Ideological Segregation and the Effects of Social Media on News Consumption*

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Abstract

Scholars have argued that online social networks and personalized web search increase ideological segregation. We investigate the impact of these potentially polarizing channels on news consumption by examining web browsing histories for 50,000 U.S.-located users who regularly read online news. We find that individuals indeed exhibit substantially higher segregation when reading articles shared on social networks or returned by search engines, a pattern driven by opinion pieces. However, these polarizing articles from social media and web search constitute only 2% of news consumption. Consequently, while recent technological changes do increase ideological segregation, the magnitude of the effect is limited.

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The Internet has dramatically reduced the cost to produce, distribute, and access diverse political information and perspectives. Online publishing, for example, circumvents much of the costly equipment required to produce physical newspapers and magazines. With the rise of social media sites such as Facebook and Twitter, individuals can now readily share their favorite stories with hundreds of their contacts, lowering the distribution costs of publishers (Bakshy et al., 2012; Goel et al., 2012b). And as web search engines and news aggregators become increasingly capable of generating personalized results, consumers can more easily find niche content tailored to their preferences (Agichtein et al., 2006; Das et al., 2007; Hannak et al., 2013; Speretta and Gauch, 2005).

These transformative effects of the Internet can be viewed as a boon for the democratization of ideas (Benkler, 2006). Search engines, for instance, facilitate choice by offering far greater access to diverse opinions than one's local paper. Several scholars and popular commentators, however, have raised concerns that instead of encouraging discussion, the combination of the larger supply of niche political perspectives and increased choice interact with algorithmic recommendation systems (used by search engines and social platforms) to generate increasingly personalized choice sets, further segregating users into so-called *echo chambers* or *filter bubbles* (Pariser, 2011; Sunstein, 2001, 2009), in which individuals are only exposed to like-minded others. Such segregation is an important concern as it has long been argued that functioning democracies depend critically on voters who are exposed to and understand a variety of political views (Downs, 1957). Further, theoretical models have shown that segregation can lead to electoral mistakes (Bernhardt et al., 2008).

These worries are supported by findings on choice and sharing from economics, psychology and sociology. In controlled experiments, people overwhelmingly opt to consume information that accords with their previously held views (Lord et al., 1984, 1979; Nickerson, 1998) and choose news articles from outlets that share their political opinions (Garrett, 2009; Iyengar and Hahn, 2009; Munson and Resnick, 2010).[1] Social networks, moreover, have long been known to exhibit homophily (McPherson et al., 2001)—the tendency for contacts to be more similar than random pairs of individuals—suggesting that social media sites expose individuals to largely congruent opinions. Furthermore, in laboratory studies people tend to share

[1] Survey evidence of blog readers (Lawrence et al., 2010) and cross-blog citations (Adamic and Glance, 2005; Herring et al., 2005) are consistent with this pattern.

information that conforms to the group's majority opinion (Moscovici and Zavalloni, 1969; Myers and Bishop, 1970; Schkade et al., 2007; Spears et al., 1990), which could reinforce the impact of homophily.

Yet despite this seemingly compelling circumstantial evidence, most metrics of political polarization in the general U.S. population have been relatively stable for the last several decades (Baldassarri and Gelman, 2008; Prior, 2013).[2] Among the top 20 most popular news sites—which in aggregate account for three-quarters of total news traffic—the ideological spectrum ranges from the *New York Times* on the left to *Fox News* on the right, comparable to the ideological span of broadcast news.[3] Further, in a comprehensive study of news consumption, Gentzkow and Shapiro (2011) found that segregation in online news was similar to that of traditional, offline newspapers. We are thus left with a puzzle: How do we reconcile past findings that suggest current online conditions should promote ideological segregation with the apparent lack of direct empirical corroboration?

We investigate this question by examining detailed web browsing records of 1.2 million anonymized U.S.-located Internet users. We have a record of *every web page* viewed by these individuals over the three-month period between March and May of 2013, a total of 2.3 billion page views. The data size and complexity (e.g. free-form text) requires us to address three methodological challenges. First, the majority of content on news sites concerns sports, entertainment, weather and other, largely apolitical topics for which ideological segregation is not particularly meaningful. We identify the substantively relevant articles by applying large-scale machine learning algorithms to article text; we further separate out descriptive reporting from opinion pieces (which we refer to as "news" and "opinion", respectively). Second, we require a measure of each news outlet's ideological leaning. Here we follow past audience-based approaches (Gentzkow and Shapiro, 2011; Tewksbury, 2005) and rely on a site's *conservative share*, the fraction of its readership that supported the Republican candidate in the most recent presidential election. We develop a method to infer this metric by examining the relationship between geographic news site access patterns in our dataset and publicly-available county-level voting records. Finally, we require

[2]Congress, by contrast, has become notably more polarized over time (Prior, 2013).

[3]Based on the Alexa ranking of news outlets (`http://www.alexa.com/topsites/category/Top/News`). Webster and Ksiazek (2012) find little evidence of audience fragmentation among major media outlets.

a metric for ideological segregation, which we define as the average difference in the conservative shares of news outlets visited by two randomly selected individuals. To estimate this measure, we apply hierarchical Bayesian regression models.

We find that segregation is marginally higher for descriptive news articles accessed via social media (0.12) than for those read by directly visiting a news outlet's home page (0.11). For opinion pieces, however, the effect is substantial, moving from 0.13 for articles directly obtained from the publisher to 0.17 for socially recommended pieces to a striking 0.20 for articles found via web search—0.20 corresponds to the ideological distance between the centrist *Yahoo News* and the left-leaning *Huffington Post* (or equivalently, *CNN* and the right-leaning *National Review*). But we also find that these more segregating socially recommended and search-based opinion stories account for only a small fraction (2%) of total news consumption; by comparison, directly accessed descriptive reporting comprises over 75% of consumption. The net result is that the overall level of news segregation is relatively moderate (0.11), corresponding to the ideological distance between *USA Today* and the *Washington Post*.

Our measure of segregation reduces each individual to her *mean* ideological position. Consequently, the moderate level of segregation we observe could be the result of two qualitatively different individual-level behaviors. On the one hand, a typical individual might regularly read a variety of liberal and conservative news outlets, but still exhibit a slight left- or right-leaning preference. On the other hand, individuals may choose to only read publications that are ideologically similar to one another, rarely reading opposing perspectives. We find strong evidence for the latter. Specifically, users who predominately visit left-leaning news outlets only very rarely ($< 5\%$ of the time) read substantive news articles from conservative sites, and vice versa for right-leaning readers, an effect that is even more pronounced for opinion articles. This finding holds both for individuals who rely on one or two sites (who comprise the majority of our sample) and for those who visit several outlets, and also holds across all the channels (direct, web search, and social media) that we investigate. So while most people typically consume centrist content, the minority who read partisan articles are typically not exposed to the other side of the political debate, especially for opinion.

Our results are thus directionally consistent with worries that the online choice environment spurs ideological segregation. However, the relative dearth of socially recommended news stories—especially those in the opinion category—and the relatively centrist preferences of most individuals lead to a moderate overall level of segregation. In particular, we do not observe the extreme choice fragmentation seen in the laboratory. An intuitive explanation for the difference is that laboratory experiments focus on highly polarizing political issues—such as the death penalty or abortion rights—that are not representative of typical descriptive news or opinion articles.

Investigating futher, we found that only about *1 in 300* outbound clicks from Facebook correspond to substantive news, with video and photo sharing sites far-and-away the most popular destinations, indicating that social media platforms are used primarily for entertainment and interpersonal communication rather than for political discussion. A potential explanation is that users may not want to isolate themselves or antagonize their online social contacts—which given Facebook's penetration is a wide circle—by expressing an opinion on a polarizing issue. Further, even though it has grown increasingly easy to produce niche content, consumers simply do not have an appetite for extreme political perspectives.[4] Regardless, the net effect is that while the technological ingredients for ideological fragmentation are in place—and indeed appear to impact consumption—serious consequences have thus far been avoided. If, however, the next generation of Internet users increasingly rely on social media to obtain news and opinion, then our results suggest that would in turn lead to higher ideological segregation.

To help situate our results in the literature, we highlight three key substantive differences between our work and the most closely related paper, Gentzkow and Shapiro (2011). First, and most importantly, whereas Gentzkow and Shapiro used browsing data aggregated at the domain level to show that online and offline segregation are comparable, our primary objective is to reconcile their striking empirical finding with the seemingly contradictory evidence that suggests so-called filter bubbles lead to relatively higher levels of online segregation. Resolving this puzzle requires carefully classifying news articles based on their textual content, and in particular separating out descriptive news from opinion pieces. Thus, the second

[4]Work in media economics, both theoretical and empirical, suggests that content creators respond to consumer preferences (Gentzkow and Shapiro, 2006; George and Waldfogel, 2006; Mullainathan and Shleifer, 2005), including their desired political slant (Baum and Groeling, 2008; Gentzkow and Shapiro, 2010, 2013).

significant difference is our use of large-scale methods from natural language processing and machine learning to estimate online segregation for different types of articles. Notably, since the polarizing role of social media and web search is most apparent for only the small set of opinion articles, without this methodological approach we would have largely missed the evidence that these channels do shape news consumption. Third, we extend our analysis to news sharing platform Twitter and find strong confirmation of our central results coming from web browsing logs.

1 Data and Methods

Our primary analysis is based on web browsing records collected via the Bing Toolbar, a popular add-on application for the Internet Explorer web browser. Upon installing the toolbar, users can consent to sharing their data via an opt-in agreement, and to protect privacy, all records are anonymized prior to our analysis. Each toolbar installation is assigned a unique identifier, giving the data a panel structure. While it is certainly possible that multiple members of a household share the same browser, we follow the literature by referring to each toolbar installation as an "individual" or "user" (Athey and Mobius, 2012; De los Santos et al., 2012; Gentzkow and Shapiro, 2011).

Based on these toolbar records, we analyze the web browsing behavior of 1.2 million U.S.-located users for the three-month period between March and May of 2013, making this one of the largest studies of web content consumption to date. To ensure this set of users was reasonably active, we drew a random sample of all toolbar users who viewed at least ten webpages during the first week of March 2013. For each user, we have a time-stamped collection of URLs opened in the browser, along with the user's geographic location, as inferred via the IP address. In total, our dataset consists of 2.3 billion distinct page views, with a median of 991 page views per individual.

