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UNDERSTANDING ECHO CHAMBERS AND FILTER BUBBLES: THE IMPACT OF SOCIAL MEDIA ON DIVERSIFICATION AND PARTISAN SHIFTS IN NEWS CONSUMPTION[1]

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Echo chambers and filter bubbles are potent metaphors that encapsulate widespread public fear that the use of social media may limit the information that users encounter or consume online. Specifically, the concern is that social media algorithms combined with tendencies to interact with like-minded others both limits users' exposure to diverse viewpoints and encourages the adoption of more extreme ideological positions. Yet empirical evidence about how social media shapes information consumption is inconclusive. We articulate how characteristics of platform algorithms and users' online social networks may combine to shape user behavior. We bring greater conceptual clarity to this phenomenon by expanding beyond discussion of a binary presence or absence of echo chambers and filter bubbles to a richer set of outcomes incorporating changes in both diversity and slant of users' information sources. Using a data set with over four years of web browsing history for a representative panel of nearly 200,000 U.S. adults, we analyzed how individuals' social media usage was associated with changes in the information sources they chose to consume. We find differentiated impacts on news consumption by platform. Increased use of Facebook was associated with increased information source diversity and a shift toward more partisan sites in news consumption; increased use of Reddit with increased diversity and a shift toward more moderate sites; and increased use of Twitter with little to no change in either. Our results demonstrate the value of adopting a nuanced multidimensional view of how social media use may shape information consumption.

Keywords: Echo chamber, filter bubble, diversity, polarization, slant, news, personalization

Introduction

Echo chambers and filter bubbles are potent metaphors that encapsulate widespread public fear that the use of social media may limit the information that users encounter or consume online, thus failing to promote a shared experience of free-flowing information. Specifically, the concern is that social media algorithms combine with tendencies to interact with like-minded others to create an environment that predominantly exposes users to congenial, opinion-reinforcing content to the exclusion of more diverse, opinion-challenging content. This intuitive understanding of echo chambers and filter bubbles is well-accepted. Yet empirical evidence about how social media and other digital platforms shape information consumption is inconclusive. Despite decades of interest in this phenomenon, researchers' ability to analyze the prevalence or formation of echo chambers and filter bubbles is stymied by a lack of consensus regarding their conceptualization and measurement.

There is growing concern that social media and other information discovery platforms promote information-limiting environments by shielding users from opinion-challenging information, thereby encouraging users to adopt more extreme

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ideological positions. Indeed, there are aspects of popular social media platforms that may foster information-limiting environments. For instance, as with offline relationships, people in online social networks interact most frequently with like-minded others. In a study of 10.1 million U.S. Facebook users with self-reported ideological affiliation, Bakshy et al. (2015) found that more than 80% of these Facebook friendships shared the same party affiliation. Accordingly, the news and information sources that individuals discover through their social relationships may also reflect a lack of ideological diversity. Further, even within this already constrained choice set, selective exposure theory predicts that individuals prefer to consume opinion-reinforcing news sources over opinion-challenging ones (Frey 1986). Garrett (2009) found support for this tendency in a field experiment with 727 online news readers: individuals expressed interest in reading online news stories they perceived to be supportive of their existing opinion and expressed disinterest in consuming opinion-challenging stories. Finally, researchers have long expressed concern about the potential for algorithmic filtering to reduce the diversity of information sources that individuals are exposed to, engage with, or consume (Van Alstyne and Brynjolfsson 1996, 2005). Personalization technology is sensitive to personal preferences; once a user engages with opinion-reinforcing content, algorithmic filtering may constrain further exposure to a narrower, more closely aligned range of content (Pariser 2011; Stroud 2010). This, in turn, may foster the adoption of more extreme opinions (Festinger 1964; Hart et al. 2009).

Thus, there is a clear potential for the use of social media to be associated with a narrowing of information diversity and a partisan shift in the slant of news consumed by their users. For example, Lawrence et al. (2010) found readers of political blogs to be more ideologically segregated and more ideologically extreme than nonreaders. Likewise, Wojcieszak and Mutz (2009) found that participants in online politics-related groups were less likely to be exposed to political information they disagree with (and more likely to be exposed to information they agree with) than participants in many other categories of online groups (e.g., hobby or leisure related). Nonetheless, the prevalence and magnitude of information-limiting environments may be overstated. Other studies have shown social media platforms to be information-expanding. Social media helps users discover new information sources, thereby potentially expanding the diversity of viewpoints, opinions, and information to which users are exposed. For example, Flaxman et al. (2016) "uncover evidence for both sides of the debate, while also finding that the magnitude of the effects [are] relatively modest" (p. 298). Gentzkow and Shapiro (2011) performed a large-scale analysis of web browsing habits of U.S. adults, concluding that "ideological segregation on the Internet is low in absolute terms" and that the Internet exposes individuals to a broader range of viewpoints than "face-to-face interactions with neighbors, co-workers, or family members" (p. 1799). In summary, despite a great deal of interest in the idea of echo chambers and filter bubbles, empirical evidence to date is inconclusive as to whether social media is information-limiting or information-expanding.

We identify six key reasons contributing to why researchers have reached conflicting conclusions about the existence of echo chambers and filter bubbles, as well as the processes that may lead to their formation. First, a fundamental issue in this body of research is the lack of conceptual clarity, with vague and conflicting definitions of constructs, processes, and outcomes. Second, imprecise conceptualization has only compounded issues of inconsistent measurement and incommensurate research designs in prior studies, precluding the systematic integration of findings. Most importantly, a variety of online platforms have been studied either independently or lumped together in aggregate, making it difficult to ascertain the relationship between social factors, technology features, and information-limiting environments. Third, empirical results are also difficult to compare when they measure disparate, nonequivalent outcomes, often measuring content exposure, sharing, or generation, while consumption may be more directly salient to the concerns surrounding information-limiting environments. Fourth, as Shore et al. (2018) note, one "likely reason for the conflicted nature of the literature is that earlier work has generally focused too narrowly on unrepresentative or incomplete data sets," such as "focusing on highly active users" (p. 850). Fifth, inferring the impact of individuals' technology use from analysis of population-level distributions may suffer from either an ecological fallacy or an aggregation bias (Freedman 1999). Finally, social media platforms frequently adjust their algorithmic filters and rarely disclose when those changes occur. The dynamic nature of the phenomenon combined with a lack of transparency by platform providers may limit the generalizability of empirical results over time.

To further understand this much-debated phenomenon, we propose the concept of *information-limiting environments* as encapsulating the primary concerns regarding echo chambers and filter bubbles—namely, that social network homophily and algorithmic filtering constrain the information sources that individuals choose to consume, shielding them from opinion-challenging information and encouraging them to adopt more extreme viewpoints. By identifying diversity and partisan slant as distinct characteristics of information consumption, we articulate how social media can shape information consumption in ways that move beyond the simple presence or absence of echo chambers and filter bubbles. We use broadly representative data to investigate how three popular social media platforms vary in their impact on content consumption by individual users, and thereby may or may not contribute to underlying outcomes associated with information-limiting environments. Through an analysis of over four years of web browsing history for a representative panel of nearly 200,000 U.S. adults, we demonstrate differentiated impacts by platform and discuss these differences in terms of the variation in platform features at the time. Increased use of Facebook was associated with increased information source diversity and a partisan shift in news site visits. Increased use of Reddit was also associated with increased diversity, but a moderating shift. Increased use of Twitter had little to no association with changes in either diversity or slant. Our results demonstrate the value of adopting a more nuanced and multidimensional conceptualization of how social media shapes information consumption.

Understanding Echo Chambers and Filter Bubbles

Given the extensive range of approaches to conceptualizing, measuring, and identifying echo chambers and filter bubbles, they can be difficult to apply as precisely definable constructs for academic research. To better understand these two terms, it is useful to consider the genesis of each. The concerns articulated by Cass Sunstein, a primary voice warning of echo chambers (Sunstein 2001, 2017), originate from earlier findings that group polarization—the individual and collective adoption of more extreme views—occurs in intensive deliberations by small groups of homogenous individuals on topics of high relevance and concern (Sunstein 2002). He noted that "widespread error and social fragmentation are likely to result when like-minded people, insulated from others, move in extreme directions simply because of limited argument pools and parochial influences" (Sunstein 2002, p. 186). Extrapolating from findings regarding small group dynamics, Sunstein (2001) predicted that algorithmic filtering would also lead to group polarization on a larger scale. Likewise, Eli Pariser's influential book *The Filter Bubble* (2011) predicted that individualized personalization by algorithmic filtering would lead to intellectual isolation and social fragmentation. His thesis is succinctly captured in the book's subtitle: *What the Internet Is Hiding from You*. Both authors drew caution from a scenario that Negroponte (1996) positively presented as the "daily me": information carefully selected to match individual preferences. But in contrast to Negroponte, both Sunstein and Pariser made equally dire predictions that the use of information discovery platforms would lead to information-limiting environments with negative individual and societal impacts.

Although both Sunstein and Pariser were concerned that social media and other information discovery platforms would shape what information individuals choose to consume—and, ultimately, an individual's viewpoints and opinions—they differed on how this might happen. Pariser identified personalization technology as the primary mechanism, voicing concern that it strengthens individual preferences for seeking out opinion-reinforcing information to the exclusion of opinion-challenging information (Frey 1986; Garrett 2009). Pariser stressed the negative impacts of individual isolation in creating epistemic bubbles where personal viewpoints persist, unchallenged and untested. Sunstein stressed the potential of technology to reinforce fragmentation at a larger scale, one where people are not individually isolated, but instead form groups in which individuals with similar ideological predilections interact exclusively with each other. Sunstein argued that online interactions can reinforce ideological segregation and thereby facilitate limited information pools that strengthen preexisting biases, promote groupthink, and encourage adoption of even more extreme viewpoints. In this way, Sunstein was concerned with interactions among homogenous groups that share a common social identity. Alternatively, Pariser was concerned with individual isolation and a lack of shared information in opinion formation. From Pariser's perspective, an individual isolated in their own personalized information bubble still may suffer from the negative impacts of limited information, even if this isolation makes them immune from the social pressures that reinforce group solidarity and engender polarizing groupthink. Despite these differences in perspectives, both Pariser and Sunstein argued that the remedy for information-limiting environments is individual consumption of ideologically diverse content that encompasses opinion-challenging viewpoints.

These conceptualizations of echo chambers and filter bubbles are reactionary, in that they portray not the creation of an observable outcome, but rather the absence of an idealized one. This ideal is not well defined, however, other than the general normative assertion that individuals should be exposed to and consume opinion-challenging information. The quantity of opinion-challenging information that an individual should consume and the degree to which it should challenge their opinions is left ambiguous, rendering it all but impossible to determine if someone is actually within an echo chamber or filter bubble. Further, it is doubtful whether this ideal of a well-informed public with rigorously examined opinions has ever existed. For example, before the creation of Internet-enabled personalization technology, news and information was disseminated largely via newspapers, magazines, radio, and TV broadcasts that catered to ideologically diverse audiences. Even then, "a number of studies … indicate[d] that persuasive mass communication functions far more frequently as an agent of reinforcement than as an agent of change" (Klapper 1960, p. 15). With commonly vague and reactionary conceptualizations, echo chambers and filter bubbles are certainly powerful metaphors, but are ill-defined for use as rigorous academic constructs.

Echo chambers and filter bubbles are also often depicted as something that an individual (or group) either is in, or is not—a simplistic binary that is unnecessarily reductionist. Focusing solely on whether or not individuals consume opinion-challenging information sources neglects more nuanced ways in which technology use may shape the consumption of information sources. For example, even though other impacts are quite plausible, Bakshy et al. (2015) considered only the consumption of ideologically discordant content (e.g., a liberal consuming conservative news or vice versa) in concluding that algorithmic ranking has limited impact on news consumption.

Furthermore, this emphasis on consumption of opinion-challenging and ideologically discordant information may be misplaced. Groupthink, extreme viewpoints, and intellectual isolation can persist even when opinion-challenging information is readily available. Individuals and groups frequently adopt extreme opinions despite being confronted with challenges to their viewpoints. For example, studies have found that exposure to divergent viewpoints may fail to have a moderating effect and can even catalyze a polarizing backlash that hardens existing ideological positions (Bail et al. 2018; Stroud 2010). Further, some individuals—particularly highly politically-engaged ones—may purposely seek out ideologically discordant information sources to gain awareness of opposing viewpoints while remaining highly antagonistic to them (Shore et al. 2018), a condition referred to as affective polarization (see Iyengar et al. 2019).

In summary, discourse regarding echo chambers and filter bubbles has often been both reactionary and reductionist. Consumption of ideologically discordant content that includes opinion-challenging viewpoints is neither a necessary nor a sufficient remedy for the fundamental ills associated with echo chambers and filter bubbles. Thus, we conclude that although Sunstein and Pariser identified key mechanisms that may contribute to information-limiting environments, a richer conceptualization of potential outcomes is needed to understand how social media platforms can impact the content that users choose to consume.

