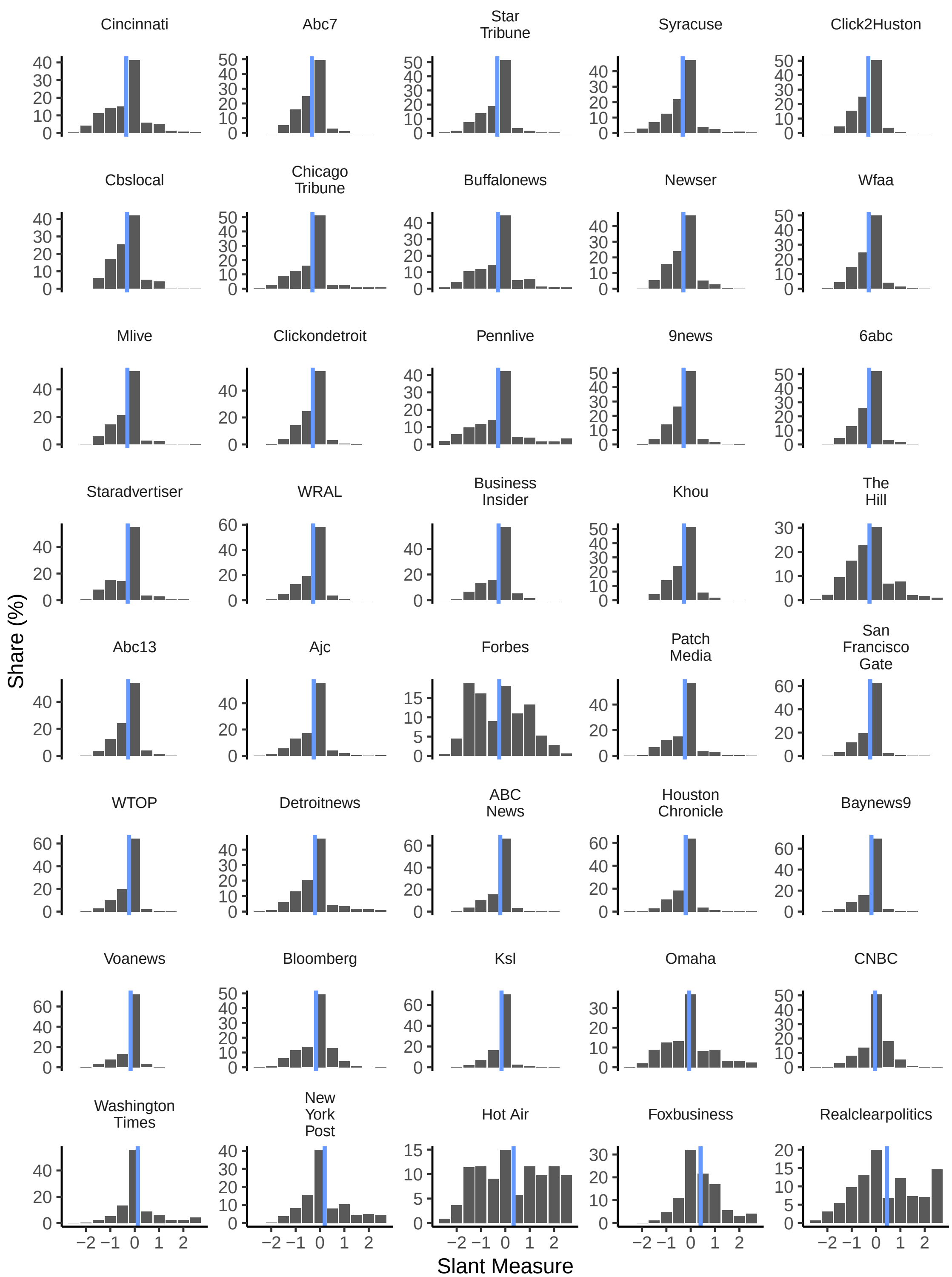
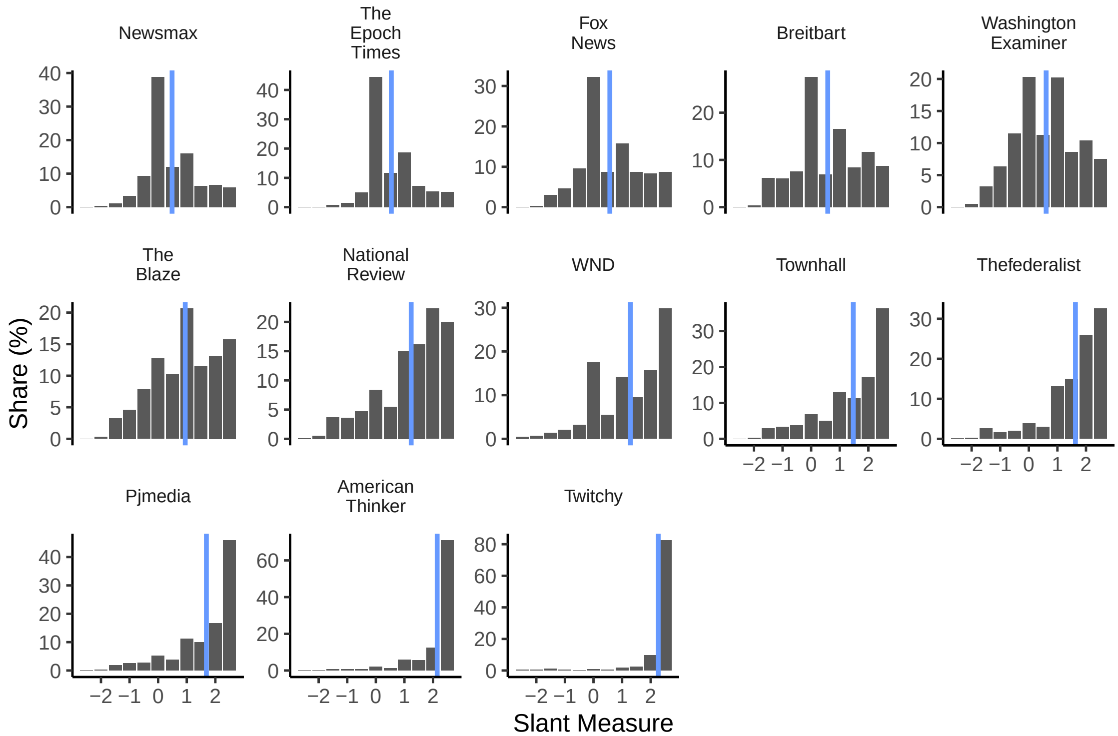


Figure J.1: Slant Distribution within Outlets (Continued)



Notes: This figure shows the distribution of slant within the outlets included in our analysis. The vertical blue line indicates the mean slant for all articles within a given outlet. Slant is given by the fine-tuned GPT-4o's prediction as described in Section 4.2. The slant scale goes from -2.5 (extremely favorable to the Democratic party) to 2.5 (extremely favorable to the Republican party).