As with nearly all observational studies of individual-level web browsing behavior, our study is restricted to individuals who voluntarily share their data, which likely creates selection issues. These users, for example, are presumably less likely to be concerned about privacy. Moreover, though our panelists did not report any demographic information, it is generally believed that Internet Explorer users are on average older than the Internet population at large. Instead of attempting to re-balance our sample using difficult-to-estimate and potentially incorrect weights, we acknowledge these shortcomings and note throughout where they might be a concern. When appropriate, we also replicate our analysis on different subsets of the full dataset, increasing the likelihood our results extend beyond the particular sample of users we study. As a further robustness check, we replicate our analysis on the set of U.S.-located users on the social network Twitter.

1.1 Identifying News and Opinion Articles

We select an initial universe of news outlets (i.e., web domains) via the Open Directory Project (ODP, dmoz.org), a collective of tens of thousands of editors who hand-label websites into a classification hierarchy. As of June 2013, 7,923 distinct domains were included in the four primary ODP news categories: news, politics/news, politics/media, and regional/news. Since the vast majority of these news sites receive relatively little traffic, to simplify our analysis we restrict to the one hundred domains that attracted the largest number of unique visitors from our sample of toolbar users.[5] This list of popular news sites includes every major national news source (e.g., *The New York Times*, *The Huffington Post*, and *Fox News*), well-known blogs (e.g., *Daily Kos* and *Breitbart*), and many regional dailies (e.g., *The Seattle Times* and *The Denver Post*). The complete list is given in the Appendix.

Our focus in this paper is on the consumption of U.S. and international text-based news and opinion, corresponding to the content that generally appears in the front section and opinion pages of newspapers. However, the bulk of articles on general news websites do not fall into these categories, but rather relate to sports, weather, lifestyle, entertainment, and similar, largely apolitical categories. Since articles from these categories are much less likely to reflect the political slant of the outlet, our first aim is to filter them out. Given the wide variety of blogs and traditional news outlets that we consider, which stories qualify as "front-section news" or opinion is not immediately obvious in the browsing records. We address this problem from a machine learning perspective, classifying each article based on the words that appear in it.

[5]This list has high overlap with the current Alexa rankings of news outlets (`http://www.alexa.com/topsites/category/Top/News`).

We build two binary classifiers using large-scale logistic regression: the first selects front-section news and opinion pieces from the universe of articles in the sample; the second starts from the set of articles chosen in the first step, and then separates out descriptive reporting from opinion pieces. To achieve these aims, we require training datasets consisting of a representative set of articles known to be front-section news, and another known not to be (i.e., a sampling of articles from the categories we wish to filter out, hereafter referred to as "non-news"); we likewise require labeled examples of descriptive versus opinion articles. To generate these sets we make use of the fact that many popular publishers indicate an article's classification in its URL (web address). For example, a prototypical story on *USA Today* (in this case, about U.S. embassy security) has the address `http://www.usatoday.com/story/news/world/2013/08/01/us-embassies-sunday-security/2609863/`, where "news/world" in the URL indicates the article's category. Identifying these URL patterns for 21 news websites, we are able to produce 70,406 examples of front-section news and opinion, and 73,535 examples of non-news. We use the same approach (looking for URLs with the word "opinion") to generate a separate training dataset to distinguish between opinion pieces and descriptive news articles.

Given these training datasets, we next build a natural language model. We first compute the 1,000 most frequently occurring words in our corpus of articles, excluding so-called stop words, such as "and", "the", and "of". We augment this list with a set of 39 first and third person pronouns (Pennebaker et al., 2007, 2001), since opinion pieces—unlike descriptive articles—are often written in the first person, and including such pronouns has been shown to improve performance (Glover et al., 2001). Each article is subsequently represented as a 1,039-dimensional vector, where the i-th component indicates the number of times the i-th word in our list appears in the article, normalized by the total number of words in the article. Using fractional scores rather than raw frequencies is a standard approach in natural language classification tasks for dealing with differences in article length (Manning and Schütze, 1999). To retain the predictive power of the pronouns, quotations are removed from the articles before representing them as vectors of relative word frequencies.

Having defined the predictors (i.e., the relative frequencies of various popular words), and having generated a set of labeled articles, we now use logistic regression

Table 1: Most predictive words for classifying articles as either news or non-news, and separately, for separating out descriptive news from opinion.

Front-section news & opinion (+) vs. "non-news" (−)

Positive	Negative
contributed, democratic economy, authorities, leadership, read republican, democrats country's, administration	film, today pretty, probably personal, learn technology, mind posted, isn't

Opinion (+) vs. descriptive news (−)

Positive	Negative
stay, seem important, seems isn't, fact actually, reason latest, simply	contributed, reporting said, say spokesman, experts interview, expected added, hers

to build the classifiers. Given the scale of the data, we fit the models with the L-BFGS algorithm (Liu and Nocedal, 1989), as implemented in the open-source machine learning package Vowpal Wabbit. Applying the fitted model to the entire collection of 4.1 million articles in our corpus, we obtained 1.9 million stories (46%) classified as front-section news or opinion, and of these 11% are classified as opinion. Note that we use the classifier even for outlets that indicate the article category in the URL, which guards against differing editorial policies biasing the results.

The accuracy of our classifiers is quite high. When tested on a 10% hold-out sample of articles whose categories can be inferred from their URLs, the front-section news and opinion classifier obtains 92% accuracy, and on a hand-labeled set of 100 randomly selected articles from the full corpus, we see 81% accuracy. Furthermore, the fitted model is relatively interpretable, as indicated in Table 1, which lists the words with the largest positive weights (indicating a story is likely front-section news or opinion) and the largest negative weights (indicating a story is likely not news). Accuracy for the opinion classifier is high as well: 96% on a hold-out set of URL-labeled articles, and 88% on a randomly selected subset of articles classified as front-section news or opinion. Table 1 also lists words with the highest positive and negative weights for the opinion classifier.

In addition to separating out descriptive news from opinion, we examine ideological segregation as a function of an article's subjectivity. We measure subjectivity with the Subjectivity Lexicon,[6] introduced by Riloff and Wiebe (2003). The lexicon was built by hand-labeling sentences in news articles, and then using natural language processing and machine learning techniques to score individual words (by part of speech) as either objective, weakly subjective or strongly subjective.

To compute each article's subjectivity, we assign a value of 0 to objective words and 1 to both weakly and strongly subjective words, and we then average the subjectivity scores of the words in the article. Several variants of determining an article's subjectivity are discussed in Liu (2010), such as the use of various weighting schemes. The simple procedure we employ, however, tends to work adequately in our setting. In particular, on a hand-labeled set of 100 front-section news and opinion articles rated as either objective, weakly subjective or strongly subjective, the Pearson correlation between the human and the algorithmic ratings was 0.49 (the Spearman correlation was 0.41).

1.2 Measuring the Political Slant of Publishers

Algorithmically measuring the ideological leanings of news articles is known to be a difficult problem. In the absence of human ratings, there are no existing methods to reliably assess an article's slant with both high recall and precision.[7] Since our sample has over 1.9 million articles classified as either front-section news or opinion, human labeling is not feasible. We thus follow the literature (Gentzkow and Shapiro, 2010, 2011; Groseclose and Milyo, 2005) and focus not on the slant of individual articles but on the slant of news outlets, ultimately assigning articles the polarity score of the outlet in which they were published. By doing so, we clearly lose some signal. For instance, we mislabel liberal op-eds on generally conservative news sites, and we mark neutral reporting of a breaking event as having the overall slant of the

[6] Available for download at `http://mpqa.cs.pitt.edu/lexicons/subj_lexicon/`.

[7] High precision is possible by focusing on the use of highly polarizing phrases such as "death panel," but the recall of this method tends to be very low, meaning most pieces of content are not rated. Cluster techniques have successfully extended a relatively small number of human ratings to a larger set of news articles (Zhou et al., 2011), but these approaches assume individuals read ideologically similar content, leading to potential tautologies in our analysis. Even with human ratings, the wide variety of sites we investigate—ranging from relatively small blogs to national newspapers—exhibit correspondingly diverse norms of language usage, making any content-level assessment of political slant quite difficult.

outlet. Nevertheless, such a compromise is common practice, and where possible, we attempt to mitigate any resulting biases.

Approaches for measuring the political slant of news outlets broadly fall into one of two categories: content-based and audience-based. Content-based approaches compare the entire body of published textual content from a source (rather than individual articles) to sources with known political slants. For example, Groseclose and Milyo (2005) use the co-citation matrix of newspapers and members of Congress referencing political think tanks. Similarly, Gentzkow and Shapiro (2010) use congressional speeches to identify words and phrases associated with a stance on a particular issue, and then tabulate the frequencies of such phrases in newspapers. Audience-based approaches, on the other hand, use the political preferences of a publication's readership base to measure political slant (Gentzkow and Shapiro, 2011; Tewksbury, 2005). Empirical evidence suggests that audience and content-based measures of slant are closely related. In particular, Iyengar and Hahn (2009) show that individuals select media outlets based on the match between the outlet's and their own political positions, and moreover, it has been shown that outlets tailor their coverage to match the preferences of their base (Baum and Groeling, 2008; DellaVigna and Kaplan, 2007; Gentzkow and Shapiro, 2010). Theoretical models also support this relationship between audience and content-based measures (Gentzkow and Shapiro, 2006; Mullainathan and Shleifer, 2005).

Here we use an audience-based measure of news outlet slant. Specifically, we estimate the fraction of each news outlet's readership that voted for the Republican candidate in the most recent presidential election (among those who voted for one of the two major-party candidates), which we call the outlet's *conservative share*. Thus, liberal outlets have conservative shares less than about 50%, and conservative outlets have conservative shares greater than about 50%, in line with the usual left-to-right ideology spectrum. To estimate the political composition of a news outlet's readership, we make use of geographical information in our dataset. Specifically, each webpage view includes the county in which the user resides, as inferred by his or her IP address. With this information, we then measure how the popularity of a news outlet varies across counties as a function of the counties' political compositions, which in turn yields the estimate we desire.

More formally, as a first approximation we start by assuming that the probability any user u_i views a particular news site s is solely a function of his or her party affiliation. Namely, for a fixed news site s, we assume Democrats view the site with probability p_d and Republicans view the site with probability p_r.[8] Reparameterizing so that $\beta_0 = p_d$ and $\beta_1 = p_r - p_d$, we have

$$\mathbb{P}(u_i \text{ views } s) = \beta_0 + \beta_1 \delta_r(u_i) \tag{1}$$

where $\delta_r(u_i)$ indicates whether user u_i is a Republican. Though our ultimate goal is to estimate β_0 and β_1, we cannot observe an individual's party affiliation. To circumvent this problem, for each county C_k we average (1) over all users in the county, yielding

$$\frac{1}{N_k} \sum_{u_i \in C_k} \mathbb{P}(u_i \text{ views } s) = \beta_0 + \beta_1 \frac{1}{N_k} \sum_{u_i \in C_k} \delta_r(u_i) \tag{2}$$

where N_k is the number of individuals in our sample who reside in county C_k.