Constituent Characteristics of Echo Chambers and Filter Bubbles

Although there is no consensus definition for echo chambers or filter bubbles, in considering the range of descriptions we identify two constituent characteristics that stand out. The first is a lack of information diversity due to restriction of information sources. In echo chambers, "individuals are exposed only to information from like-minded individuals" (Bakshy et al. 2015, p. 1130), that "confirms their previously-held opinions" (Shore et al. 2018, p. 850), and "is devoid of other viewpoints" (Garrett 2009, p. 279). Filter bubbles are a "unique universe of information for each of us" (Pariser 2011, p. 9), "devoid of attitude-challenging content" (Bakshy et al. 2015, p. 1130), where "individuals only see posts that they agree with" (Lazer 2015, p. 1090). Reduced information diversity exaggerates confirmation bias—the individual and collective tendency to seek out information that supports preexisting beliefs (Nickerson 1998). It also facilitates ideological groupthink—a collective manifestation of closed-mindedness and an overestimation of the value of collective beliefs that are reinforced by pressure towards uniformity (Janis 1982). Narrowing of information sources is problematic, as "exposure to differing political views increases people's knowledge of rationales for political perspectives other than their own and also fosters political tolerance" (Mutz and Martin 2001, p. 140).

Second, both echo chambers and filter bubbles are commonly characterized by ideological segregation (the tendency of individuals to associate with others who share their viewpoints) and by partisan polarization (the adoption of more extreme views). Echo chambers are associated with "fragmentation of users into ideologically narrow groups" (Shore et al. 2018, p. 850), with "political fragmentation and social polarization" (Garrett 2009, p. 278), and with "segregation by interest or opinion [that] will … increase political polarization" (Dubois and Blank 2018, pp. 1-2) and "foster social extremism" (Barberá 2015, p. 86). Similarly, filter bubbles are a "centrifugal force pulling us apart" (Pariser 2011, p. 10), "in which algorithms inadvertently amplify ideological segregation" (Flaxman et al. 2016, p. 299). In this way, the increasing ability to interact online is viewed not as a unifying force but, rather, one that may tear apart the fabric of society as individuals adopt more extreme views.

In summary, we argue that while echo chambers and filter bubbles are potent, flexible metaphors that have broadly captured the public's imagination and serve as a distillation of widespread fears, their vague and disparate conceptualizations make them difficult to study. To make these attractive metaphors concrete, we propose that research into information-limiting environments requires a more nuanced focus on the separate characteristics of information source diversity and information source slant. *Information source diversity* reflects separation, variety, and disparity among information sources an individual consumes (see Harrison and Klein 2007). A change in the consumption of information sources may lead to a broadening increase or a narrowing decrease in information source diversity. *Information source slant* reflects the dominant ideological perspective provided by information sources an individual consumes. A change in consumption of information sources may lead to a partisan shift towards more extreme information sources or a moderating shift toward more centrist ones. Our objective is to examine how social media use may be associated with changes in the diversity and slant of the information sources an individual chooses to consume.

Categorizing Changes in Information Consumption

Information Source Diversity

Information source diversity is an area of interest across academic disciplines, including management, communications, and political science. Receiving information from diverse sources can help individuals better understand the world around them, develop more robust opinions, and make better decisions (Jehn et al. 1999; Mutz and Martin 2001; Van Alstyne and Brynjolfsson 1996). Information source diversity captures the idea that the value of information sources derives from providing nonredundant information and alternative viewpoints. There are many ways to conceptualize and measure diversity (see Harrison and Klein 2007; Page 2010). Most approaches involve summarizing how elements of interest, such as unique information sources, are allocated along a continuum or across a set of categories (McDonald and Dimmick 2003). We identify constructs related to the diversity of information sources an individual chooses to consume, following Harrison and Klein's (2007) dimensions of separation, variety, and disparity. Together, these constructs provide a holistic view of information source diversity (see Table 1 for a summary). We also consider a precursor to these measures: *information source quantity* (the number of unique information sources an individual consumes). Although this construct does not reflect how information sources may vary in the kinds of information they provide, as the quantity of information sources increases, so does the potential for nonredundant information.

Separation describes the degree of diversity along a single lateral dimension (Harrison and Klein 2007)—such as the dimension of political ideology. Differentiation by ideological slant is particularly evident in the contemporary U.S. media landscape (Jurkowitz et al. 2020) where there is increasing separation of information sources by dominant ideological perspective (Flaxman et al. 2016). This specialization allows reliable categorization of information sources based on the predominant viewpoint of typical content (Gentzkow and Shapiro 2011; Shore et al. 2018). *Information source dispersion* reflects ideological separation among a set of information sources an individual chooses to consume (Shore et al. 2018). When an individual consumes information sources from a narrow ideological range, they are less likely to be exposed to a diversity of viewpoints and opinions than when they read sites encompassing a broader range.

However, dominant ideological perspectives may be insufficient for understanding differences among information sources. For example, some news and information sources are not overtly ideological, and even among those with similar ideological slant, there are other bases for differentiation. Drawing on the concept of interorganizational competition and niche overlap theory (Burt 1992; Sohn 2001), we conceptualize *information source variety* as reflecting how likely a set of information sources is to provide nonredundant information along an assortment of dimensions. Similar to the idea of brokerage across structural holes in a communication network (Burt 1992), when an individual consumes multiple information sources with minimally overlapping audiences, they are likely to be exposed to more nonredundant information and divergent viewpoints than if they consumed multiple information sources with substantial audience overlap. Thus, increased information source variety reflects the consumption of a broader range of knowledge, expertise, and unique information.

Finally, disparity complements separation and variety as an additional form of diversity. Disparity is frequently used to assess income inequality, but may also be applied to the distribution of attention (e.g., Li et al. 2019). In considering consumption of multiple information sources, an increasing disparity of the time spent per source reflects a concentration of attention that effectively reduces diversity. For example, if an individual regularly visits five information sources but spends the preponderance of their time with only two of them, they are less likely to consume nonredundant information than when they give all five equal attention. Thus, *information source parity* reflects equality of attention given to different information sources.

Information Source Slant

In addition to considering changes in information source diversity, we focus on the complementary, yet distinct, concept of changes in *information source slant*—where slant represents the dominant ideological perspective of the information sources an individual consumes. This concept relates to the conclusion that interaction among like-minded individuals can lead to *more extreme* (less centrist) opinions (Sunstein 2009). Such individual-level change is a form of

Table 1. Dimensions of Information Consumption			
Dimension	**Construct**	**Description**	**Categorization**
Diversity	Information source quantity	Quantity of unique information sources consumed	None
	Information source dispersion	Separation of information sources along a single ideological dimension	Slant (continuous)
	Information source variety	Variety of information among information sources	Information source audience overlaps (continuous)
	Information source parity	Equality of time spent consuming information sources	Time (continuous)
Slant	Information source slant	Dominant ideological perspective among information sources	Slant (continuous)
Diversity and slant	Cross-cutting content consumption	Proportion of information sources with opposing viewpoints	Slant (discrete categories)

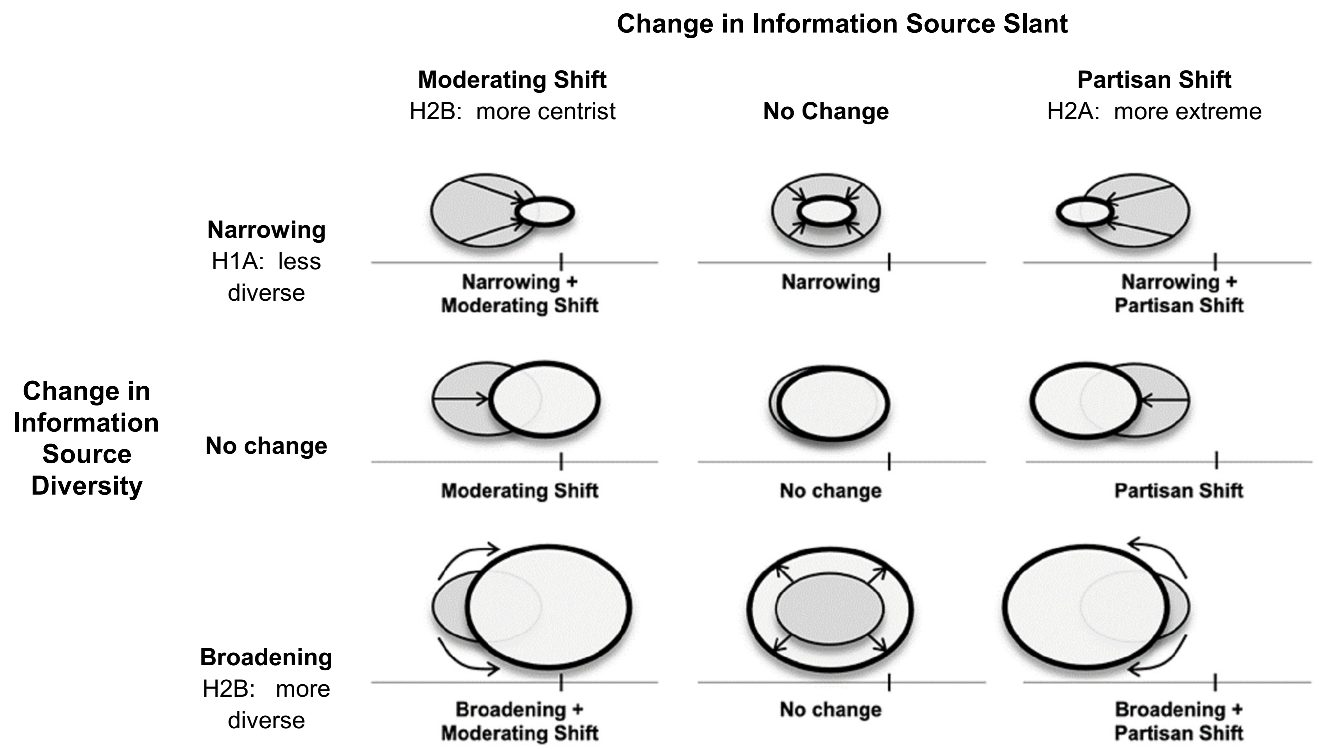
polarization that reflects a process of shifting or strengthening "one's original position" (Stroud 2010, p. 557) "further in the direction of … original views" (Mutz 2006, p. 227). Yet, a partisan shift is but one possibility; the slant of news sources consumed could also shift in a centrist direction. We define a shift in slant in terms of differences in an individual's consumption choices between points in time. In comparing the information sources consumed at various times, a change in the dominant ideological position towards a more centrist perspective represents a *moderating shift* and a change towards the extreme represents a *partisan shift*.

The concept of polarization (and its less frequently articulated converse, moderation) is multifaceted. We identify three alternative conceptualizations of polarization that encompass antecedents or consequences of individual information source consumption. First, *social polarization* is reflected in particular patterns of interactions and affiliations. For example, the preference of individuals to maintain social relationships with like-minded others manifests as modularity in social networks (Baldassarri and Bearman 2007). This homophilous tendency, which has been observed in Facebook friendships (Bakshy et al. 2015) and in interactions among Twitter users (Bright 2018), may impact individuals' consumption behaviors. Second, *attitudinal polarization* represents segmentation of beliefs and attitudes (Baldassarri and Bearman 2007; Boxell et al. 2017). For example, individuals are more trusting of and more likely to consume information sources that align with their ideological views (Adamic and Glance 2005; Jurkowitz et al. 2020). At the group or population level, this may be observed as audience fragmentation in information sources that individuals engage with and consume (Jacobson et al. 2016; Lawrence et al. 2010). Third, *affective polarization* is a phenomenon of animosity between individuals in opposing political parties that stems from partisanship as a social identity (Iyengar et al. 2019). Individuals with high affective polarization may frequently engage with or consume opinion-challenging content, but remain unchanged in or even strengthen their views as a result. This is consistent with users who "read at least some information from both sides of the political spectrum, but only tweet out information consistent with their own side" (Shore et al. 2018, p. 852).

In summary, polarization is an individual-, group-, and population-level phenomenon encompassing static states and dynamic processes (Mutz 2006). In the discussion of echo chambers and filter bubbles, polarization is a frequently raised theme, yet often without precise conceptualization or distinction among its many forms. Social, attitudinal, and affective polarization are all potential antecedents or consequences of the content a user is exposed to, engages with, and consumes. To better understand how social media platforms may influence information consumption, we focus on the individual-level behavioral outcome of partisan or moderating shifts in slant of information a user consumes across periods of varied platform use.

Cross-Cutting Content Consumption

Cross-cutting content consumption measures the extent to which an individual consumes information sources that provide ideologically discordant information (Bakshy et al. 2015). Assuming that an individual's attitudes and behaviors are grounded in and reflect a dominant ideological viewpoint, an information source is considered cross-cutting when there is sufficient ideological difference between the slant of the information source and the individual's dominant viewpoint (Lawrence et al. 2010). When cross-cutting consumption is high, an individual is regularly consuming information sources that are opinion-challenging. A low amount of cross-



In each scenario, the gray bubble represents the original mean slant (left-right position) and diversity (size) of news consumed by an example user. This user's original consumption is liberal, as it is left of the center as denoted by the vertical hash along the axis. The white bubble represents the changed consumption of the end user under a treatment condition (e.g., in a period of higher social media use).

Figure 1. Categorizing Changes in Information Consumption

cutting consumption is consistent with being in an information-limiting environment. However, a focus on cross-cutting content can distract researchers from understanding more modest shifts in consumption, such as a highly conservative user reading more moderately conservative news.

Decreasing consumption of cross-cutting information sources results in both narrowed information diversity and a partisan shift. Alternatively, increasing cross-cutting content consumption concurrently results in both a broadening of information diversity as well as a moderating shift in information source slant. Because the cross-cutting consumption construct conflates both diversity and slant of information sources, we argue that it is a poor measure of either and that it fails to capture the nuance provided by their separate measurement.

Categorizing Information Source Consumption

Considering changes in the diversity and slant of information sources as two separate dimensions provides a richer categorization of the potential impacts of social media platforms on information source consumption. As depicted in Figure 1, three possible changes in information source diversity (narrowing, no change, broadening) can combine with three possible changes in information source slant (moderating shift, no change, partisan shift) for nine potential scenarios (see Figure 1).