While the left-hand side of (2) is observable—or at least is well approximated by the fraction of users in our sample that visit the news site—we cannot directly measure the fraction of Republicans in our sample (i.e., the sum on the right-hand side of (2) is not directly observable). To address this issue, we make a further assumption that our sample of users is representative of the county's voting population, a population for which we can estimate party composition via the 2012 election returns. We thus have the following model:

$$P_k = \beta_0 + \beta_1 R_k \tag{3}$$

where P_k is the fraction of toolbar users in county C_k that visit the particular news outlet s, and R_k is the fraction of voters in county C_k that supported the Republican candidate, Mitt Romney, in the 2012 U.S. presidential election. To estimate the parameters β_0 and β_1 in (3), we fit a weighted least squares regression over the 2,654 counties for which we have at least one toolbar user in our sample, weighting each observation by N_k (i.e., the number of people in our dataset in county C_k).

Clearly, (3) is only an approximation of actual behavior, with our specification ruling out the possibility that a generally liberal outlet is disproportionately popular

[8] As discussed later, by "Democrats" we in fact mean those who voted for the Democratic candidate in the last presidential election, and similarly for "Republicans."

in conservative counties. In particular, our model ignores the impact of local news coverage, with individuals living in the outlet's county of publication visiting the site regardless of its political slant. Addressing this local effect, we modify our generative model to include an additional term. Namely, outside a news outlet's local geographic region, we continue to assume that Democrats visit the site with probability p_d, and Republican's visit the site with probability p_r, and we use (3)—fit on all non-local counties—to estimate p_r and p_d. Inside the local region we assume individuals visit the site with probability p_ℓ, irrespective of their political affiliation, and we estimate p_ℓ to be the empirically observed fraction of local toolbar users who visited the news outlet.

Finally, we approximate the conservative share $p(s)$ of a news outlet s as the estimated fraction of Republicans that visit the site normalized by the total number of Democratic and Republican visitors. Specifically,

$$p(s) = \left[N_\ell r_\ell p_\ell + p_r \sum_{k\,:\,C_k \text{ non-local}} N_k r_k\right] \Bigg/ \left[N_\ell p_\ell + \sum_{k\,:\,C_k \text{ non-local}} N_k(r_k p_r + (1 - r_k)p_d)\right]$$

where N_k is the number of people in our dataset in county C_k, $p_d = \beta_0$, $p_r = \beta_0 + \beta_1$, r_k is the two-party Romney vote share in county C_k (i.e., the number of Romney supporters divided by the total number of Romney and Obama supporters, excluding third party candidates), and parameters subscripted with ℓ indicate values for the outlet's local county of publication. This entire process is repeated for each of the 100 news outlets in our dataset.

Table 2 lists estimated conservative shares for the 20 news outlets attracting the most number of unique visitors in our dataset, ranging from the *BBC* and *The New York Times* on the left to *Fox News* and *Newsmax* on the right. While our measure of conservative share is admittedly imperfect, the list does seem largely consistent with commonly held beliefs on the slant of particular outlets.[9] Furthermore, as shown in Figure 1, our ranking of news sites is quite similar to the Gentzkow and

[9]One exception is *The Wall Street Journal*, which we characterize as left-leaning even though it is generally thought to be politically conservative. We note, however, that the most common audience and content-based measures of slant also characterize the paper as relatively liberal (Gentzkow and Shapiro, 2011; Groseclose and Milyo, 2005). Moreover, as a robustness check, we repeated our analysis after omitting *The Wall Street Journal* from our dataset, and found that none of our substantive results changed.

Table 2: For the 20 most popular news outlets, each outlet's estimated conservative share (i.e., the two-party fraction of its readership that voted for the Republican candidate in the last presidential election).

Publication	Cons. share	Publication	Cons. share
BBC	0.30	L.A. Times	0.46
New York Times	0.31	Yahoo News	0.47
Huffington Post	0.35	USA Today	0.47
Washington Post	0.37	Daily Mail	0.47
Wall Street Journal	0.39	CNBC	0.47
U.S. News & World Rep.	0.39	Christian Sci. Monitor	0.47
Time Magazine	0.40	ABC News	0.48
Reuters	0.41	NBC News	0.50
CNN	0.42	Fox News	0.59
CBS News	0.45	Newsmax	0.61

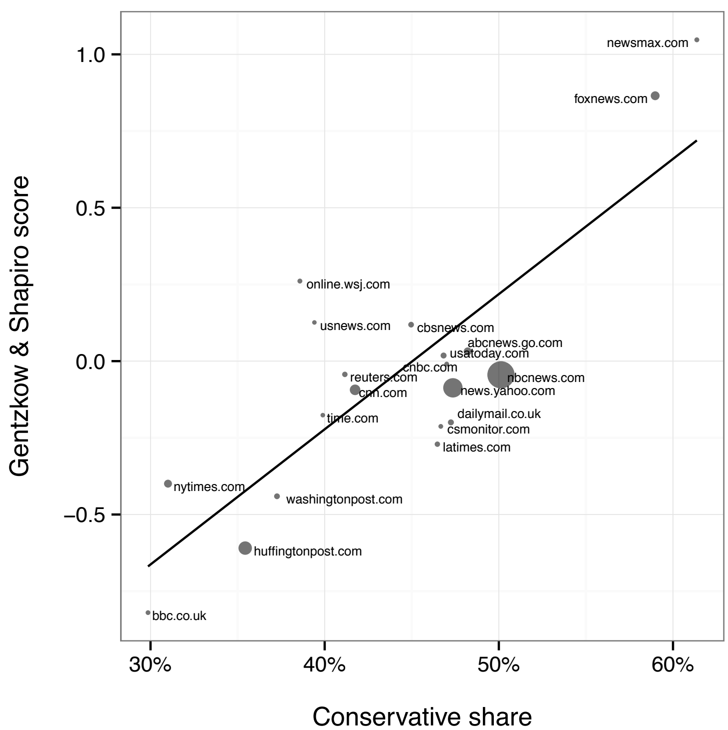


Figure 1: For the 20 most popular news outlets, a comparison of each outlet's estimated conservative share to an alternate measure of its ideological slant as estimated by Gentzkow and Shapiro (2011), where point sizes are proportional to popularity. Among these 20 publications, the correlation between the two scores is 0.82.

Shapiro (2011) list based on 2008 audience data in which users' party affiliations were explicitly collected.[10] Among the top 20 domains, we find a correlation of 0.82 between the two rankings, and across the full set of 41 sites appearing in both lists, the correlation is 0.40. Conservative shares for our full list of 100 domains are given in the Appendix.

1.3 Inferring Consumption Channels

We define and investigate four channels through which an individual can discover a news story: direct, aggregator, social, and search. Direct discovery means a user directly and independently visits a top-level news domain such as `nytimes.com` (e.g., by typing the URL into the browser's address bar, accessing it through a bookmark, or performing a "navigational search," explained below), and then proceeds to read articles within that outlet. The aggregator channel refers to referrals from *Google News*—one of the last remaining popular news aggregators—which presents users with links to stories hosted on other news sites.[11] We define the social channel to include referrals from Facebook, Twitter, and various web-based email services. Finally, the search category refers to news stories accessed as the result of web search queries on Google, Bing and Yahoo.

The time series of webpage views for an individual is not sufficient to perfectly determine discovery channel of a news article. We get around this problem with a "short" vs. "long" URL distinction in the following simple heuristic: define the "referrer" of a news article to be the most recently viewed URL that is a top-level domain such as `nytimes.com` or `facebook.com` (short URL), but not a specific story link, such as `nytimes.com/a-news-story` (long URL). We then use the referrer to classify the discovery channel. For example, if the referrer is a news domain, such as `foxnews.com`, then the channel is "direct navigation," whereas the channel is "social" if the referrer is, for instance, `facebook.com`. Since users often us a search engine simply to navigate to a publisher's front page (by searching for the publication's name). This type of "navigational search" query is widely regarded as

[10]The measure from Gentzkow and Shapiro (2011) to which we compare is not precisely conservative share, but is closely related.

[11]Most former news aggregators have switched to either producing their own original content, as in the case of *Yahoo News*, or hosting stories primarily from a single news site, such as AOL directing traffic to their subsidiary, *The Huffington Post*.

a convenient shortcut to typing in a web address (Broder, 2002) so we define it as direct navigation. The heuristic thus is based on two key assumptions: first, users do not typically type in the long, unwieldy web addresses assigned to individual articles, but rather are directed there via a previous visit to a top-level domain and a subsequent chain of clicks; and second, top-level domains are not typically shared or posted via email, social media or aggregators.

Even when referring pages can be perfectly inferred, there is still genuine ambiguity in how to determine the channel. For example, if an individual follows a Facebook link to a *New York Times* article and then proceeds to read three additional articles at that outlet, are all four articles "social" or just the first? Our solution is to take the middle ground: in this example, any subsequent article-to-article views (e.g., clicks on a"related story") are classified as "social," whereas an intermediate visit to the outlet's front page results in subsequent views being classified as "direct."

1.4 Limiting to Active News Consumers

As recent studies have noted, only a minority of individuals regularly read online news. For example, a 2012 survey by Pew Research showed that 39% of adults claimed to have read online news in the previous day,[12] a finding supported by observational studies of browsing behavior (Goel et al., 2012a). Because our aim is to understand the preferences and choices of individuals who actively read front-section news and opinion, we limit to the even smaller subset of the population who have read at least 10 substantive news articles (i.e., excluding stories in sports, entertainment, and other apolitical categories) in the three-month timeframe we consider, and who have additionally read at least two opinion pieces. This first requirement of having read at least 10 substantive news articles reduces our initial sample of 1.2 million individuals to 173,450; and the second requirement of having read at least two opinion pieces further reduces the sample to 50,383. Our primary analysis focuses on this 4% of our sample who are active news consumers. Though this subgroup comprises a small fraction of our sample, it is both a natural subpopulation to consider, and arguably one that has a disproportionate impact on political outcomes and policy decisions, a point we return to in the discussion.

[12] http://www.people-press.org/2012/09/27/in-changing-news-landscape-even-television-is-vulnerable/

2 Ideological Segregation

2.1 Overall Segregation

Recall that the conservative share of a news outlet—which we also refer to as the outlet's *polarity*—is the estimated fraction of the publication's readership that voted for the Republican candidate in the most recent presidential election. We first define the polarity of an *individual* to be the typical polarity of the news outlet that he or she visits. We then define segregation to be the expected distance between the polarity scores of two randomly selected users. Our definition of segregation is in line with past work (Gentzkow and Shapiro, 2011; White, 1986),[13] and intuitively captures the idea that segregated populations are those in which individuals are, on average, exposed to disparate points of view. However, due to sparsity in the data, this measure of segregation is not entirely straightforward to estimate. In particular, under a naive inference strategy, noisy estimates of user polarities would inflate the estimate of segregation. We thus estimate segregation via a hierarchical Bayesian model (Gelman and Hill, 2007).

We define the polarity score of an *article* to be the polarity score of the news outlet in which it was published.[14] Now, let X_{ij} be the polarity score of the j-th article read by user i. We model:

$$X_{ij} \sim N(\mu_i, \sigma_d^2) \tag{4}$$

where μ_i is the latent polarity score for user i, and σ_d is a global dispersion parameter (to be estimated from the data). To mitigate data sparsity, we further assume the latent variables μ_i are themselves drawn from a normal distribution. That is,

$$\mu_i \sim N(\mu_p, \sigma_p^2). \tag{5}$$

To complete the model specification, we assign weak priors to the hyperparameters

[13] One difference is that in traditional measures of residential segregation, individuals are modeled as belonging to one of several discrete groups (e.g., based on race); in our setting, however, individuals lie on a continuous polarity spectrum.

[14] While this is standard practice, it ignores, for example, the possibility of a conservative outlet publishing liberal editorials. Ideally, the classification would be done at the article level, but there are no known methods for reliably doing so.

σ_d, μ_p and σ_p. Ideally, we would perform a fully Bayesian analysis to obtain the posterior distribution of the parameters. However, for computational convenience, we use the approximate marginal maximum likelihood estimates obtained from the `lmer()` function in the `R` package `lme4` (Bates et al., 2013).

Though the distributional assumptions we make are standard in the literature (Gelman and Hill, 2007), our modeling choices of course affect the estimates we obtain. As a robustness check, we note that a naive, model-free estimation procedure yields qualitatively similar, though ostensibly less precise, results.[15]

Having specified the model, we can now formally define segregation, which we do in terms of the expected squared distance between individuals' polarity scores. Namely, we define segregation to be $\sqrt{\mathbb{E}(\mu_i - \mu_j)^2}$. After simple algebraic manipulation, our measure of segregation further reduces to $\sqrt{2}\sigma_p$. Higher values of this measure correspond to higher levels of segregation, with individuals more spread out across the ideological spectrum.

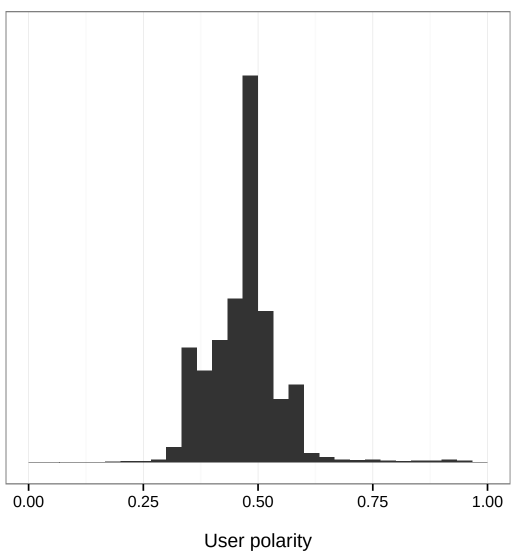


Figure 2: The distribution of individual-level polarity, where each individual's polarity score is the (model-estimated) average conservative share of the news outlets he or she visits.

Figure 2 shows the distribution of polarity scores (i.e., the distribution of μ_i) for

[15]Moreover, in our analysis of Twitter in Section 3—a setting where sparsity is not an issue—we estimate user polarity scores directly and find that they are indeed approximately normally distributed.

users in our sample. We find that most individuals are relatively centrist, with two-thirds of people having polarity scores between 0.41 and 0.54. Overall segregation is estimated to be 0.11, which means that for two randomly selected users, the ideological distance between the publications they typically read is on par with that between the centrist *NBC News* and the left-leaning *Daily Kos* (or equivalently, *ABC News* and *Fox News*). Thus, though we certainly find a degree of ideological segregation, it would seem to be relatively moderate, and largely in line with the most recent past assessment, based primarily on 2006 data (Gentzkow and Shapiro, 2011). Notably, given the interim rise of social media and personalization—and the accompanying predictions of ideological fragmentation—it is surprising that this would be the case, an issue we investigate in detail below.

2.2 Segregation by Channel and Article Subjectivity

When measuring segregation across various distribution channels and levels of article subjectivity, the data sparsity issues we encountered above are exacerbated. For example, even among active news consumers, relatively few individuals regularly read news articles from both aggregators and social media sites. And when we further segment articles into opinion and descriptive news, it compounds the problem. However, the polarity of consumption for a user across channels should be correlated; for example, the opinion pieces one reads from Facebook are likely ideologically related to the articles one reads from Google News. There is thus opportunity to improve our estimates by "sharing strength" across channels and subjectivity levels, and accordingly to jointly estimate the segregation parameters of interest. Joint estimation with weak priors also mitigates channel selection issues.

The four consumption channels (aggregator, direct, web search and social media) and two subjectivity classes (descriptive reporting and opinion) give eight subjectivity-by-channel dimensions. Let X_{ijk} denote the polarity of the j-th article that user i reads in the k-th subjectivity-by-channel category, where we recall that the polarity of an article is defined to be the conservative share of the site on which it was published. Generalizing our hierarchical Bayesian framework, we model

$$X_{ijk} \sim N(\mu_i^k, \sigma_d^2) \tag{6}$$

where μ_i^k is the k-th component in the latent 8-dimensional polarity vector $\vec{\mu_i}$ for

	Front-section news		Opinion	
Consumption channel	μ_p	σ_p	μ_p	σ_p
Aggregator	0.44	0.051	0.44	0.092
Direct	0.47	0.076	0.47	0.094
Social	0.46	0.087	0.47	0.12
Search	0.46	0.087	0.46	0.14

Table 3: Bayesian model estimates of ideological consumption by channel and subjectivity type. The column μ_p indicates the corresponding entry of $\vec{\mu_p}$, and the column σ_p indicates the corresponding diagonal entry of the model-estimated covariance matrix Σ_p.

user i, and σ_d is a global dispersion parameter. As before, we deal with sparsity by further assuming a distribution on the latent variables $\vec{\mu_i}$ themselves. In this case, we model each individual's polarity vector as being drawn from a multivariate normal:

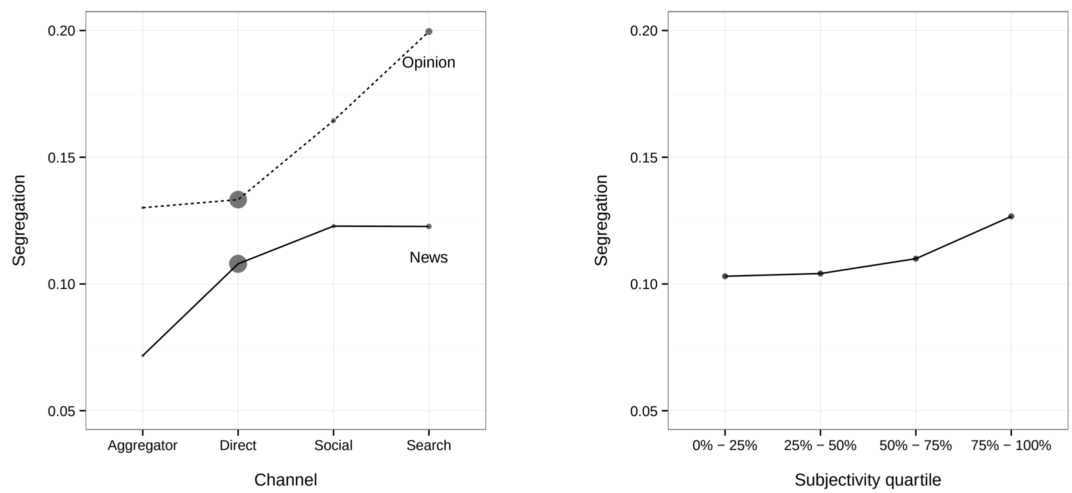
$$\vec{\mu_i} \sim N(\vec{\mu_p}, \Sigma_p) \tag{7}$$

where $\vec{\mu_p}$ and Σ_p are global hyperparameters. The full Bayesian model is analyzed by assigning weak priors to the hyperparameters and computing posterior distributions of the latent variables, but in practice we simply fit the model with marginal maximum likelihood.

As with the analysis in Section 2.1, the diagonal entries of the covariance matrix Σ_p yield estimates of segregation for each of the eight subjectivity-by-channel categories. In particular, letting σ_k^2 denote the k-th diagonal entry of Σ_p, segregation in the k-th category is $\sqrt{2}\sigma_k$. Table 3 lists these diagonal parameter estimates.[16] The off-diagonal entries of Σ_p measure the relationship between categories of one's ideological exposure. For example, after normalizing Σ_p to generate the corresponding correlation matrix, we find the correlation between social media-driven descriptive news and opinion is 0.71. The full correlation matrix is included in the Appendix.

To help visualize these model estimates, Figure 3a plots segregation across the four consumption channels, for both opinion and descriptive news. The size of the markers is proportional to total consumption within the corresponding channel, normalized separately for opinion and descriptive news. To ground the scale of the

[16]Given the large sample size, all estimates are statistically significant well beyond conventional levels.



(a) Descriptive news (solid line) and opinion (dotted line). Point sizes indicate traffic fraction, normalized separately within the news and opinion lines.

(b) Segregation as a function of article subjectivity (as estimated by word usage), with the most objective articles appearing in the left-most bin, and the most subjective in the right-most bin.

Figure 3: Estimates of ideological segregation across consumption channels (a) and subjectivity types (b).

y-axis, we note that among the top 20 most popular news outlets, conservative share ranges from 0.30 for the liberal *BBC* to 0.61 for the conservative *Newsmax*.

Figure 3a indicates that social media is indeed associated with higher segregation than direct browsing. For descriptive news this effect is subtle, with segregation increasing from 0.11 for direct browsing to 0.12 for articles linked to from social media. However for opinion pieces, the effect is more pronounced, rising from 0.13 to 0.17. It is unclear whether this increased segregation is the effect of active algorithmic filtering of the news stories appearing in one's social feed (Pariser, 2011), the result of ideological similarity among one's social contacts (Goel et al., 2010; McPherson et al., 2001), or both. In any case, however, our results are directionally consistent with worries that social media increase segregation.