Explicitly considering changes in both dimensions is essential for moving beyond a simplistic conclusion that information-limiting environments either do or do not exist and leads to a more nuanced understanding of how social media use could be associated with a wide range of outcomes. Of the scenarios shown in Figure 1, any of those involving a narrowing decrease in information source diversity (the top row), as well as those involving a partisan shift (the right-hand column), could be considered as information-limiting environments; yet each has unique characteristics and implications. Research into how technology shapes information consumption would, therefore, be enhanced by independently considering changes in both information source diversity and slant when developing theory, designing studies, and selecting measures.

Information Source Consumption

To frame our investigation of how social media platforms shape the information sources an individual chooses to consume, we provide a general model of how social network homophily, algorithmic filtering, and individual behavioral responses can lead to variation in information source consumption. We then detail how this model relates to three popular social media platforms. Finally, we hypothesize how, based on these factors, social media use may be associated with changes in information diversity and slant in information source consumption.

As depicted in Figure 2, social network homophily (path A) and algorithmic filtering (path B) are two key determinants of the information sources a social media to which a user is exposed. Individuals' social networks vary widely in size, the density of shared ties, and the frequency of interactions. Likewise, social media users vary in their social networks, including who they are connected with on a platform. The preponderance of information sources shared on social media is generated by platform users. Yet, there is wide variability among platforms in how user-generated content is organized, the extent to which algorithmic filtering is used in prioritizing which content is displayed, and the factors considered in that prioritization. Once a platform presents a user with a preview of potential information sources, the user has the opportunity (path C) to engage on that platform and/or to "click-through" to the external source itself. Additionally, an individual's response to content exposure can serve as an input for subsequent algorithmic filtering (path E) and influence who that user affiliates with in the future (path D).

Next, we build on Figure 2 to discuss how social media platforms vary in the prioritization of information sources that users are exposed to. As noted in Table 2, Facebook is an example of a platform with high levels of social network homophily and extensive algorithmic filtering. Facebook determines what content to show users based on an estimated likelihood of engagement (Bakshy et al. 2015; Vaidhyanathan 2018). In deciding what to present, Facebook chooses from among recent posts made by others in a user's social network (e.g., by Facebook "friends"). Facebook considers an individual's past engagement history as well as the overall popularity of content. Thus, algorithmic filtering on Facebook is highly personalized: even if two users have an identical set of Facebook friends, what each user sees may vary considerably based on their prior engagement with similar content.

Twitter also has a high level of social network homophily. Twitter users build their online social network by identifying other Twitter accounts to "follow." For the first 10 years of its existence (from 2006 to mid-2016), Twitter presented a primary timeline of Tweets posted by others in a user's social network (those whom they "follow") in reverse chronological order. During this period, algorithmic filtering was minimal: two users who followed the same Twitter accounts would see the same content, in the same order. Recently, Twitter has implemented more extensive algorithmic filtering (similar to Facebook). However, the data analyzed in this study was collected prior to this implementation, and therefore provides a contrast to Facebook.

Finally, Reddit is an example of a platform that is primarily interest-based, with content shared by users through a hierarchy of topic-based communities (a.k.a. subreddits). Users self-identify their interests by joining these communities. Users may directly communicate with one another, but these connections are not used to filter content. Indeed, Reddit performs minimal algorithmic filtering, merely prioritizing content based on popularity determined by up- and down-votes. A Reddit user can choose to sort and filter content based on recency or popularity, but members of the same communities see the same content by default (Jürgens and Stark 2017).

In summary, because social media platforms embody a wide variety of features and uses, it is not reasonable to make blanket statements regarding how their use may produce information-limiting environments. It is more useful to discuss how—through the interplay of social networks, algorithmic filtering, and individual choices—the mechanisms in Figure 2 may be associated with changes in diversity and slant in the information sources an individual chooses to consume. Because of conflicting theoretical claims and mixed empirical evidence to date, we divide studies into rival camps and articulate competing hypotheses (e.g., Gray and Cooper 2010). While only one of each pair of hypotheses can survive a given empirical test, the reality that there are likely many different boundary conditions—such as differentiated effects by technology platform—suggests the need for a systematic program of research over time to identify the conditions under which each effect may dominate (Burton-Jones et al. 2017).

Narrowing Diversity

The argument that social media use is associated with narrowing diversity in information source consumption begins with the observation that social networks frequently exhibit ideological homophily (e.g., Bakshy et al. 2015; Himelboim et al. 2013). Individuals are more likely to affiliate with others who share similar experiences, perspectives, and opinions. To the extent that individuals are part of ideologically segregated social networks, the content posted by others

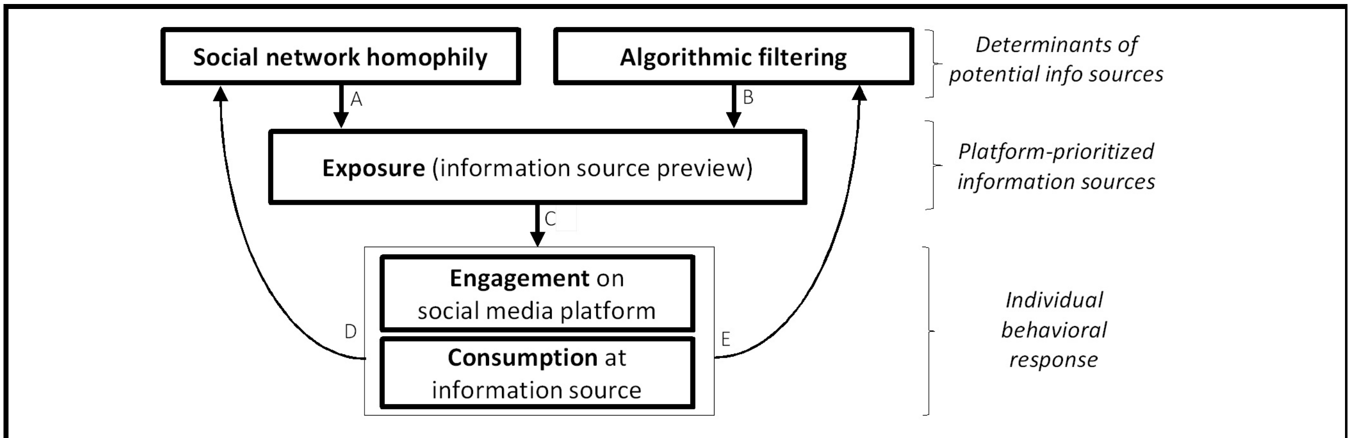


Figure 2. Social Media Use and Information Source Consumption

Table 2. Determinants of Prioritization of Information Sources by Social Media Platform

		Facebook	Twitter	Reddit
Social Network Homophily	Platform social graph	High	High	Low
Algorithmic Filtering	Engagement history	High	Low†	Low
	Content popularity	High	Low	High
	Topic-based	Low	Low	High

†Low for chronological Twitter feed before mid-2016, high for curated feed initiated in mid-2016.

with whom they interact on social media may also be ideologically constrained (*path A* in Figure 2). For example, a study of news links in partisan Facebook pages showed that commenters in both liberal- and conservative-oriented groups posted links to a small number of information sources, with little overlap between the two groups (Jacobson et al. 2016).

To the extent that a social media platform algorithmically filters or prioritizes content based on users' prior engagement (*path B*), users may also be presented with a narrower range of content (Bozdag and van den Hoven 2015; Pariser 2011). When this constrains information sources available to engage with (*path C*) it can also create a feedback loop (*path D, E*) that further constrains variation in subsequent exposure (Prawesh and Padmanabhan 2011). Algorithmic filtering and prioritization based on general popularity can also lead to a narrowing of information sources in a rich-get-richer dynamic (Welch et al. 2011). Further, among information sources to which users are exposed, individuals' preference to engage with opinion-confirming sources rather than opinion-challenging ones—referred to as selective exposure theory (e.g., Garrett 2009)—may reduce engagement with and consumption of diverse information sources (*paths C*). Indeed, Schmidt et al. (2017) found "that the more active a user is, the more the user tends to focus on a small number of news sources" (p. 4). Bakshy et al. (2015) concluded that restricted information diversity occurs in part due to algorithmic filter effects on exposure (*path B*), but more so because of individual choices in engagement and consumption (*paths C, D, E*). Thus, we propose:

H1a: *Social media use is associated with a narrowing in the diversity of information source consumption.*

Broadening Diversity

A contrasting argument holds that the social media use may be associated with a broadening of information diversity in information source consumption. Although the argument follows similar logic and pathways as the narrowing effect (H1a), it arises from different assumptions about ideological segregation in online social networks, associated content exposure, and individual preferences in content engagement and consumption.

There is some evidence that ideological segregation may be less prevalent in online relationships than it is in offline ones. As such, online social networks may even broaden the ideological range of social interactions (*path A*). For example, Goel et al. (2010) found that people's ties on Facebook often included others who held different ideological views—for example, through familial, professional, and hobby-related associations. These diverse social interactions can increase individuals' incidental exposure to ideologically diverse information sources (*path A*) (Fletcher and Nielsen 2016).

Platforms that filter and curate information sources relative to topics of interest (*path B*) must cater to a variety of users. Heterogeneity of user interests provides incentives for these algorithms to increase the diversity of information sources. This works against the rich-get-richer popularity bias mentioned previously and leads to increased variety (Fortunato et al. 2006). This rationale applies to generic filtering algorithms, but not necessarily to personalized filtering (*path G, D*). Personalized filtering algorithms are essentially sophisticated recommender systems, a domain in which the novelty-accuracy tradeoff has long been a well-known and researched issue—intuitively, "it would be almost always correct, but useless, to recommend bananas, bread, milk, and eggs" to grocery shoppers (Herlocker et al. 2004, p. 14). Understanding the value of novel information, recommender systems are commonly designed with diversity, serendipity, coverage, and related objectives in mind, all of which would increase the breadth of information sources to which users are exposed (Kaminskas and Bridge 2016).

Finally, as a platform for information discovery, a fundamental purpose of social media is to provide access to information sources otherwise unknown to users. Because individuals have a limited capacity for search and exploration, it has long been recognized that intermediate tools are needed in order to overcome the difficulty of finding information (Bakos 1997). Although there are a variety of use cases for social media, the value of these platforms is broadly derived from their ability to connect users with content that is informative, engaging, or entertaining. It stands to reason, therefore, that platform usage may be associated with discovery of novel information sources that enhance an individual's information source diversity. This assertion is supported by the finding that news site visits from social media platforms were more diverse than direct visits (Flaxman et al. 2016). In summary, we propose:

H1b: *Social media use is associated with a broadening in the diversity of information source consumption.*

Partisan Shift

The argument that social media use is associated with a partisan shift in information source consumption is difficult to disentangle from the argument for the narrowing of information diversity (*H1a* above). It is therefore unsurprising that the consumption of cross-cutting content, which shifts both information diversity and slant, is viewed as an antidote to information-limiting environments. Indeed, researchers often discuss a narrowing of diversity and a partisan shift in information sources as occurring together. For example, the large-scale study of Facebook usage by Schmidt et al. (2017) concluded that "users [tend] to limit their exposure to a few sites" and "there is major segregation and growing polarization in online news consumption" (p. 4). Moreover, an important argument for a partisan shift follows a logic similar to that for narrowing of diversity: exposure to opinion-reinforcing information is high due to ideological segregation (*path A*), individuals prefer opinion-conforming information (*path C*), and algorithms reinforce these preferences (*paths B, E*). Bakshy et al. (2015, p. 2) found the "factor decrease in the likelihood that an individual clicks on a cross-cutting article relative to the proportion available in News Feed to be 17% for conservatives and 6% for liberals" (*path C*). This reduction in cross-cutting content consumption contributes to both a narrowing of information diversity as well as a partisan shift.

We identify three distinct arguments for how partisan shifts may occur independently of narrowing. First, individuals who primarily interact with like-minded others online (*path A*) are likely to experience the same group solidarity and in-group identification that occur offline, with a polarizing effect on ideological beliefs (e.g., Schkade et al. 2007; Sunstein 2009). Second, a Twitter experiment by Bail et al. (2018) demonstrated that exposure to opposing viewpoints resulted in a partisan shift in engagement (*path C*), albeit only for conservatives. However, Bail et al.'s experimental conditions were extreme and may not represent either typical use of social media or typical patterns of ideological content exposure. Third, social media platforms may include partisan content created and promoted by zealots or malicious actors attempting to convince others or actively sow discord through Facebook groups, Twitter hashtags, and Reddit subreddits (e.g., Allcott and Gentzkow 2017; Lazer et al. 2018). In summary, we propose:

H2a: *Social media use is associated with a partisan shift in the slant of information source consumption.*

Moderating Shift

However, other research suggests the opposite effect. Just as narrowing of information diversity and a partisan shift are often complementary, so too is the opposite combination of broadening diversity and a moderating shift. The studies in support of broadening of information diversity (in H1b above) often assume that broadening occurs through exposure to opinion-challenging, cross-cutting content.

To the extent that individuals' online social networks are diverse, users may experience increased exposure to moderating news sources (*path A*). Based on experimental manipulation of social endorsements and online news consumption choices, Messing and Westwood (2014) concluded that "the mere presence of social endorsements reduced partisan selectivity to levels indistinguishable from chance" (p. 1056). Thus, when an individual observes others in their social network engaging with content—a form of social endorsement—they are more likely to engage with it themselves, regardless of perceived slant. Selective exposure to opinion-confirming content appears to be even lower when mediated by online platforms than through more direct interaction with others, causing users to encounter information with dissimilar political views (Mutz and Martin 2001, p. 98).