We further find that search engines are associated with the highest levels of segregation among the four channels we investigate: 0.12 for descriptive news and 0.20 for opinion. Some authors have argued that web search personalization is a key driver of such effects (Pariser, 2011). There are two alternative explanations. The first is that users implicitly influence the ideological leanings of search results through their query formulation by, for example, issuing a query such as "obamacare" instead of "health care reform" (Borra and Weber, 2012). The second is that even when presented with the same search results, users are more likely to select outlets that share their own political ideology, especially for opinion content, has been found in laboratory studies (Garrett, 2009; Iyengar and Hahn, 2009; Munson and Resnick, 2010). While we cannot determine the relative importance of each explanation our findings do suggest that the relatively recent ability to instantly query large corpora of news articles—vastly expanding choices sets—contributes to increased ideological segregation at least marginally for descriptive news and substantially for opinion stories.

At the other end of the spectrum aggregators exhibit the lowest segregation. In particular, even though aggregators return personalized news results from a broad set of publications with disparate ideological leanings (Das et al., 2007), the overall effect is relatively low segregation. Though even for aggregators, segregation for opinion (0.13) is *far higher* than for descriptive news (0.07).

Given that our results are directionally consistent with filter bubble concerns, how is it that in Section 2.1 we found largely moderate overall levels of segregation? The answer is simply that only a relatively small fraction of consumption is of opinion pieces or from polarizing channels (social and search). Indeed even after removing apolitical categories like sports and entertainment (which account for a substantial fraction of traffic), opinion still only constitutes 6% of the remaining stories. Further, for both descriptive news and opinion direct browsing is the dominant consumption channel (79% and 67%, respectively), dwarfing social media and search engines. To help explain this result we investigated further and found that only *only 1 in 300* referrals (outbound links) from social media lead to substantive news articles; rather, the vast majority of referrals go to video and photo sharing sites. So while sharing information is popular on social media the dissemination of news is not a primary function. A potential explanation that we alluded to earlier is that since most Americans are on Facebook a typical user has a large circle of contacts with varied political allegiances (Goel et al., 2010), which may create negative social consequences of sharing polarizing material.

Finally, we observe that even the most extreme segregation that we observe (0.20 for opinion articles returned by search engines) is not, in our view, astronomically high. In particular, that level of segregation corresponds to the ideological distance between *Fox News* and *Daily Kos*, which represents meaningful differences in coverage (Baum and Groeling, 2008), but is within the mainstream political spectrum. Consequently, though the predicted filter bubble and echo chamber mechanisms do appear to increase online segregation, their overall effects at this time are somewhat limited.

We conclude this section with a sensitivity analysis in which we examine segregation with a finer-grained measure of article subjectivity. As described in Section 1.1, we assign each article a score between 0 and 1 that indicates the fraction of words in the article that convey a subjective stance. For simplicity and consistency with our previous analysis, we bin articles into four discrete quartiles, and then fit a model analogous to the one described above. Specifically, letting X_{ijk} indicate the j-th article read by user i in the k-th subjectivity quartile ($1 \leq k \leq 4$), we model

$$X_{ijk} \sim N(\mu_i^k, \sigma_d^2) \qquad \vec{\mu_i} \sim N(\mu_p, \Sigma_p). \tag{8}$$

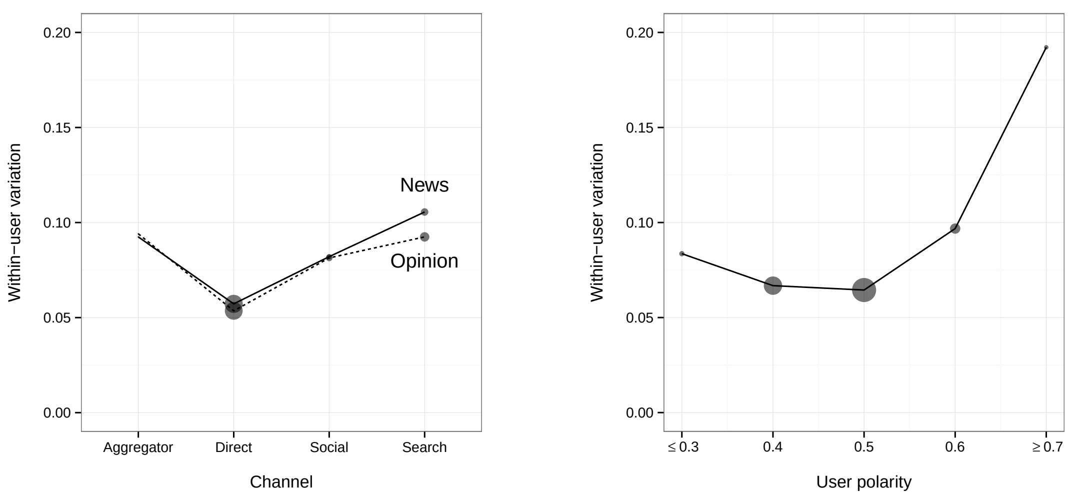
Estimates of segregation by article subjectivity are presented in Figure 3b. Consistent with our finding that opinion articles are associated with higher segregation than descriptive news, Figure 3b shows that segregation increases with this measure of subjectivity as well. However, we note that even though the Internet has likely made it easier to publish, promote and discover subjective news content, the most subjective quartile of news stories is still not alarmingly more segregating than the least subjective (0.10 versus 0.13).

2.3 Ideological Isolation

We have thus far examined segregation in terms of the distance between individuals' *mean* ideological positions. It could be the case, for example, that individuals typically consume content from a variety of ideological viewpoints, though ultimately skewing toward the left or right, leading to moderate overall segregation. Alternatively, individuals might be tightly concentrated around their ideological centers, only rarely reading content from across the political spectrum. These two potential patterns have markedly different implications for the broader issues of political discussion and consensus formation (Benkler, 2006).

To investigate this question of within-user variation, we start by looking at the dispersion parameter σ_d in the overall consumption model described by Eqs. (4) and (5). We find that $\sigma_d = 0.06$, indicating that individuals typically read publications that are tightly concentrated ideologically.

This finding of within-user ideological concentration is driven in part by the fact that individuals often simply turn to a single news source for information: 78% of users get the majority of their news from a single publication, and 94% get a majority from at most two sources. As shown in the Appendix, however, this concentration effect holds even for those who visit multiple news outlets. In particular, Figure 8 plots estimates of within-user variation as a function of the number of news outlets an individual visits. For example, among individuals who visited at least 10 news outlets, we find $\sigma = 0.09$, approximately the distance between *Reuters* and *NBC News*. Thus, even when individuals visit a variety of news outlets, they are, by and large, frequenting publications with similar ideological perspectives.



(a) Descriptive news (solid line) and opinion (dotted line). Point sizes indicate the relative fraction of traffic attributed to each source, normalized separately by category.

(b) Point sizes indicate the relative number of individuals in each polarity bin.

Figure 4: Within-user variation across consumption channel (a) and by mean polarity (b).

We now investigate ideological isolation across consumption channels and subjectivity categories. For each of the eight subjectivity-by-channel categories and for each user, we first estimate the variance of the polarities of articles read by that user in that category.[17] For each category, we then average these individual-level estimates of variance (and take the square root of the result) to attain category-level estimates. Figure 4a plots these estimates of within-user variation by channel and subjectivity.

Across all four consumption channels, Figure 4a shows that descriptive and opinion articles are associated with similar levels of within-user variation. Social media, however, is associated with higher variation than direct browsing. Though this may at first seem surprising given that social media also has relatively high segregation, the explanation is clear in retrospect: when browsing directly, individuals typically visit only a handful of news sources, whereas social media sites expose users to more variety. Likewise, web search engines, while associated with high segregation, also have relatively high diversity. Finally, relatively high levels of within-user spread are observed for aggregators, as one might have expected.

We similarly examine within-user ideological variation as a function of user polarity (i.e., mean ideological preference). In this case, we first bin individuals by their polarity—as estimated in Section 2.1—and then compute the individual-level variation of article polarity, averaged over users in each group. As shown in Figure 4b, within-user variation is small and quite similar for users with polarity ranging from 0.3 to 0.6. Interestingly, however, the 2% of individuals with polarity of approximately 0.7 or more (significantly to the right of Fox News) exhibit a strikingly high within-user variation of 0.17.

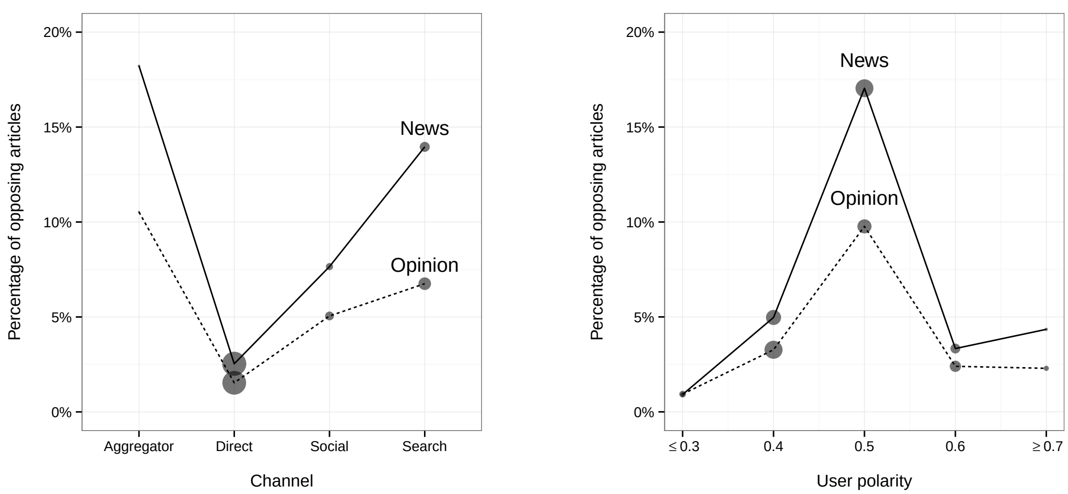
This preceding result prompts a question: Does the high within-user variation we see among extreme right-leaning readers result from them reading articles from across the political divide, or are they simply reading a variety of right-leaning publications? More generally, across channels and subjectivity types, what is the relationship between within-user variation and exposure to ideologically divergent news stories? We conclude our analysis of ideological isolation by examining these questions.

We start by defining a news outlet as left-leaning (resp., right-leaning) if it is in the bottom (resp., top) third of the 100 outlets we consider; the full ranked list of publications is given in the Appendix. The left-leaning publications include newspapers from liberal areas, such as the *San Francisco Chronicle* and the *New*

[17] For each category, we restrict to users who read at least two articles in that category.