Filtering and prioritization algorithms (*path B*) may also show users more mainstream, moderate content because it is typically more popular and commercially viable (Cooper 2003). Particularly if a platform is ad-supported, there may be incentive to avoid polarizing content in order to appease advertisers (Gabszewicz et al. 2002). For similar reasons, platforms may also choose to present a balance of ideological perspectives (Fletcher and Neilsen 2018b).

There is also direct empirical evidence consistent with a moderating effect of social media use. For example, a population-level analysis of technology use found that the demographic groups most likely to use social media were also the least likely to be ideologically segregated (Boxell et al. 2017). Shore et al. (2018) offer empirical evidence of a potential moderating effect of platform usage, finding that Twitter users typically share news links that are more centrist than the news links to which they are exposed (thereby creating more opportunity for others to encounter centrist news through). Thus, we propose:

> **H2b**: *Social media use is associated with a moderating shift in the slant of information source consumption.*

Data and Methods

Research Setting

To investigate how social media use is associated with information source consumption, we obtained data from Comscore, a leading provider of digital audience measurement services. They recruit and compensate a demographically representative sample of active U.S. Internet users who install an apparatus that automatically records and reports granular Internet usage. This apparatus enables Comscore to gather accurate data about the timing and duration of all web pages visited by each panelist, including use of social media and visits to news sites. Companies widely trust this data to accurately reflect the reach and effectiveness of marketing efforts, similar to Neilsen ratings for television. Although they usually report audience data in aggregate format, we obtained de-identified user-level clickstream browsing data for over 3 million U.S. adults who were panelists between January 2012 and June 2016.

Panel membership rotates, with existing users leaving and new users joining the panel at variable intervals. To understand within-person behavioral trends over time, we limited our analysis to users who remained on the panel for at least 365 consecutive days. Although social desirability bias could be a concern as users are aware of the monitoring they agreed to, we empirically established that panel users continued to browse all manner of sites and conclude that it is unlikely that users systematically altered their browsing behaviors.

A limitation of our data set is that it only includes browsing behavior originating from desktop and laptop computers (PCs); the data set does not include mobile device usage. While it would be optimal to have a view of online usage that encompasses mobile devices, this data set can still provide robust insights into the association between social media use and news site visits. An analysis of similar Comscore data by Mitchell and Jurkowitz (2014) found that online news consumption patterns were similar for PCs and mobile devices. Also, we conducted an additional survey to better understand mobile and PC device visits to social media and news sites. We randomly surveyed 426 individuals through Qualtrics (results available upon request), asking respondents how often they read news and access social media on desktops or laptops (PC), as well as smartphones or tablets (mobile). The number of users who access news on various devices is almost identical, with 82% of users reading news on a PC at least weekly, compared to 83% reading news on mobile devices at least weekly. The difference is only slightly more pronounced for accessing social media, with 88% doing so on mobile at least weekly, compared to 73% by PC. Further, we found no evidence of significant substitution of one device type for the other. It is important to note that this survey was conducted in February 2020, whereas our data encompasses panelists' web site visits from 2012 through mid-2016. Mobile device usage has increased significantly from the years 2012–2016, while PC usage has largely remained stable, particularly for news consumption (Walker 2019). In summary, it is reason-

Table 3. Independent Variables	
Measure	**Description**
Facebook referrals	Number of visits to news sites attributable as referrals from each platform; that is, web pages in the domains facebook.com, reddit.com, and twitter.com (count)
Reddit referrals	
Twitter referrals	
Time on Facebook	Duration of all visits to each platform (hours) **Note**: In all models, this is Log_2 transformed such that the coefficient represents the impact on the odds ratio of a doubling of time spent.
Time on Twitter	
Time on Reddit	
Direct visits	Number of direct visits to news sites (count)
Total time online	Total duration of all website visits (hours). Transformed Log_2 in all models.

Table 4: Outcome Measures for an Individual's Within-Period News Site Visits					
Dimension	**Construct**	**Measure**	**Description**	**Minimum**	**Maximum**
Diversity	Information source quantity	Distinct news sites	Number of unique news sites visited (count)	No news site visits	Visit all 177 news sites in the sample
	Information source dispersion	Slant dispersion	The time-weighted standard deviation of political slant of news sites visited	All visited news sites have the same political slant	50% of visits to the most liberal news site, 50% to the most conservative
	Information source parity	Reverse Gini Index	(1 - Gini Index)*100 calculated based on time spent on each visited news site (0 to 100 range)	One news site predominates with minimal time on others	An equal amount of time spent at multiple news sites
	Information source variety	Audience variety	Time-weighted mean variety of news site visits based on the frequency of overlapping site visitors (0 to 100 range)	Visit a small set of news sites that have the same readership	Visit multiple sites with minimal audience overlap
Slant	Information source slant	Mean slant	Time-weighted average of political slant for visits to any of 177 news sites (-100 to 100 range; lower values more liberal, higher values more conservative)	Either all visits to single most-centrist site or visits to a perfectly balanced set of sites	All visits to either the most liberal news site or the most conservative news site
Diversity and slant	Cross-cutting content consumption	Cross-cutting proportion	Time-weighted percentage of news sites visited with political slant scores opposite to a user's base ideology (0 to 100 range)	All news sites visits in the same category of political slant	A user spends a significant amount of time at news sites opposing their base ideology

able to conclude that the data represents a meaningful portion of users' news browsing and social media activity (possibly even a significant majority given the period of data collection).

Measures and Analysis

To test our hypotheses, we estimated fixed effects within-person models over a panel comprised of 4-week periods. For each individual in our sample, we calculated measures per nonoverlapping four-week period of their tenure (see Tables 3 and 4 for a summary of measures). To better understand information source consumption, we focused on information diversity and slant of news consumption among active users. Limiting our analyses to user-periods containing at least one news site visit resulted in an unbalanced panel of 185,548 individuals with a total of 1,096,480 user-period observations for an average of 5.9 observations per individual in our sample. Summary statistics and correlations are reported in the Appendix. In such a within-person model, the results may be interpreted as estimated differences for an individual, comparing periods when they use social media platforms more to those periods in which that same individual uses them less. This design avoids the potentially problematic comparison of light and heavy platforms users to each other and helps to isolate the impacts of changes in an individual's platform use from other characteristics of the user.

The independent variables relate to the use of three social media platforms (Facebook, Twitter, and Reddit) that provide links to news sites. We measured the number of visits to news sites occurring via referrals from each platform to assess the effect of these referrals on diversity and slant. Also, we measured the number of visits made directly to the home page of a news site (for instance, by typing the URL of the news site directly into the browser navigation bar). Because these direct visits are made independent of exposure to platform-prioritized information sources, they provide a baseline against which to assess the impact of diversity and slant of news site visits referred by social media platforms. Beyond the primary effect of news site referrals, we also expected that general usage of these platforms may influence news consumption, and therefore also measured the time individuals spent on each platform, as well as their total time online. Finally, as a control for use of other popular information discovery platforms, we include time and count variables for individuals' use of email and search.

Information Diversity

We adopted four distinct but complementary measures that together provide a holistic view of information source diversity of news site visits, as described in Table 4. First, the number of distinct sites visited by each user during each a period measures information source quantity. Next, we measure slant dispersion as separation on the horizontal dimension of partisan slant by calculating the time-weighted standard deviation of the slant of news sites visited by a user during a period (measurement of slant itself is detailed in the next section). Intuitively, this represents the spread of a user's news consumption along the ideological continuum. Third, we measure information source parity as the vertical distribution of news source consumption, calculated as the reverse-coded Gini index of time spent by a user on each distinct news site within a period.[2] If a user visits 10 diverse sites, but spends 99% of their time on one of these, the level of diver sity is still effectively low, which will be captured by this measure.

Information source variety represents diversity across any number of dimensions or categories. From the perspective of news, this could be by a topic (politics, sports, celebrity), presentation mode (short-form prose, long-form prose, info-graphic, video), exposition (fact reporting, opinion, editorial), etc. Instead of attempting to identify all possible underlying factors of variety, we used the site visit history of all 3 million panel members to estimate these latent factors that drive users to visit different sites. The intuition behind this measure is that sets of news sites with higher levels of audience variety—that is, a lower overlap of actual audiences—are more likely to provide diverse information. To calculate this measure, we first defined a co-visitation network of all users to all news sites. For each pair of news sites p and q, we calculated v_{pq}, the number of users who visited both sites, and defined an intermediate measure of the audience overlap of these sites, $v_{pq} / \min(v_p, v_q)$; note $0 \le v_{pq} / \min(v_p, v_q) \le 1$.[3] Time-weighted audience variety is then calculated across all pairs of news sites visited by user i in period t:[4]

$$Audience\ Variety_{it} = \left(1 - \left(\frac{\sum_{p}^{time_{ipt}>0} \sum_{q}^{time_{iqt}>0} \frac{v_{pq}}{\min(v_p, v_q)}}{\sum_{p}^{time_{ipt}>0} \sum_{q}^{time_{iqt}>0} 1}\right)\right) * 100$$

Partisan Shift

Hypotheses 2a and 2b concern the relationship between social media use and change in the slant of information sources consumed. For outcomes related to slant, we based the measurement on slant scores for 177 commonly visited online news sites published in Shore et al. (2018), as detailed in the Appendix. We calculated the time-weighted average slant of online news sites visited by a user during a given period. Our scores are scaled from their range of ±3.602 to a range of ±100 for ease of exposition. Because a change in partisan slant is relative to a referent base ideological position for each user, we also categorized individuals as being in conservative, centrist, or liberal terciles of our sample by calculating a time-weighted average slant score per individual based on all of their news sites visits while on the panel. We used a categorical, rather than continuous, measure following prior research that has shown qualitative differences between liberals and conservatives (e.g., Bakshy et al. 2015; Bail et al. 2018).

[2] The Gini index is a measure of concentration, so it must be reverse coded to reflect increasing diversity.

[3] The choice of $\min(v_p, v_q)$ prevents relatedness scores from being biased downward when comparing sites with large discrepancy in visitation rates. We also used the maximum and average of v_p and v_q with similar results.

[4] We are fortunate to be able to calculate this measure due to the rich nature of our data. Harrison and Klein (2007) suggest the Blau index as a more generic measure of variety, which we also tested with results consistent with the measures presented.

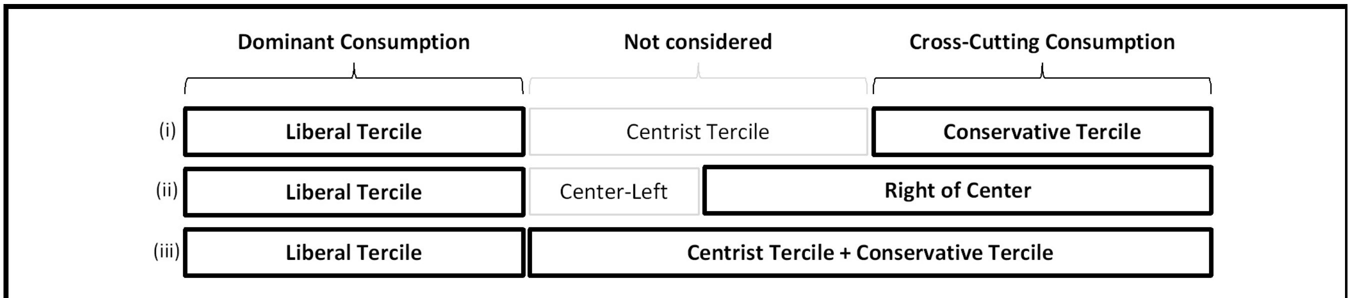


Figure 3. Alternative Measures of Cross-Cutting Content (Illustrated for Liberal Users)

We acknowledge that assigning a single score to describe the political slant of all content on a given news site is a simplification. Any given article on a news site may express a political ideology that is well-aligned or misaligned with the perceived or actual ideology typical for that site. However, we build on prior work showing that slant scores provide insight into general user behaviors (Gentzkow and Shapiro 2011; Shore et al. 2018). Indeed, a survey conducted by Pew Research Center of 12,043 adults concludes that "deep partisan divisions exist in the news sources Americans trust, distrust and rely on" (Jurkowitz et al. 2020, p. 4). Thus, when users choose to consume information sources, the dominant ideological position of the information source (in this case, a news site) is a salient factor in their decision.

To further confirm the external validity of assigning slant scores to online news sites, we surveyed 426 individuals regarding their political affiliation and likelihood to read news from a set of websites. Analysis of these survey responses demonstrates a clear relationship between an individual's political affiliation and their likelihood to visit various news sites. The correlation between the slant scores of news sites and the coefficients of simple linear regressions of political affiliation on the likelihood to visit them is 0.73. These results (available upon request) suggest that individuals perceive the site that hosts a news article as a strong signal of potential alignment with their political affiliation.

Cross-Cutting Content Consumption

Finally, we calculated the percentage of cross-cutting content consumed by each user. As discussed earlier, changes in this measure reflect a change in both diversity and slant. Because there is no generally accepted approach for identifying cross-cutting content, we calculated the proportion of content in three distinct ways as illustrated in Figure 3. These alternative measurements incorporate different thresholds for how different an information source's slant needs to be from a user's baseline position in order to be considered cross-cutting. First, for users in conservative or liberal terciles, we calculated the proportion of content they consumed that is in the opposite tercile (i). Second, we calculated the proportion of content users in these terciles consume that was at least across the median (ii). Third, we calculated the proportion of content users in these terciles consumed in the opposite or centrist tercile (iii).