York Times, as well as blogs such as the *Huffington Post* and *Daily Kos*; the right-leaning set includes newspapers from historically conservative areas, such as the *Fort Worth Star-Telegram* and the *Salt Lake Tribune*, and online outlets such as *Newsmax* and *Breitbart*; and centrist publications (i.e., the middle third) include, for example, *Yahoo News* and *USA Today*. We refer to the combined collection of left- and right-leaning outlets as *partisan*.

For each user who reads at least two partisan articles, define his or her liberal exposure ℓ_i to be the fraction of partisan articles read that are left-leaning. We define an individual's *opposing partisan exposure* $o_i = \min(\ell_i, 1 - \ell_i)$. Thus, for individuals who predominantly read left-leaning articles, o_i is the proportion of partisan articles they read that are right-leaning, and vice-versa. We note o_i is only defined for the 82% of individuals in our sample that have read at least two partisan articles.



(a) By channel

(b) By mean polarity

Figure 5: Opposing partisan exposure by channel (a) and polarity (b). Descriptive news (solid line) and opinion (dotted line). Point sizes indicate the relative fraction of traffic attributed to each source, normalized separately by article category.

Figure 5 shows average opposing partisan exposure, partitioned by article channel and subjectivity (Figure 5a), and by user polarity (Figure 5b).[18] For every subset we consider, only a small minority of articles—less than 20% in all cases,

[18]To compute the estimates of average opposing partisan exposure shown in 5a, o_i is computed separately for each of the eight subjectivity-by-channel categories by restricting to the relevant articles, and limiting to users who read at least two partisan articles in that category.

and less than 5% for all non-centrist users—comes from the opposite side of an individual's preferred partisan perspective. Additionally, for every subset this opposing exposure is lower for opinion. Answering the question posed above, even extreme right-leaning readers have strikingly low opposing partisan exposure (3%); thus, their relatively high within-user variation is a product of reading a variety of centrist and right-leaning outlets, and not exposure to truly ideologically diverse content. In contrast, the relatively higher levels of within-user variation associated with social media and web search (Figure 4a) do translate to increased exposure to opposing viewpoints, though this effect is still small. Lastly, we note that these findings are only partially a consequence of individuals typically visiting just a small number of news outlets. As shown in Figure 9, even among those who visit 5–9 news outlets, average opposing partisan exposure is only 14%; and it is still just 20% for those users visiting 10–14 outlets.

Summarizing our results on ideological isolation, we find that individuals generally read publications that are ideologically quite similar, and moreover, users that regularly read partisan articles are almost exclusively exposed to only one side of the political spectrum. In this sense, many, indeed nearly all, users exist in a so-called echo chamber. We note, however, two key differences between our findings and some previous discussions of this topic (Pariser, 2011; Sunstein, 2009). First, we should that while social media and search do contribute to segregation the lack of within-user variation is primarily driven by direct browsing. Second, consistent with Gentzkow and Shapiro (2011), the outlets that dominate partisan news coverage are still relatively mainstream, ranging from *The New York Times* on the left to *Fox News* on the right; the more extreme ideological sites (e.g., *Breitbart*), which presumably benefited from the rise of online publishing, do not appear to qualitatively impact the dynamics of news consumption.

3 Ideological Segregation on Twitter

While our preceding analysis investigated a variety of channels through which individuals read the news, it was limited to a particular opt-in sample of individuals. In this section, we augment our analysis by examining the news consumption habits of a nearly complete set of users on one specific social information channel, Twitter, one of the largest online social networks, and arguable the largest designed primarily for information discovery and dissemination, as exemplified by their instructions to users to “simply find the accounts you find most compelling and follow the conversations.”[19]

The Twitter and toolbar datasets differ on two additional substantively important dimensions. First, Internet Explorer and Twitter users are demographically quite different. For example, whereas Internet Explorer users are believed to be, on average, older than those in the general Internet population, Twitter users skew younger. In particular, 27% of 18–29 year-olds use Twitter, compared to 10% of those aged 50–64 (Pew Research, 2013). Second, because of differing levels of information in the two datasets, in the toolbar analysis we examine the articles that an individual *viewed*, whereas with Twitter we look at the articles that were merely *shared* with that individual, regardless of whether or not he or she read the story. Thus, given these differences, to the extent that our results extend to this setting, we can be further assured of the robustness of our findings.

To generate the Twitter dataset, we start with the nearly complete set of U.S.-located individuals who posted a tweet during the two-month period March–April, 2013.[20] We focus on accounts maintained and used by an individual (as opposed to corporate accounts), and so further restrict to those that receive content from (“follow”) between 10 and 1,000 users on the network. This process yields approximately 7.5 million individuals. Finally, similar to our restriction in the toolbar analysis, we limit to active news consumers, who received (i.e., followed individuals who posted) at least 10 front-section news articles and at least 2 opinion pieces.[21] In total, 1.5 million users meet all of these restrictions.

We begin our analysis by estimating the distribution of user polarity. In this setting, user polarity is the typical polarity of the articles to which a user is exposed (i.e., articles that are posted by an account the user follows), where we recall that the polarity of an article is the conservative share of the outlet in which it was published. Since users on Twitter often receive news by following the accounts of major news

[19]Twitter positions itself as a fully-customizable information portal, this quote comes from www.twitter.com/about.

[20]Twitter offers the option of “protected accounts,” which are not publicly accessible. These accounts are rare and are not part of our study.

[21]As with the toolbar analysis, articles were classified as front-section news and opinion according to the methods described in Section 1.

outlets rather than accounts of actual individuals (Kwak et al., 2010), and since these news outlets typically post hundreds of articles per day, individuals in our sample are generally exposed to large numbers of news articles—4,008 on average during the two-month time frame we study. As a consequence, data sparsity is not a serious concern, which in turn significantly simplifies our estimation procedure. Specifically, for each Twitter user, we estimate polarity by simply averaging the polarities of the articles to which he or she is exposed.

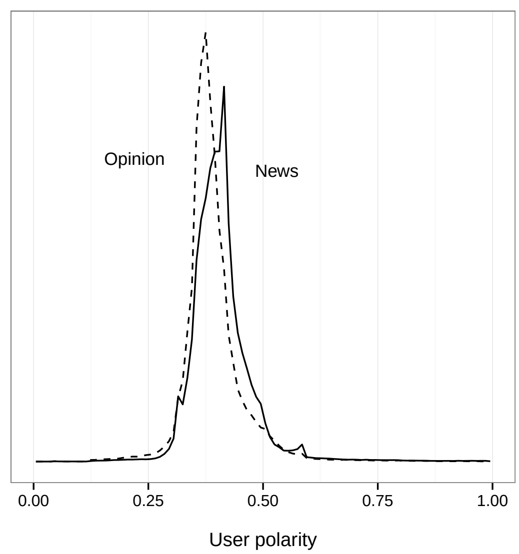
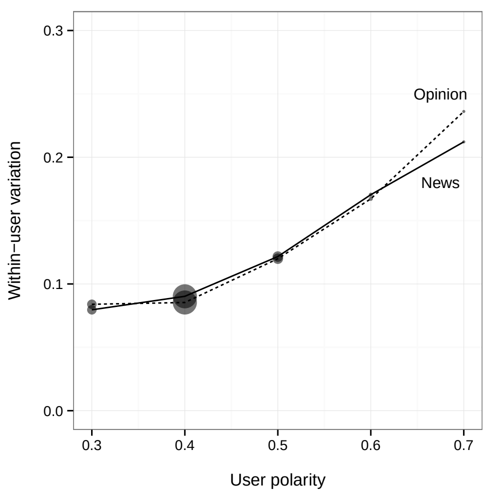
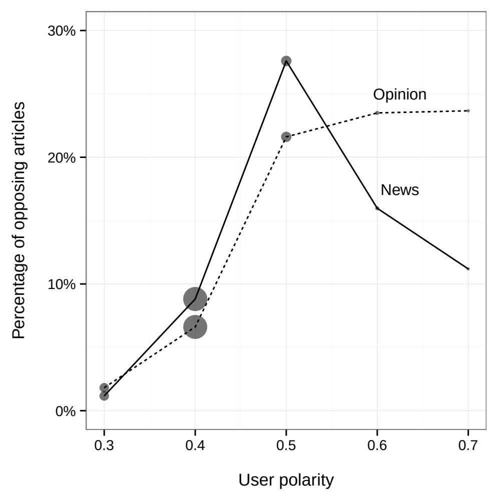


Figure 6: Distribution of individual-level polarity for Twitter users, where an individual's polarity score is the average conservative share of news outlets to which he or she is exposed, computed separately for descriptive news articles (solid line) and opinion pieces (dashed line).

Figure 6 shows the resulting distribution of user polarity, where we separately plot the user polarity distribution computed for descriptive news articles (solid line) and opinion stories (dashed line). This plot illustrates two points. First, despite a slight leftward ideological skew relative to toolbar users, the bulk of Twitter users exhibit quite moderate news preferences. For example, 70% of Twitter users have polarity scores between 0.35 and 0.45, ranging from *The Huffington Post* to *CBS*. Second, segregation is correspondingly moderate, 0.10, and remarkably similar to our estimate from the toolbar data (0.11). Thus, despite the relative ease with which individuals may elect to follow politically extreme news publishers, and despite the



(a) Within-user variation.



(b) Opposing partisan views.

Figure 7: Within-user variation (a) and opposing partisan views (b) on Twitter, as a function of individual-level polarity. The sizes of the points indicate the relative number of individuals in each polarity bin, normalized separately for front-section news (solid line) and opinion (dashed line).

worry that algorithmic recommendations of whom to follow could spur segregation, ideological segregation on Twitter looks very much like what we observe in direct navigation web browsing.

We investigate the exposure distribution further with two individual-level metrics: (1) within-user variation, defined as the standard deviation of the polarities of articles to which an individual is exposed; and (2) opposing partisan views, defined as the fraction of partisan articles from an individual's less preferred ideological perspective. The results are plotted in Figure 7, as a function of user polarity.

As indicated by Figure 7a, average within-user variation—averaged over all individuals in our sample of Twitter users—is 0.10, significantly higher than the 0.05 we observed for direct web browsing, but comparable to the 0.09 we found for articles obtained through aggregators (Figure 4a), consistent with the general view of Twitter as a custom aggregator. Further, as we saw before, within-user variation increases substantially as we move to the conservative end of the spectrum; that is, individuals who on average consume more conservative content also tend to consume content from a wider variety of ideological viewpoints.

We plot opposing partisan exposure in Figure 7b, restricting to individuals who are exposed to at least two partisan articles (as we required in the toolbar analysis). Average opposing partisan exposure is 11%, very close to the 10% we observe in the toolbar dataset—the vast majority of an individual's partisan views come from their preferred political side. However, a notable difference between the two datasets is that whereas in the toolbar data both left- and right-leaning individuals have little exposure to opposing views, on Twitter, right-leaning individuals have considerably more exposure to opposing views than left-leaning users. Though it is not entirely clear what is driving this effect, it is likely in part due to the overall leftward skew of Twitter, where it is thus harder for right-leaning individuals to isolate themselves from the majority view.