Results

Information Diversity

To test H1, we used fixed effects within-person models to estimate the association between the use of popular social media platforms and four measures of information diversity (results shown in Tables 5 and 6). All models control for direct news site visits and total time spent online, as well as all time-invariant user characteristics removed via the fixed effect within transformation. Because of the relatively large sample size, as suggested by Lin et al. (2013) we report coefficient confidence intervals for each of our models across a range of subsample sizes in Appendix Figure A1. Additionally, we present an intuitive analysis of effect sizes in the discussion section.

For the first measure of information diversity, the number of distinct news sites visited within a period (Table 5, Panel A), we found that each referral from a social media platform to a news site was associated with an increase in the number of distinct news sites visited by an individual within the same 4-week time period. By comparison, the estimated association between the number of direct visits and total distinct news site visits was very low. This result is consistent with the intuitive understanding that, whereas direct site visits are more likely to be return visits to a previous site, individuals are exposed to additional information sources through their use of social media. Nonetheless, we found significant variation among platforms in the strength of the association between referrals

Table 5: Association of Platform Use and Information Source Diversity: Quantity and Separation

	Panel A: DV = Distinct News Sites				Panel B: DV = Slant Dispersion			
	I	II	III	IV	I	II	III	IV
Facebook referrals		0.268*** (0.0012)		0.261*** (0.0012)		0.299*** (0.0052)		0.260*** (0.0053)
Reddit referrals		0.884*** (0.0051)		0.767*** (0.0055)		0.354*** (0.0215)		0.196*** (0.0235)
Twitter referrals		0.506*** (0.0077)		0.476*** (0.0078)		0.014 (0.0328)		-0.014 (0.0332)
Search referrals		0.418*** (0.0009)		0.407*** (0.0009)		0.377*** (0.0039)		0.343*** (0.0039)
Email referrals		0.086*** (0.0025)		0.085*** (0.0025)		0.039*** (0.0106)		0.035** (0.0106)
Direct visits	0.018*** (0.0001)	0.012*** (0.0001)	0.018*** (0.0001)	0.012*** (0.0001)	0.001 (0.0004)	-0.005*** (0.0004)	0.001 (0.0004)	-0.004*** (0.0004)
Time on Facebook (Log_2 of hours)			0.197*** (0.0033)	0.062*** (0.0029)			0.562*** (0.0123)	0.432*** (0.0124)
Time on Reddit (Log_2 of hours)			1.803*** (0.0164)	0.804*** (0.0156)			1.418*** (0.0611)	1.090*** (0.0665)
Time on Twitter (Log_2 of hours)			0.425*** (0.0110)	0.186*** (0.0097)			0.229*** (0.0410)	0.116** (0.0414)
Time on search (Log_2 of hours)			0.572*** (0.0047)	0.240*** (0.0042)			0.988*** (0.0177)	0.707*** (0.0178)
Time on email (Log_2 of hours)			-0.135*** (0.0046)	-0.062*** (0.0040)			-0.209*** (0.0171)	-0.143*** (0.0171)
Total time online (Log_2 of hours)	0.614*** (0.0024)	0.418*** (0.0021)	0.289*** (0.0032)	0.297*** (0.0028)	1.301*** (0.0089)	1.126*** (0.0089)	0.680*** (0.0119)	0.688*** (0.0119)
Intercept	-0.019 (0.0118)	0.318*** (0.0101)	0.373*** (0.0119)	0.459*** (0.0103)	0.325*** (0.0432)	0.620*** (0.0429)	1.062*** (0.0443)	1.130*** (0.0440)
Observations	1,096,480	1,096,480	1,096,480	1,096,480	1,096,480	1,096,480	1,096,480	1,096,480
Individuals	185,548	185,548	185,548	185,548	185,548	185,548	185,548	185,548
R-squared	0.0920	0.3349	0.1273	0.3404	0.0231	0.0384	0.0306	0.0423

Standard errors shown in parenthesis below estimated coefficients.
*p < 0.05, **p < 0.01, ***p < 0.001

and distinct news sites. For example, for every 10 Reddit referrals there are almost 8 distinct news sites visited during the period, whereas 10 Facebook referrals relates to less than 3 new distinct news sites visited.

We also found that time spent on each platform was significantly and positively associated with the number of distinct news sites visited, with relative estimated effect sizes among platforms substantially similar to that of referrals. The sole exception was time spent on email, which was associated with a slight reduction in the number of distinct news sites visited. Because time variables are base-2 logged, their coefficients represent the effect of a doubling of time spent on each platform. A user doubling their typical amount of time spent using Reddit visited 0.8 additional distinct sites in a period, while a user doubling time on Facebook visited only 0.06 additional distinct sites.

We report the results for slant dispersion in Panel B of Table 5. Among social media platforms, we found that the use of Reddit was associated with the most substantial magnitude increases in slant dispersion, particularly for time spent on each platform. Facebook referrals and time on Facebook both had moderate positive associations with slant dispersion.

Table 6. Association of Platform Use and Information Source Diversity: Variety and Parity

	Panel C: DV = Audience Variety				Panel D: DV = Reverse Gini Idex			
	I	II	III	IV	I	II	III	IV
Facebook referrals		0.700*** (0.0200)		0.557*** (0.0203)		0.887*** (0.0104)		0.823*** (0.0105)
Reddit referrals		0.699*** (0.0822)		0.098 (0.0897)		0.824*** (0.0426)		0.425*** (0.0465)
Twitter referrals		-0.231 (0.1251)		-0.368** (0.1266)		0.373*** (0.0648)		0.259*** (0.0656)
Search referrals		1.758*** (0.0148)		1.591*** (0.0150)		1.432*** (0.0077)		1.355*** (0.0078)
Email referrals		0.144*** (0.0405)		0.138*** (0.0405)		0.518*** (0.0209)		0.513*** (0.0210)
Direct visits	0.016*** (0.0017)	-0.005** (0.0017)	0.015*** (0.0017)	-0.003 (0.0017)	0.059*** (0.0009)	0.039*** (0.0009)	0.058*** (0.0009)	0.040*** (0.0009)
Time on Facebook ($\mathbf{Log_2}$ of hours)			1.861*** (0.0469)	1.524*** (0.0473)			1.093*** (0.0247)	0.664*** (0.0245)
Time on Reddit ($\mathbf{Log_2}$ of hours)			4.572*** (0.2334)	4.108*** (0.2538)			3.587*** (0.1228)	2.730*** (0.1315)
Time on Twitter ($\mathbf{Log_2}$ of hours)			1.055*** (0.1566)	0.643*** (0.1579)			1.160*** (0.0824)	0.654*** (0.0818)
Time on search ($\mathbf{Log_2}$ of hours)			5.021*** (0.0675)	3.758*** (0.0680)			2.813*** (0.0355)	1.716*** (0.0352)
Time on email ($\mathbf{Log_2}$ of hours)			-1.438*** (0.0654)	-1.110*** (0.0653)			-0.693*** (0.0344)	-0.474*** (0.0338)
Total time online ($\mathbf{Log_2}$ of hours)	7.761*** (0.0340)	7.072*** (0.0342)	5.152*** (0.0456)	5.161*** (0.0453)	4.781*** (0.0179)	4.145*** (0.0177)	3.233*** (0.0240)	3.256*** (0.0235)
Intercept	5.869*** (0.1650)	6.981*** (0.1639)	8.859*** (0.1691)	9.119*** (0.1680)	-3.339*** (0.0869)	-2.273*** (0.0848)	-1.519*** (0.0890)	-1.260*** (0.0870)
Observations	1,096,480	1,096,480	1,096,480	1,096,480	1,096,480	1,096,480	1,096,480	1,096,480
Individuals	185,548	185,548	185,548	185,548	185,548	185,548	185,548	185,548
R-squared	0.0549	0.0718	0.0640	0.0769	0.0797	0.1264	0.0909	0.1304

Standard errors shown in parenthesis below estimated coefficients.
**p* < 0.05, ***p* < 0.01, ****p* < 0.001

Finally, Twitter use was associated with minimal change in slant dispersion. In comparing the analyses for distinct site visits (Panel A) and slant dispersion (Panel B), the R^2 for the latter is lower than the former. Nonetheless, there is nearly a doubling in R^2 from Panel B Model I including only direct visits and total time online to Panel B Model IV also including social media usage. In all, we conclude that the relationships between slant dispersion and the use of Reddit and Facebook are modest but nontrivial.

Panels C and D in Table 6 provide results for the information source diversity measures of audience variety and reverse Gini index, respectively. Among the social media platforms, we found again that the use of Reddit was associated with the most substantial magnitude increase in both measures, followed by Facebook. Similarly, Twitter was associated with minimal changes. In summary, in considering all four diversity measures, we conclude that for Facebook and Reddit there is consistent support of hypothesis H1b, predicting a *broadening* association between platform use and information source consumption. For these platforms, there is no support of the alternative H1a. With inconsistent sign and significance as well as lower magnitude of observed effects associated with Twitter usage, we find weak, mixed support for either H1a (narrowing) and for H1b (broadening).

Partisan Shift

To measure shifts in the slant of news consumed, we divided users into conservative, centrist, and liberal terciles and used a fixed effects within-person model to estimate the relative mean slant of news consumed by these users during periods of higher or lower usage of each social media platform.[5] Each variable is interacted with a tercile indicator variable, with the main effect of the tercile indicator subsumed by the fixed effect. This effectively allows separate models for each tercile to be estimated simultaneously within one model. With slant scores ranging from negative (indicating liberal) to positive (indicating conservative), a positive coefficient for users in the conservative tercile indicates a partisan shift (i.e., a shift from conservative to more conservative), whereas a negative coefficient indicates a moderating shift. The opposite signs apply for the liberal tercile.

As shown in Table 7, an increase in referrals from and time spent using Facebook were associated with a partisan shift in the slant of news consumed. In periods when conservative individuals used Facebook more, their news site visits were more conservative. The same applies to liberal users, but with lower magnitude. For Reddit, increased referrals were associated with a moderating shift for conservative users, yet there was no association found for liberal users. Twitter usage had no significant association with changes in slant. Overall, these results support H2a for Facebook, where greater use was associated with a *partisan shift* in information source consumption. The results support H2b for Reddit, with greater use associated with a *moderating shift*, albeit for conservative users only. However, R^2 values are very low, meaning that the vast majority of variance in the mean slant of information sources consumed by users remains unexplained by their social media usage.

Cross-Cutting

As a final analysis, we estimated the relationship between social media use and the percentage of cross-cutting content consumption using three classifications for cross-cutting content. The three panels in Table 8 (F, G, and H) correspond with the classifications of cross-cutting illustrated in Figure 3 as alternatives (i), (ii), and (iii), respectively. The results are largely consistent for all three measurement approaches.[6] In all three cases, Facebook referrals were associated with a decrease in the percentage of cross-cutting content consumed by users. However, as highlighted by a shaded band in Table 8, for time spent on Facebook, results vary depending upon what threshold is applied to define cross-cutting. Results ranged from significantly positive for the most stringent categorization (i.e., cross-cutting news is only news from the opposite side) to significantly negative for the least stringent categorization (i.e., cross-cutting news also includes a large segment of centrist content). We find little to no evidence for an association of Reddit or Twitter with cross-cutting.

It is also interesting to note that, although cross-cutting consumption conflates both diversity and slant, the estimated effects for cross-cutting were more closely aligned with estimated effects for shifts in slant, particularly for Facebook and the reference platforms of search and email. The R^2 values were also very low, which more closely resembles those for shifts in slant. This stands in contrast to prior research that considers cross-cutting consumption as a measure of diversity (e.g., Bakshy et al. 2015). Our findings support the conclusion that a holistic view encompassing separate dimensions of information source diversity and slant provides a more complete and nuanced understanding of information consumption than considering cross-cutting content consumption alone.

Discussion

Summary of Findings

In summary, we found that the use of different social media platforms had varying associations with changes in information consumption. Tables 9 and 10 summarize estimated referral and time coefficients across platforms for each dependent variable. These coefficients were drawn from the fully specified Model IV of each panel and are shaded by magnitude. For comparison we also included the results for search and email. Use of Facebook and Reddit were each associated with increases in information source diversity across all measures, with the estimated effects of Reddit significantly larger than those of Facebook. Use of Twitter

[5] We tested a variety of divisions, including median split, quartiles, quintiles, sextiles, and deciles, with varying sizes for the centrist component, finding results consistent across a wide range of measurement choices.

[6] We also calculated these measures with alternatives that varied both the size of the partisan groups as well as the categorization of cross-cutting content. Those results are consistent with variations reported here.