4 Discussion and Conclusion

We began our investigation with a puzzle: laboratory experiments and theoretical arguments suggest that the rise of online publishing, social media, and personalized recommendations should create a so-called filter bubble or echo chamber in which individuals are ideologically isolated (Pariser, 2011; Sunstein, 2001, 2009); yet mainstream news outlets still dominate the market, and by most metrics political polarization in the general U.S. population has not spiked in recent years (Baldassarri and Gelman, 2008; Prior, 2013). We reach a simple and intuitive resolution to this apparent paradox by conducting one of the largest studies of online news consumption to date.

We find that stories shared on social media or found via web search engines are indeed more segregating than those an individual reads by directly visiting news sites, an effect that is almost entirely driven by opinion articles. However, a relatively small amount of online news consumption is driven by the polarizing social and search channels, and opinion pieces—which are typically the focus of laboratory studies—constitute just 6% of articles relating to world or national news. Indeed, we may have missed the effect entirely if we had not carefully separated out opinion content using natural language processing. Rather, we find that individuals typically consume descriptive reporting, and do so by directly visiting a handful of their preferred news outlets. Even within opinion, moreover, we do not see the extreme choice segmentation observed in the lab, perhaps because the hot-button issues used in those studies, such as the death penalty and abortion rights, are poor analogs for typical opinion pieces. Thus, though many elements of ideological fragmentation are operating as predicted by filter bubble theories, the overall impact of these factors appears to be limited at this time.

Although we validate our core findings on two different datasets, our study is subject to some limitations. First, as with past work (Gentzkow and Shapiro, 2010, 2011; Groseclose and Milyo, 2005), for methodological tractability we focus on the ideological slant of news outlets, as opposed to that of specific articles. As such, we would misinterpret, for example, the news preferences of an individual who primarily reads liberal articles from generally conservative sites. We suspect, however, that this type of behavior is relatively limited, in part because individuals typically visit ideologically similar news outlets, suggesting their own preferences are in line with those of the sites that they frequent. Second, we focus exclusively on news consumption itself, and not on the consequences such choices have on, for example, voting behavior or policy preferences.[22] Given that we find social media and web search have limited impact on news exposure—although these channels are more important for opinion—it is likely that their effects on attitudes and behaviors are correspondingly small. It is, however, possible—and even plausible—that of the hundreds of news articles one reads, a single, persuasive opinion story shared via social media could have the greatest impact. Finally, and related to the previous point, as we have focused our study on the (natural) subpopulation of active news consumers, it is unclear what impact recent technological changes have on the majority of individuals who have little exposure to the news, but who may get that limited amount largely from social media.

Looking forward, our substantive and methodological contributions provide a framework for understanding and monitoring the effects of future systems for producing, distributing, and consuming online news. While it seems we have thus far largely avoided the detrimental, segregating effects of social media and personalization, what the next generation of Internet users will experience is less certain. In particular, given that social networking services are disproportionately comprised of younger individuals (Pew, 2013), social media could become a more dominant channel for disseminating news, a transformation that could in turn increase ideological

[22]Establishing and measuring the causal effects of partisan news exposure is difficult, though not impossible (Prior, 2013).

segregation.

References

Adamic, L. A. and Glance, N. (2005). The political blogosphere and the 2004 us election: divided they blog. In *Proceedings of the 3rd international workshop on Link discovery*, pages 36–43. ACM.

Agichtein, E., Brill, E., and Dumais, S. (2006). Improving web search ranking by incorporating user behavior information. In *Proceedings of the 29th annual international ACM SIGIR conference on Research and development in information retrieval*, pages 19–26. ACM.

Athey, S. and Mobius, M. (2012). The impact of news aggregators on internet news consumption: The case of localization. Technical report, Harvard University.

Bakshy, E., Rosenn, I., Marlow, C., and Adamic, L. (2012). The role of social networks in information diffusion. In *Proceedings of the 21st international conference on World Wide Web*, pages 519–528. ACM.

Baldassarri, D. and Gelman, A. (2008). Partisans without constraint: Political polarization and trends in american public opinion1. *American Journal of Sociology*, 114(2):408–446.

Bates, D., Maechler, M., and Bolker, B. (2013). *lme4: Linear mixed-effects models using S4 classes*. R package version 0.999999-2.

Baum, M. A. and Groeling, T. (2008). New media and the polarization of american political discourse. *Political Communication*, 25(4):345–365.

Benkler, Y. (2006). *The wealth of networks: How social production transforms markets and freedom*. Yale University Press.

Bernhardt, D., Krasa, S., and Polborn, M. (2008). Political polarization and the electoral effects of media bias. *Journal of Public Economics*, 92(5):1092–1104.

Borra, E. and Weber, I. (2012). Political insights: exploring partisanship in web search queries. *First Monday*, 17(7).

Broder, A. (2002). A taxonomy of web search. In *ACM Sigir forum*, volume 36, pages 3–10. ACM.

Das, A. S., Datar, M., Garg, A., and Rajaram, S. (2007). Google news personalization: scalable online collaborative filtering. In *Proceedings of the 16th international conference on World Wide Web*, pages 271–280. ACM.

De los Santos, B., Hortacsu, A., and Wildenbeest, M. R. (2012). Testing models of consumer search using data on web browsing and purchasing behavior. *The American Economic Review*, 102(6):2955–2980.

DellaVigna, S. and Kaplan, E. (2007). The Fox News effect: media bias and voting. *The Quarterly Journal of Economics*, 122(3):1187–1234.

Downs, A. (1957). *An economic theory of democracy*. New York.

Garrett, R. K. (2009). Echo chambers online?: Politically motivated selective exposure among internet news users. *Journal of Computer-Mediated Communication*, 14(2):265–285.

Gelman, A. and Hill, J. (2007). *Data analysis using regression and multilevel/hierarchical models*. Cambridge University Press.

Gentzkow, M. and Shapiro, J. M. (2006). Media bias and reputation. *Journal of Political Economy*, 114(2):280–316.

Gentzkow, M. and Shapiro, J. M. (2010). What drives media slant? evidence from US daily newspapers. *Econometrica*, 78(1):35–71.

Gentzkow, M. and Shapiro, J. M. (2011). Ideological segregation online and offline. *The Quarterly Journal of Economics*, 126(4):1799–1839.

Gentzkow, M. and Shapiro, J. M. (2013). Ideology and online news. Working paper.

George, L. M. and Waldfogel, J. (2006). The "New York Times" and the market for local newspapers. *The American Economic Review*, 96(1):435–447.

Glover, E. J., Flake, G. W., Lawrence, S., Birmingham, W. P., Kruger, A., Giles, C. L., and Pennock, D. M. (2001). Improving category specific web search by learning query modifications. In *Symposium on Applications and the Internet*, pages 23–32. IEEE.

Goel, S., Hofman, J. M., and Sirer, M. I. (2012a). Who does what on the web: A large-scale study of browsing behavior. In *ICWSM*.

Goel, S., Mason, W., and Watts, D. J. (2010). Real and perceived attitude agreement in social networks. *Journal of Personality and Social Psychology*, 99(4):611.

Goel, S., Watts, D. J., and Goldstein, D. G. (2012b). The structure of online diffusion networks. In *Proceedings of the 13th ACM Conference on Electronic Commerce*, pages 623–638. ACM.

Groseclose, T. and Milyo, J. (2005). A measure of media bias. *The Quarterly Journal of Economics*, 120(4):1191–1237.

Hannak, A., Sapiezynski, P., Molavi Kakhki, A., Krishnamurthy, B., Lazer, D., Mislove, A., and Wilson, C. (2013). Measuring personalization of web search. In *Proceedings of the 22nd international conference on World Wide Web*, pages 527–538. International World Wide Web Conferences Steering Committee.

Herring, S. C., Kouper, I., Paolillo, J. C., Scheidt, L. A., Tyworth, M., Welsch, P., Wright, E., and Yu, N. (2005). Conversations in the blogosphere: An analysis. In *System Sciences, 2005. HICSS'05. Proceedings of the 38th Annual Hawaii International Conference on*, pages 107b–107b. IEEE.

Iyengar, S. and Hahn, K. S. (2009). Red media, blue media: Evidence of ideological selectivity in media use. *Journal of Communication*, 59(1):19–39.

Kwak, H., Lee, C., Park, H., and Moon, S. (2010). What is Twitter, a social network or a news media? In *WWW '10: Proceedings of the 19th international conference on World wide web*, pages 591–600, New York, NY, USA. ACM.

Lawrence, E., Sides, J., and Farrell, H. (2010). Self-segregation or deliberation? blog readership, participation, and polarization in American politics. *Perspectives on Politics*, 8(01):141–157.

Liu, B. (2010). Sentiment analysis and subjectivity. *Handbook of Natural Language Processing*, 2:568.

Liu, D. C. and Nocedal, J. (1989). On the limited memory BFGS method for large scale optimization. *Mathematical programming*, 45(1-3):503–528.

Lord, C. G., Lepper, M. R., and Preston, E. (1984). Considering the opposite: A corrective strategy for social judgment. *Journal of personality and social psychology*, 47(6):1231.

Lord, C. G., Ross, L., and Lepper, M. R. (1979). Biased assimilation and attitude polarization: The effects of prior theories on subsequently considered evidence. *Journal of Personality and Social Psychology*, 37(11):2098.

Manning, C. D. and Schütze, H. (1999). *Foundations of statistical natural language processing*, volume 1. MIT Press.

McPherson, M., Smith-Lovin, L., and Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual review of sociology*, pages 415–444.

Moscovici, S. and Zavalloni, M. (1969). The group as a polarizer of attitudes. *Journal of personality and social psychology*, 12(2):125.

Mullainathan, S. and Shleifer, A. (2005). The market for news. *American Economic Review*, pages 1031–1053.

Munson, S. A. and Resnick, P. (2010). Presenting diverse political opinions: how and how much. In *Proceedings of the SIGCHI conference on human factors in computing systems*, pages 1457–1466. ACM.

Myers, D. G. and Bishop, G. D. (1970). Discussion effects on racial attitudes. *Science*.

Nickerson, R. S. (1998). Confirmation bias: a ubiquitous phenomenon in many guises. *Review of General Psychology*, 2(2):175.

Pariser, E. (2011). *The filter bubble: What the Internet is hiding from you*. Penguin UK.