Table 7. Association of Platform Use and Mean Slant					
		Panel E: DV = Mean Slant			
Measure	**Tercile**	**I**	**II**	**III**	**IV**
Facebook referrals	**Liberal**		-0.078***		-0.069***
	Centrist		-0.053*		-0.033
	Conservative		0.396***		0.384***
Reddit referrals	**Liberal**		-0.002		-0.019
	Centrist		-0.242**		-0.130
	Conservative		-0.784***		-0.599**
Twitter referrals	**Liberal**		-0.055		-0.073
	Centrist		-0.162		-0.110
	Conservative		-0.132		-0.116
Search referrals	**Liberal**		0.195***		0.184***
	Centrist		0.074***		0.076***
	Conservative		-0.273***		-0.261***
Email referrals	**Liberal**		-0.066*		-0.064*
	Centrist		-0.032		-0.033
	Conservative		0.425***		0.423***
Direct visits	**Liberal**	-0.002	-0.005	-0.002	-0.005
	Centrist	0.007**	0.006**	0.007**	0.006**
	Conservative	0.016***	0.015***	0.016***	0.016***
Time on Facebook (Log_2 Hours)	**Liberal**			-0.160***	-0.137**
	Centrist			-0.161***	-0.158***
	Conservative			0.360***	0.207***
Time on Reddit (Log_2 Hours)	**Liberal**			0.114	0.121
	Centrist			-0.847***	-0.713**
	Conservative			-1.275***	-0.731
Time on Twitter (Log_2 Hours)	**Liberal**			0.142	0.121
	Centrist			-0.231*	-0.235*
	Conservative			-0.217	-0.170
Time on search (Log_2 Hours)	**Liberal**			0.388***	0.269***
	Centrist			0.080	0.022
	Conservative			-0.617***	-0.416***
Time on email (Log_2 Hours)	**Liberal**			-0.188**	-0.144*
	Centrist			-0.042	-0.022
	Conservative			0.394***	0.247***
Time online (Log_2 Hours)	**Liberal**	0.131***	0.094**	0.08	0.074
	Centrist	0.010	-0.006	0.065	0.063
	Conservative	-0.188***	-0.183***	-0.175***	-0.156***
Intercept	**Intercept**	-4.315***	-4.289***	-4.325***	-4.325***
Observations		1,096,480	1,096,480	1,096,480	1,096,480
R-squared		0.0004	0.0020	0.0007	0.0021
Number of individuals		185,548	185,548	185,548	185,548

Standard errors omitted for space and can be provided upon request.
**p* < 0.05, ***p* < 0.01, ****p* < 0.001

Table 8. Association of Platform Use and Consumption of Cross-Cutting News

	Panel F: DV = Cross-Cutting (user tercile to opposite news site tercile)				Panel G: DV = Cross-Cutting (user tercile to opposite news site half)				Panel H: DV = Cross-Cutting (user tercile to centrist or opposite news site tercile)			
	I	II	III	IV	I	II	III	IV	I	II	III	IV
Facebook referrals		-0.083***		-0.099***		-0.203***		-0.205***		-0.362***		-0.339***
		(0.0121)		(0.0123)		(0.0161)		(0.0163)		(0.0170)		(0.0173)
Reddit referrals		0.036		0.012		0.062		0.047		0.144*		0.092
		(0.0497)		(0.0544)		(0.0659)		(0.0722)		(0.0699)		(0.0765)
Twitter referrals		-0.049		-0.037		-0.010		-0.001		0.009		-0.008
		(0.0756)		(0.0767)		(0.1003)		(0.1018)		(0.1064)		(0.1080)
Search referrals		0.104***		0.096***		0.177***		0.167***		0.251***		0.240***
		(0.0090)		(0.0091)		(0.0119)		(0.0121)		(0.0126)		(0.0128)
Email referrals		-0.119***		-0.115***		-0.139***		-0.134***		-0.180***		-0.179***
		(0.0245)		(0.0246)		(0.0324)		(0.0326)		(0.0344)		(0.0345)
Direct visits	-0.012***	-0.013***	-0.012***	-0.013***	-0.015***	-0.016***	-0.015***	-0.016***	-0.017***	-0.017***	-0.017***	-0.017***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0013)	(0.0014)	(0.0013)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Time on Facebook			0.166***	0.199***			-0.064	0.008			-0.453***	-0.331***
			(0.0283)	(0.0288)			(0.0376)	(0.0381)			(0.0398)	(0.0405)
Time on Reddit			0.178	0.168			0.141	0.098			0.424*	0.342
			(0.1406)	(0.1539)			(0.1865)	(0.2042)			(0.1979)	(0.2166)
Time on Twitter			-0.098	-0.109			-0.041	-0.072			0.170	0.129
			(0.0944)	(0.0959)			(0.1252)	(0.1272)			(0.1329)	(0.1349)
Time on search			0.253***	0.184***			0.390***	0.272***			0.531***	0.364***
			(0.0407)	(0.0413)			(0.0540)	(0.0548)			(0.0573)	(0.0581)
Time on email			-0.150***	-0.111**			-0.257***	-0.196***			-0.295***	-0.208***
			(0.0394)	(0.0396)			(0.0523)	(0.0526)			(0.0555)	(0.0558)
Time online	0.369***	0.353***	0.239***	0.234***	0.201***	0.182***	0.134***	0.124***	-0.076**	-0.093**	-0.050	-0.066
	(0.0204)	(0.0207)	(0.0275)	(0.0275)	(0.0271)	(0.0275)	(0.0365)	(0.0365)	(0.0287)	(0.0291)	(0.0387)	(0.0387)
Intercept	6.873***	6.886***	7.010***	7.014***	15.750***	15.758***	15.787***	15.794***	29.713***	29.704***	29.623***	29.631***
	(0.0992)	(0.0994)	(0.1022)	(0.1022)	(0.1316)	(0.1318)	(0.1355)	(0.1355)	(0.1396)	(0.1398)	(0.1438)	(0.1437)
Observations	1,092,010	1,092,010	1,092,010	1,092,010	1,092,010	1,092,010	1,092,010	1,092,010	1,092,010	1,092,010	1,092,010	1,092,010
Number of Individuals	185,282	185,282	185,282	185,282	185,282	185,282	185,282	185,282	185,282	185,282	185,282	185,282
R-squared	0.0005	0.0007	0.0006	0.0008	0.0002	0.0006	0.0003	0.0006	0.0002	0.0011	0.0004	0.0012

Standard errors shown in parenthesis below estimated coefficients.
*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Table 9. Summary of Estimated Coefficients for Changes in Information Source Diversity

	Distinct News Sites		Slant Dispersion		Audience Variety		Gini Index		Hyp. Support
	Referrals	Time	Referrals	Time	Referrals	Time	Referrals	Time	
Facebook	0.261	0.062	0.260	0.432	0.557	1.524	0.823	0.664	H1a
Reddit	0.767	0.804	0.196	1.090		4.108	0.425	2.73	H1a
Twitter	0.476	0.186		0.116	-0.368	0.643	0.259	0.654	Mixed/low
Search	0.407	0.240	0.343	0.707	1.591	3.758	1.355	1.716	
Email	0.085	-0.062	0.035	-0.143	0.138	-1.110	0.513	-0.474	

Darker shading represents increasing absolute magnitude of coefficients within DV (coefficients with $p > 0.05$ omitted).
Green cells with black text are positive estimated coefficients, and orange cells with white text negative.

Table 10. Summary of Estimated Coefficients for Changes in Information Source Slant

	Liberal Tercile		Centrist Tercile		Conservative Tercile		Hyp. Support
	Referrals	Time	Referrals	Time	Referrals	Time	
Facebook	-0.069	-0.137		-0.158	0.384	0.207	H2a
Reddit				-0.713	-0.599		H2b (cons)
Twitter				-0.235			None
Search	0.184	0.269	0.076		-0.261	-0.416	
Email	-0.064	-0.144			0.423	0.247	

Darker shading represents increasing absolute magnitude of coefficients (coefficients with $p > 0.05$ omitted).
Blue cells with white text are negative estimated coefficients (more liberal), red cells with black text are positive (more conservative).

had mixed associations with diversity with low magnitudes. Use of Facebook was associated with partisan shifts in slant, notably larger for conservatives than for liberals. Conversely, use of Reddit was associated with moderating shifts in slant for conservatives.

The R^2 values for partisan shift and cross-cutting models (all less than 1%) were much lower than those for diversity (ranging from 4% to 34%). Thus, while social media platforms are associated with changes in each of these measures, there is much less unexplained variation in diversity after accounting for platform use. This further underscores the need to isolate and separately study the underlying dimensions of information-limiting environments.

To demonstrate the magnitude of effects, we calculated example estimated effects by platform for a concurrent increase in both referrals and time. These measures of use were jointly estimated, and it is intuitive to imagine that increased referral activity from a platform corresponded with increased time on the platform, and vice versa. Figure 4 demonstrates the marginal change in information diversity and slant associated with a user who clicked on an additional six referrals to news sites from a platform and had a four-fold increase in time spent on the platform (e.g., an increase from 1 hour to 4 hours). Our measures are calculated per individual by month, so this may be interpreted as a comparison of a month when a user had significant use of a platform to a month when that user had limited use of that platform. In a period when an average user has this type of increase on Facebook (6 more referrals and 4times more time spent), their standard deviation of slant would be 37% higher, moving from 6.5 to 9.0. If conservative, their mean slant would have increased by 2.7; if liberal, it would have decreased by 0.7.

To illustrate these effects in combination, we provide an example in Figure 5 for a representative conservative user with monthly news site visits that have a mean slant of 10 and standard deviation of 6.5. For this user, a ±2 standard deviation range of online news consumption (e.g., -3 to 23) encompasses both *USA Today* (-0.4) and the *New York Post* (21.5). In a month with 6 additional news referrals from and 4 times more time spent on Facebook than average, their consumption would shift to a more conservative mean, but also broaden. Their estimated range of ±2 standard deviations (-4.6 to 31.2) would increase by encompassing some additional news sources to the left, but even more to the right (almost including *Fox News*). If not for the rightward, partisan shift in mean, the increase in diversity alone would have resulted in a range of -7.9 to 27.9 (thereby including *CNN* to the left). A similar example is also shown in Figure 5 for the combina-

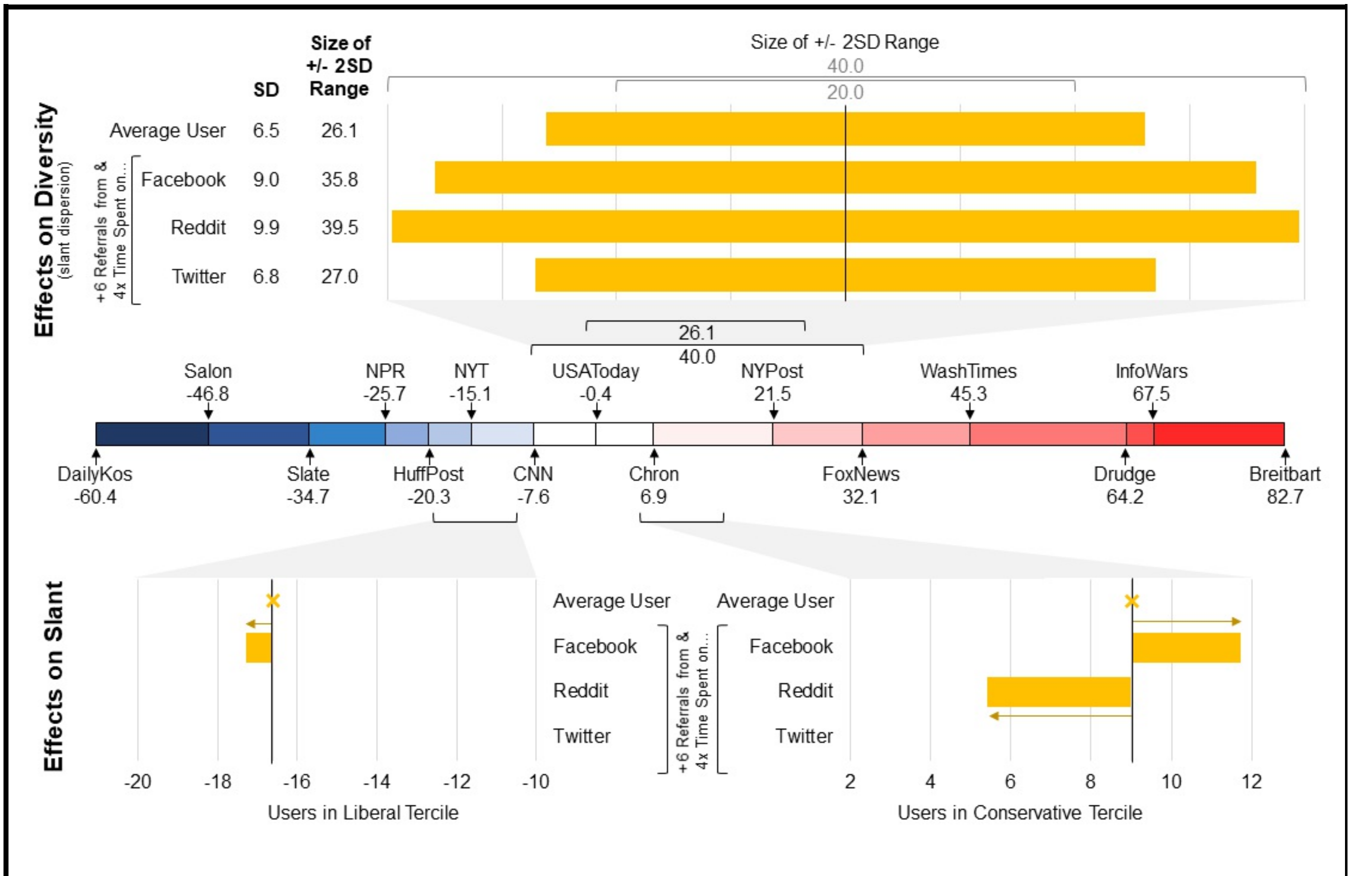


Figure 4. Social Media Platform Use, Diversification, and Partisan Shift

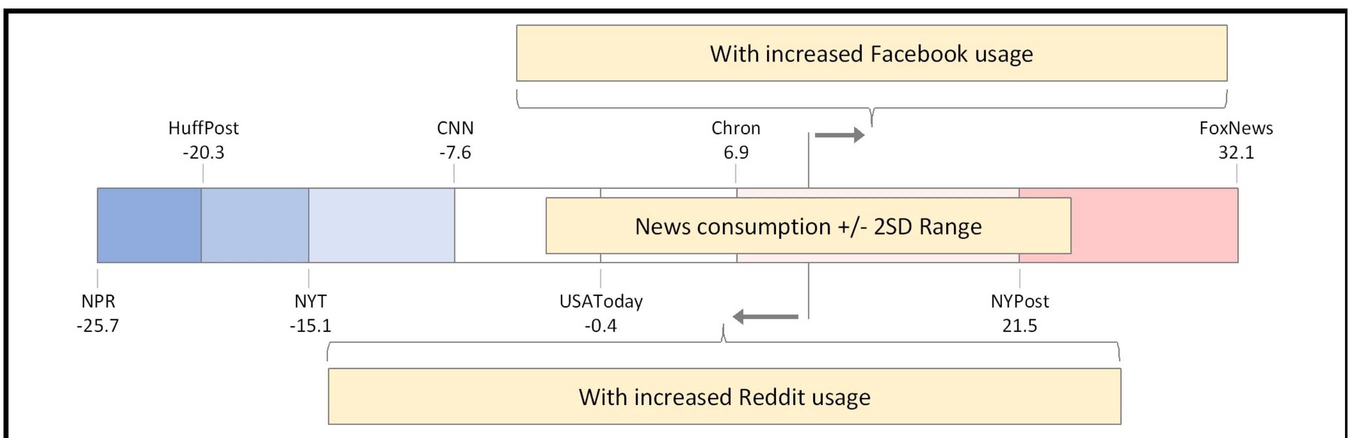


Figure 5. Effects of Increased Platform Use for a Representative Conservative User

tion of broadening diversity with a moderating shift associated with an increased use of Reddit. These stylized examples demonstrate that associations with diversity and slant differ in important ways by platform.