Pennebaker, J. W., Chung, C. K., Ireland, M., Gonzales, A., and Booth, R. J. (2007). The development and psychometric properties of liwc2007. *Austin, TX, LIWC. Net*.

Pennebaker, J. W., Francis, M. E., and Booth, R. J. (2001). Linguistic inquiry and word count: Liwc 2001. *Mahway: Lawrence Erlbaum Associates*, page 71.

Prior, M. (2013). Media and political polarization. *Annual Review of Political Science*, 16:101–127.

Riloff, E. and Wiebe, J. (2003). Learning extraction patterns for subjective expressions. In *Proceedings of the 2003 conference on Empirical methods in natural language processing*, pages 105–112. Association for Computational Linguistics.

Schkade, D., Sunstein, C. R., and Hastie, R. (2007). What happened on deliberation day? *California Law Review*, pages 915–940.

Spears, R., Lea, M., and Lee, S. (1990). De-individuation and group polarization in computer-mediated communication. *British Journal of Social Psychology*, 29(2):121–134.

Speretta, M. and Gauch, S. (2005). Personalized search based on user search histories. In *Web Intelligence, 2005. Proceedings. The 2005 IEEE/WIC/ACM International Conference on*, pages 622–628. IEEE.

Sunstein, C. (2001). *Republic.com*. Princeton University Press.

Sunstein, C. R. (2009). *Republic.com 2.0*. Princeton University Press.

Tewksbury, D. (2005). The seeds of audience fragmentation: Specialization in the use of online news sites. *Journal of broadcasting & electronic media*, 49(3):332–348.

Webster, J. G. and Ksiazek, T. B. (2012). The dynamics of audience fragmentation: Public attention in an age of digital media. *Journal of communication*, 62(1):39–56.

White, M. J. (1986). Segregation and diversity measures in population distribution. *Population index*, 52(2):198–221.

Zhou, D. X., Resnick, P., and Mei, Q. (2011). Classifying the political leaning of news articles and users from user votes. In *ICWSM*.

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Table 4: Conservative shares for the top 100 news outlets, ranked by share.

	Domain	Publication Name	Conservative Share
1	timesofindia.indiatimes.com	Times of India	0.04
2	economist.com	The Economist	0.12
3	northjersey.com	North Jersey.com	0.14
4	ocregister.com	Orange Country Register	0.15
5	mercurynews.com	San Jose Mercury News	0.17
6	nj.com	NewJersey.com†	0.17
7	sfgate.com	San Francisco Chronicle	0.19
8	baltimoresun.com	Baltimore Sun	0.19
9	courant.com	Hartford Courant	0.22
10	jpost.com	Jerusalem Post (EN-Israel)	0.25
11	prnewswire.com	PR Newswire	0.27
12	sun-sentinel.com	South Florida Sun Sentinal	0.27
13	nationalpost.com	National Post (CA)	0.28
14	thestar.com	Tornoto Star	0.28
15	bbc.co.uk	BBC (UK)	0.30
16	wickedlocal.com	Wicked Local (Boston)	0.30
17	nytimes.com	New York Times	0.31
18	independent.co.uk	The Independent	0.32
19	philly.com	Philadelphia Herald	0.32
20	hollywoodreporter.com	Hollywood Reporter	0.33
21	miamiherald.com	Miami Herald	0.35
22	huffingtonpost.com	Huffington Post	0.35
23	guardian.co.uk	The Guardian	0.37
24	washingtonpost.com	Washington Post	0.37
25	online.wsj.com	Wall Street Journal	0.39
26	news.com.au	News.com (AU)	0.39
27	dailykos.com	Daily Kos	0.39
28	bloomberg.com	Bloomberg	0.39
29	dailyfinance.com	Daily Finance	0.39
30	syracuse.com	Syracuse Gazette	0.39
31	usnews.com	US News and World Report	0.39
32	timesunion.com	Times Union (Albany)	0.40
33	time.com	Time Magazine	0.40
34	reuters.com	Reuters	0.41
35	telegraph.co.uk	Daily Telegraph (UK)	0.41
36	businessweek.com	Business Week	0.42
37	cnn.com	CNN	0.42
38	politico.com	Politico	0.42
39	theatlantic.com	The Atlantic	0.42
40	nationaljournal.com	National Journal	0.43
41	alternet.org	Alternet	0.43
42	ajc.com	Atlanta Journal Constitution	0.44
43	forbes.com	Forbes	0.44
44	seattletimes.com	Seattle Times	0.44
45	rawstory.com	The Raw Story	0.44
46	newsday.com	News Day	0.44
47	cbsnews.com	CBS	0.45
48	rt.com	Russia Today	0.45
49	theepochtimes.com	The Epoch Times	0.46
50	latimes.com	Los Angleles Times	0.47

	Domain	Publication Name	Conservative Share
51	csmonitor.com	Christian Science Monitor	0.47
52	realclearpolitics.com	Real Clear Politics	0.47
53	usatoday.com	USA Today	0.47
54	cnbc.com	CNBC	0.47
55	dailymail.co.uk	The Daily Mail (UK)	0.47
56	mirror.co.uk	Daily Mirror (UK)	0.47
57	news.yahoo.com	Yahoo! News	0.47
58	abcnews.go.com	ABC News	0.48
59	upi.com	United Press International	0.48
60	chicagotribune.com	Chicago Tribune	0.49
61	ap.org	Associated Press	0.50
62	nbcnews.com	NBC News	0.50
63	suntimes.com	Chicago Sun-Times	0.51
64	freep.com	Detriot Free Press	0.52
65	azcentral.com	Arizona Republics	0.53
66	tampabay.com	Tamba Bay Times	0.54
67	orlandosentinel.com	Orlando Sentinel	0.54
68	thehill.com	The Hill	0.57
69	nationalreview.com	The National Review	0.57
70	news.sky.com	SKY	0.58
71	detroitnews.com	Detroit News	0.59
72	express.co.uk	The Daily Express (UK)	0.59
73	weeklystandard.com	The Weekly Standard	0.59
74	foxnews.com	Fox News	0.59
75	washingtontimes.com	Washington Times	0.59
76	jsonline.com	Milwaukee Journal Sentinel	0.61
77	newsmax.com	Newsmax	0.61
78	factcheck.org	factcheck.org	0.62
79	reason.com	Reason Magazine	0.63
80	washingtonexaminer.com	Washington Examiner	0.63
81	ecanadanow.com	E Canada Now	0.63
82	americanthinker.com	American Thinker	0.65
83	twincities.com	St. Paul Pioneer Press	0.67
84	jacksonville.com	Florida Times Union	0.67
85	opposingviews.com	Opposing Views	0.67
86	chron.com	Houston Chronicle	0.67
87	startribune.com	Minneapolis Star Tribune	0.68
88	breitbart.com	Breitbart	0.70
89	star-telegram.com	Ft. Worth Star-Telegram	0.74
90	stltoday.com	St. Louis Post-Dispatch	0.75
91	mysanantonio.com	San Antonio Express News	0.77
92	denverpost.com	Denver Post	0.80
93	triblive.com	Pittsburg Tribune-Review	0.85
94	sltrib.com	Salt Lake Tribune	0.85
95	dallasnews.com	Dallas Morning News	0.86
96	kansascity.com	Kansas City Star	0.93
97	deseretnews.com	Deseret News (Salt Lake City)	0.94
98	topix.com	Topix	0.96
99	knoxnews.com	Knoxville News Sentinel	0.96
100	al.com	Huntsville News/Mobile Press Register/Birmingham News	1.00

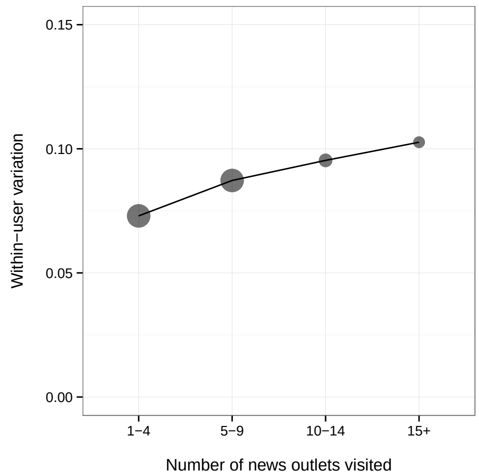

Figure 8: For a typical individual, within-user variation (i.e., standard deviation) of the conservative share of news outlets he or she visits, as a function of the number of outlets visited.

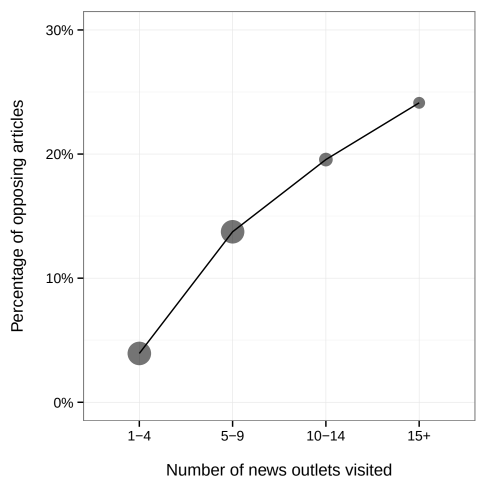

Figure 9: For a typical individual, fraction of partisan articles that are on the opposite side of the ideological spectrum from those he or she generally reads, as a function of the number of news outlets visited.

		News				Opinion			
		aggregator	direct	search	social	aggregator	direct	search	social
News	aggregator	0.0026							
	direct	0.0007	0.0058						
	search	0.0008	0.0033	0.0075					
	social	0.0010	0.0043	0.0042	0.0075				
Opinion	aggregator	0.0018	0.0013	0.0011	0.0010	0.0085			
	direct	0.0007	0.0064	0.0039	0.0050	0.0024	0.0089		
	search	0.0011	0.0038	0.0068	0.0048	0.0030	0.0057	0.0199	
	social	0.0008	0.0043	0.0048	0.0072	0.0030	0.0064	0.0089	0.0135

Table 5: Variance-covariance matrix for the model used to estimate ideological consumption by channel and subjectivity type, as described in Eqs. (6) and (7).

		News				Opinion			
		aggregator	direct	search	social	aggregator	direct	search	social
News	aggregator								
	direct	0.17							
	search	0.18	0.51						
	social	0.23	0.65	0.56					
Opinion	aggregator	0.39	0.18	0.14	0.12				
	direct	0.15	0.89	0.48	0.61	0.28			
	search	0.16	0.35	0.56	0.4	0.23	0.43		
	social	0.13	0.49	0.47	0.71	0.28	0.58	0.54	

Table 6: Correlation matrix for the model used to estimate ideological consumption by channel and subjectivity type, as described in Eqs. (6) and (7).