Implications for Conceptualizing Echo Chambers and Filter Bubbles

We identify five contributions that this study makes to the conceptualization of echo chambers and filter bubbles. First, we adopt a generative framing of information-limiting environments as reflecting concerns raised in discussion of these captivating, yet elusive, phenomena. By considering more nuanced ways that social media usage may shape information consumption, we highlight both the hopes and fears for online technology. On one hand, there is a widespread fear that homophily and algorithmic filtering will amplify personal preference for congenial, ideologically congruent content and foster information-limiting environments that exclude opinion-challenging information (Pariser 2011; Sunstein 2017). On the other, there is the hopeful potential for social media and other information discovery platforms to expand individuals' information consumption by connecting them with a broad range of relevant information sources. To appropriately address this tension, we move beyond a limiting, muddled question of whether information-limiting environments exist to a more generative framing of how platforms influence information source consumption.

Second, by examining in detail the constituent elements of diversity and slant of information consumption we provide a deeper understanding of the phenomenon. There is a long-standing interest in understanding preferences for opinion-challenging versus opinion-confirming information (see Hart et al. 2009). This interest has often informed the understanding of filter bubbles and echo chambers as being manifest in a binary outcome: the presence or absence of cross-cutting content consumption (Bakshy et al. 2015; Mutz and Martin 2001). The joint consideration of diversity and slant provides a richer depiction of the variety of ways that platforms may help shape exposure, engagement, and consumption of information sources. Indeed, empirically we find a range of outcomes across both dimensions.

Third, we demonstrate the value of conceptualizing the relationship between platform use and information source consumption at an individual-level, using panel data to identify within-user effects. Prior research has often focused on ideological segregation at a population-level by comparing the distribution of information source consumption among categories of users (Gentzkow and Shapiro 2011). For example, conservative and liberal platform users prefer different online news sources (Flaxman et al. 2016; Jacobson et al. 2016). However, a cross-sectional observation of aggregated user preferences is insufficient to fully address how platform usage shapes consumption. Relationships observed at a group level do not necessarily hold for individuals within the same groups (Freedman 1999); thus, individual-level effects are best understood by analyzing individual-level data. Our inquiry complements studies that focused on individual-level outcomes associated with usage of Facebook (Bakshy et al. 2015) and Twitter (Shore et al. 2018). We extend this prior work further by concurrently analyzing individual-level usage across multiple social media platforms. By considering variation in platform use and information source consumption for the same individual, we provide a more nuanced explication of the differential effects of various platforms.

Fourth, incorporating a multifaceted view of diversity (Harrison and Klein 2007) provides additional insights into information source consumption. Social media platforms are important pathways for individuals to discover new sources of information, and ideological differences are just one form of differentiation among information sources. In defining information source diversity in terms of separation, variety, and disparity among information sources, we extend prior work that focused on dominant ideological stance of an information source as a source of information diversity (Shore et al. 2018). The consistency of our results suggests there are additional ways to reliably conceptualize and measure information source diversity beyond political ideology, which may be particularly useful for studying contexts where dominant ideology of an information source is not evident or relevant.

Finally, our conceptual model illustrates the importance of considering how the underlying characteristics of platforms may each uniquely shape information consumption. Our differentiation of usage by platform expands on prior work that considered multiple platforms together, such as the combination of email plus multiple social media platforms as a single technology category by Flaxman et al. (2016). We find wide variation in outcomes among the platforms that Flaxman et al. aggregated together, thereby demonstrating the value of considering them individually. By analyzing patterns of results across different platforms, we can make inferences about the impacts of individual features and mechanisms. Next, we present possibilities following this line of thought.

Implications of Mechanisms for Determining Information Sources

The variation of results by platform provides some suggestive evidence about the most salient factors shaping information source consumption. In comparing observed outcomes by

Compared to Direct Visits	Moderating Shift	No Change	Partisan Shift
Narrowing Diversity			
No Change in Diversity		Twitter	Email
Broadening Diversity	Search Reddit		Facebook

Figure 6. Platform Use, Diversification, and Partisan Shift

platform (summarized in Figure 6) with how these platforms prioritize the content provided to users (identified in Figure 2 and Table 2), we draw four broad inferences on the relative importance of social network homophily and various approaches to algorithmic filtering.

First, our findings provide insight about the potential role of social influence in partisan shifts. On Facebook, as well as the reference platform of email, the information sources a user is exposed to are strongly influenced by other individuals with whom the user has a strong sense of social identification and affiliation (e.g., friends, family, and coworkers). In contrast, social affiliation is somewhat less salient on Twitter (where users form nonreciprocal relationships) and Reddit (where content is largely organized in topic-based communities). From this lens, a partisan shift is consistent with concerns that platforms may reinforce social influence within heterogenous social groups, and, thereby cause a hardening of partisan beliefs (Sunstein 2002, 2009). In addition, Facebook and email also both utilize some form of engagement-based curation—Facebook's curated news feed and email's prioritized inbox—that could also contribute to a partisan shift (Pariser 2011).[7]

Second, for Reddit, as well as the reference platform of search, algorithmic filtering is more heavily influenced by an individual's topics of interest than by their social network or prior engagement with content. A broadening effect here is consistent with prior work arguing that, in the course of interactions on other topics, individuals experience an incidental exposure to additional sources of news and information (Fletcher and Nielsen 2018a; Weeks et al. 2017).

Third, our results highlight trade-offs inherent in the study of information source consumption. By isolating within-person variation over time in both platform use and news site consumption, we are able to quantify variation among multiple social media platforms and draw inferences about the impact of platform characteristics in relation to consumption behaviors. Yet, our ability to draw inferences about individual characteristics and attitudes is limited. For example, we are unable to assess the impact of selective exposure due to individual preference for opinion-confirming content (Festinger 1964; Hart et al. 2009). Further, the relatively small amount of variation in partisan shifts explained by platform usage in our analyses suggests there are significant unobserved factors that shape consumption. Because no single study can capture all of the factors that influence consumption decisions, particularly when considering multiple platform use by heterogeneous individuals, it is important to further develop the conceptualization of information-limiting environments in ways that can drive future empirical research, as well as help integrate and reconcile findings.

Finally, the variation in our results across platforms implies that rather than making broad-brush assertions about how they may be information-limiting or information-expanding, more focused attention should be paid to the range of individual factors that determine how and to what extent platforms may shape users' choices. Further, our findings represent average effects for a typical platform user, not a universal outcome for all users. Platforms themselves are not monolithic; there may be wide variation in how people use each platform as well as changes in platform implementations over time. For example, the impact of using interest-oriented features such as Facebook pages (Jacobson et al. 2016; Skjerdal and Gebru 2020) may differ from using only the primary Facebook news feed. Thus, future research should take into account not only differences across platforms but also differences among users in how they use those platforms.

[7] As noted, Twitter only implemented engagement-based feed curation in 2016, after our data collection.

Practical Implications

Our findings have implications for a practical understanding of information consumption. We find no support for a prevalence of the popular, intuitive understanding of echo chambers and filter bubbles. Specifically, we find no evidence that the use of social media is limiting the information sources that users choose to consume—instead, with respect to information diversity we find a range of outcomes from effectively neutral (no change) to positive (broadening diversity). Nonetheless, we do find important variation between platforms whose use was associated with moderating shifts (Reddit) or partisan shifts (Facebook).

Of the platforms we consider, Facebook represents the most complete embodiment of features that may impact users' news consumption choices. It hosts user-generated content, suggests additions to users' social networks, and provides several content engagement options that influence the algorithmic curation of information. Given the high level of personalization that Facebook deploys in determining what content to expose users to, we reiterate calls for further study of Facebook's algorithmic filtering (Sunstein 2017; Vaidhyanathan 2018). Likewise, more research is needed to understand the impacts of Twitter's recent implementation of more comprehensive algorithmic filtering. Yet, the study of these features is stymied by a lack of transparency of platform operations. As platform providers are unlikely to unilaterally provide outside researchers with sufficient data on the implementation and effects of algorithmic filtering, there is an important role for public policy oversight of these influential platforms.

Limitations and Future Research

We acknowledge that our study has multiple limitations related to the scope of the conceptual model, the scope of the empirical test, and the research method. First, our conceptual model focuses on individual and platform characteristics that explain variation between platforms. There are additional characteristics, including level of interest in politics (Dubois and Blank 2018; Lawrence et al. 2010), reaction to content topics (Baldassarri and Bearman 2007), and intensity of platform use (Shore et al. 2018), that may help explain variation among individual users of the same platform. Also, our scope is limited with regard to platform characteristics. Technology providers frequently update algorithms to determine the most engaging and relevant information sources and content to present to users; more research is needed to encompass the full range of characteristics that influence this presentation (Johnson et al. 2019). Likewise, our hypotheses are focused on information source consumption. More research is also needed to understand the antecedents and consequences of exposure, engagement, and consumption. For example, there is considerable research on opinion formation that could be expanded upon to examine how usage of social media relates to changes in opinions.

Second, the scope of empirical tests of our model is constrained by available data. The majority of the pathways in our conceptual model are only observable at scale by platform providers. For example, we could not observe the information sources an individual was exposed to or engaged with on a platform, nor other characteristics of those information sources and their presentation. More research is needed to better understand how exposure and engagement relate to the information sources an individual chooses to consume. Likewise, we were unable to observe how individuals varied in their social networks and topic interests. Although the within-person research design strengthens the robustness of our results, these individual characteristics may change over time and may even be shaped by platform usage. For these reasons and others, it is impossible to establish causality within our research design. The associations we identify are informative of the variation among platforms and illustrative of the importance of nuance in measurement. But more research is required to establish causal effects and establish the mechanisms that influence these outcomes.

Third, there are numerous limitations related to our data source and measurements. Our sample only included adults residing in the United States and may not be representative of other populations. Another data limitation is that we only observed desktop use of information discovery platforms and online news sites. As discussed, we believe this still represents an important portion of user activity, but particularly as mobile usage continues to replaces desktop use, additional research is needed regarding how behavior on mobile devices may differ. Another key operationalization in our study involved attributing a slant score to all content on a single news site domain. While we established that the news domain provides a meaningful signal to the user, this is ultimately a simplification of the potential information value of that content. Further, our measures of ideological diversity and news source slant are most relevant in high media choice environments with a dominant liberal, centrist, and conservative ideological configuration of public opinion; they may not generalize to other settings.

Conclusion

The question of how social media platforms shape the consumption of information and may foster the creation of information-limiting environments is crucial to society. Our study provides a deeper conceptualization of this phenomenon, supported by insights obtained through observation of user behaviors across various platforms in a natural environment, interacting with their naturally occurring social network, without artificial intervention by researchers. As implied by the complex variety in social media platforms, we found considerable variation in observed impacts among them, which helps explain prior conflicting conclusions, but also leads to new unanswered questions. Based on our conceptualization and findings, we see a strong need for future research to focus on the nuance of how the details of platform implementations and individual choices combine to influence a variety of outcomes that underlie the concerns that have been raised in the discussion of echo chambers and filter bubbles.

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References

Adamic, L. A., and Glance, N. 2005. "The Political Blogosphere and the 2004 U.S. Election: Divided They Blog," in *Proceedings of the 3rd International Workshop on Link Discovery*, New York: ACM, pp. 36-43.

Allcott, H., and Gentzkow, M. 2017. "Social Media and Fake News in the 2016 Election," *Journal of Economic Perspectives* (31:2), pp. 211-236.

Bail, C. A., Argyle, L. P., Brown, T. W., Bumpus, J. P., Chen, H., Hunzaker, M. F., Lee, J., Mann, M., Merhout, F., and Volfovsky, A. 2018. "Exposure to Opposing Views on Social Media Can Increase Political Polarization," *Proceedings of the National Academy of Sciences* (115:37), pp. 9216-9221.

Bakos, J. Y. 1997. "Reducing Buyer Search Costs: Implications for Electronic Marketplaces," *Management Science* (43:12), pp. 1676-1692.

Bakshy, E., Messing, S., and Adamic, L. A. 2015. "Exposure to Ideologically Diverse News and Opinion on Facebook," *Science* (348:6239), pp. 1130-1132.

Baldassarri, D., and Bearman, P. 2007. "Dynamics of Political Polarization," *American Sociological Review* (72:5), pp. 784-811.

Barberá, P. 2015. "Birds of the Same Feather Tweet Together: Bayesian Ideal Point Estimation Using Twitter Data," *Political Analysis* (23:1), pp. 76-91.

Boxell, L., Gentzkow, M., and Shapiro, J. M. 2017. "Greater Internet Use Is Not Associated with Faster Growth in Political Polarization among US Demographic Groups," *Proceedings of the National Academy of Sciences* (114:40), pp. 10612-10617.

Bozdag, E., and van den Hoven, J. 2015. "Breaking the Filter Bubble: Democracy and Design," *Ethics and Information Technology* (17:4), pp. 249-265.

Bright, J. 2018. "Explaining the Emergence of Political Fragmentation on Social Media: The Role of Ideology and Extremism," *Journal of Computer-Mediated Communication* (23:1), pp. 17-33.

Burt, R. S. 1992. *Structural Holes: The Social Structure of Competition*, Boston: Harvard University Press.

Burton-Jones, A., Recker, J., Indulska, M., Green, P. F., and Weber, R. 2017. "Assessing Representation Theory with a Framework for Pursuing Success and Failure," *MIS Quarterly* (41:4), pp. 1307-1333.

Cooper, M. 2003. *Media Ownership and Democracy in the Digital Information Age*, Center for Internet & Society, Stanford Law School.

Dubois, E., and Blank, G. 2018. "The Echo Chamber Is Overstated: The Moderating Effect of Political Interest and Diverse Media," *Information, Communication & Society* (21:5), pp. 729-745.

Festinger, L. 1964. *Conflict, Decision, and Dissonance* (Vol. 3), Stanford, CA: Stanford University Press.

Flaxman, S., Goel, S., and Rao, J. M. 2016. "Filter Bubbles, Echo Chambers, and Online News Consumption," *Public Opinion Quarterly* (80:S1), pp. 298-320.

Fletcher, R., and Nielsen, R. K. 2016. "Is Social Media Use Associated with More or Less Diverse News Use?," November 25 (https://rasmuskleisnielsen.net/2016/11/25/is-social-media-use-associated-with-more-or-less-diverse-news-use/; accessed May 27, 2018).

Fletcher, R., and Nielsen, R. K. 2018a. "Are People Incidentally Exposed to News on Social Media? A Comparative Analysis," *New Media & Society* (20:7), pp. 2450-2468.

Fletcher, R., and Nielsen, R. K. 2018b. "Automated Serendipity," *Digital Journalism* (6:8), pp. 976-989.

Fortunato, S., Flammini, A., Menczer, F., and Vespignani, A. 2006. "Topical Interests and the Mitigation of Search Engine Bias," *Proceedings of the National Academy of Sciences* (103:34), pp. 12684-12689.

Freedman, D. A. 1999. "Ecological Inference and the Ecological Fallacy," *International Encyclopedia of the Social & Behavioral Sciences* (6), pp. 4027-4030.

Frey, D. 1986. "Recent Research on Selective Exposure to Information," in *Advances in Experimental Social Psychology* (Vol. 19), L. Berkowitz (ed.), Cambridge, MA: Academic Press, pp. 41-80.

Gabszewicz, J. J., Laussel, D., and Sonnac, N. 2002. "Press Advertising and the Political Differentiation of Newspapers," *Journal of Public Economic Theory* (4:3), pp. 317-334.

Garrett, R. K. 2009. "Echo Chambers Online? Politically Motivated Selective Exposure among Internet News Users," *Journal of Computer-Mediated Communication* (14:2), pp. 265-285.

Gentzkow, M., and Shapiro, J. M. 2011. "Ideological Segregation Online and Offline," *The Quarterly Journal of Economics* (126:4), pp. 1799-1839.

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), pp. 611-621.

Gray, P. H., and Cooper, W. H. 2010. "Pursuing Failure," *Organizational Research Methods* (13:4), pp. 620-643.

Harrison, D. A., and Klein, K. J. 2007. "What's the Difference? Diversity Constructs as Separation, Variety, or Disparity in Organizations," *Academy of Management Review* (32:4), pp. 1199-1228.

Hart, W., Albarracín, D., Eagly, A. H., Brechan, I., Lindberg, M. J., and Merrill, L. 2009. "Feeling Validated Versus Being Correct: A Meta-Analysis of Selective Exposure to Information," *Psychological Bulletin* (135:4), pp. 555-588.

Herlocker, J. L., Konstan, J. A., Terveen, L. G., and Riedl, J. T. 2004. "Evaluating Collaborative Filtering Recommender Systems," *ACM Transactions on Information Systems* (22:1), pp. 5-53.

Himelboim, I., McCreery, S., and Smith, M. 2013. "Birds of a Feather Tweet Together: Integrating Network and Content Analyses to Examine Cross-Ideology Exposure on Twitter," *Journal of Computer-Mediated Communication* (18:2), pp. 154-174.

Iyengar, S., Lelkes, Y., Levendusky, M., Malhotra, N., and Westwood, S. J. 2019. "The Origins and Consequences of Affective Polarization in the United States," *Annual Review of Political Science* (22), pp. 129-146.

Jacobson, S., Myung, E., and Johnson, S. L. 2016. "Open Media or Echo Chamber: The Use of Links in Audience Discussions on the Facebook Pages of Partisan News Organizations," *Information, Communication & Society* (19:7), pp. 875-891.

Janis, I. L. 1982. *Groupthink: Psychological Studies of Policy Decisions and Fiascoes* (Vol. 349), Boston: Houghton Mifflin Company.

Jehn, K. A., Northcraft, G. B., and Neale, M. A. 1999. "Why Differences Make a Difference: A Field Study of Diversity, Conflict and Performance in Workgroups," *Administrative Science Quarterly* (44:4), pp. 741-763.

Johnson, S. L., Gray, P., and Sarker, S. 2019. "Revisiting IS Research Practice in the Era of Big Data," *Information and Organization* (29:1), pp. 41-56.

Jürgens, P., and Stark, B. 2017. "The Power of Default on Reddit: A General Model to Measure the Influence of Information Intermediaries: The Influence of Information Intermediaries," *Policy & Internet* (9:4), pp. 395-419.

Jurkowitz, M., Mitchell, A., Shearer, E., and Walker, M. 2020. "U.S. Media Polarization and the 2020 Election: A Nation Divided," , January 24 (https://www.journalism.org/2020/01/24/u-s-media-polarization-and-the-2020-election-a-nation-divided/).

Kaminskas, M., and Bridge, D. 2016. "Diversity, Serendipity, Novelty, and Coverage: A Survey and Empirical Analysis of Beyond-Accuracy Objectives in Recommender Systems," *ACM Transactions on Interactive Intelligent Systems* (7:1), pp. 1-42.

Klapper, J. T. 1960. *The Effects of Mass Communication*, Glencoe, IL: Free Press.

Lawrence, E., Sides, J., and Farrell, H. 2010. "Self-Segregation or Deliberation? Blog Readership, Participation, and Polarization in American Politics," *Perspectives on Politics* (8:1), pp. 141-157.

Lazer, D. 2015. "The Rise of the Social Algorithm," *Science* (348:6239), pp. 1090-1091.

Lazer, D. M. J., Baum, M. A., Benkler, Y., Berinsky, A. J., Greenhill, K. M., Menczer, F., Metzger, M. J., Nyhan, B., Pennycook, G., Rothschild, D., Schudson, M., Sloman, S. A., Sunstein, C. R., Thorson, E. A., Watts, D. J., and Zittrain, J. L. 2018. "The Science of Fake News," *Science* (359:6380), pp. 1094-1096.

Li, K. G., Mithas, S., Zhang, Z., and Tam, K. Y. 2019. "How Does Algorithmic Filtering Influence Attention Inequality on Social Media?," in *Proceedings of the 40th International Conference on Information Systems*, Munich.

Lin, M., Lucas Jr., H. C., and Shmueli, G. 2013. "Research Commentary—Too Big to Fail: Large Samples and the p-Value Problem," *Information Systems Research* (24:4), pp. 906-917.

McDonald, D., and Dimmick, J. 2003. "The Conceptualization and Measurement of Diversity," *Communication Research* (30:1), pp. 60-79.

Messing, S., and Westwood, S. J. 2014. "Selective Exposure in the Age of Social Media: Endorsements Trump Partisan Source Affiliation When Selecting News Online," *Communication Research* (41:8), pp. 1042-1063.

Mitchell, A., and Jurkowitz, D. 2014. "Social, Search & Direct: Pathways to Digital News," Pew Research Center (https://www.journalism.org/2014/03/13/social-search-direct/).

Mutz, D. C. 2006. "How the Mass Media Divide Us," in *Red and Blue Nation? Characteristics and Causes of America's Polarized Politics* (Vol. 1), P. S. Nivola and D. W. Brady (eds.), Washington, DC: Brookings Institution Press.

Mutz, D. C., and Martin, P. S. 2001. "Facilitating Communication across Lines of Political Difference: The Role of Mass Media," *American Political Science Review* (95:1), pp. 97-114.

Negroponte, N. 1996. *Being Digital*, New York: Vintage Books.

Nickerson, R. S. 1998. "Confirmation Bias: A Ubiquitous Phenomenon in Many Guises," *Review of General Psychology* (2:2), pp. 175-220.

Page, S. E. 2010. *Diversity and Complexity* (Vol. 2), Princeton, NJ: Princeton University Press.

Pariser, E. 2011. *The Filter Bubble: What the Internet Is Hiding from You*, New York: Penguin Press.

Prawesh, S., and Padmanabhan, B. 2011. "The 'Top N' News Recommender: Count Distortion and Manipulation Resistance," in *Proceedings of the 5th ACM Conference on Recommender Systems*, New York: ACM, pp. 237-244.

Schkade, D., Sunstein, C. R., and Hastie, R. 2007. "What Happened on Deliberation Day," *California Law Review* (95), pp. 915-940.

Schmidt, A. L., Zollo, F., Vicario, M. D., Bessi, A., Scala, A., Caldarelli, G., Stanley, H. E., and Quattrociocchi, W. 2017. "Anatomy of News Consumption on Facebook," *Proceedings of the National Academy of Sciences* (114:12), pp. 3035-3039.

Shore, J., Baek, J., and Dellarocas, C. 2018. "Network Structure and Patterns of Information Diversity on Twitter," *MIS Quarterly* (42:3), pp. 849-872.

Skjerdal, T., and Gebru, S. 2020. "Not Quite an Echo Chamber: Ethnic Debate on Ethiopian Facebook Pages during Times of Unrest," *Media, Culture & Society* (42:3), pp. 365-379.

Sohn, M.-W. 2001. "Distance and Cosine Measures of Niche Overlap," *Social Networks* (23:2), pp. 141-165.

Stroud, N. J. 2010. "Polarization and Partisan Selective Exposure," *Journal of Communication* (60:3), pp. 556-576.

Sunstein, C. R. 2001. *Republic.com*, Princeton, NJ: Princeton University Press.

Sunstein, C. R. 2002. "The Law of Group Polarization," *Journal of Political Philosophy* (10:2), pp. 175-195.

Sunstein, C. R. 2009. *Going to Extremes: How Like Minds Unite and Divide*, New York: Oxford University Press.

Sunstein, C. R. 2017. *#Republic: Divided Democracy in the Age of Social Media*, Princeton, NJ: Princeton University Press.

Vaidhyanathan, S. 2018. *Antisocial Media: How Facebook Disconnects Us and Undermines Democracy*, New York: Oxford University Press.

Van Alstyne, M., and Brynjolfsson, E. 1996. "Could the Internet Balkanize Science?," *Science* (274:5292), pp. 1479-1480.

Van Alstyne, M., and Brynjolfsson, E. 2005. "Global Village or Cyber-Balkans? Modeling and Measuring the Integration of Electronic Communities," *Management Science* (51:6), pp. 851-868.

Walker, M. 2019. "Americans Favor Mobile Devices over Desktops and Laptops for Getting News," Pew Research Center, November 19 (https://www.pewresearch.org/fact-tank/2019/11/19/americans-favor-mobile-devices-over-desktops-and-laptops-for-getting-news/).

Weeks, B. E., Lane, D. S., Kim, D. H., Lee, S. S., and Kwak, N. 2017. "Incidental Exposure, Selective Exposure, and Political Information Sharing: Integrating Online Exposure Patterns and Expression on Social Media," *Journal of Computer-Mediated Communication* (22:6), pp. 363-379.

Welch, M. J., Cho, J., and Olston, C. 2011. "Search Result Diversity for Informational Queries," in *Proceedings of the 20th International Conference on World Wide Web*, pp. 237-246.

Wojcieszak, M. E., and Mutz, D. C. 2009. "Online Groups and Political Discourse: Do Online Discussion Spaces Facilitate Exposure to Political Disagreement?," *Journal of Communication* (59:1), pp. 40-56.

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Appendix

Shore et al. (2018) identified the slant of 186 news URLs, which we used as the basis for multiple measures in this paper. Unless otherwise noted, we used the scores they identify as is. However, because their unit of analysis was a URL associated with a Twitter account, there were certain necessary exceptions or deviations from their list as described in Table A1. First, a small number of the URLs they identified contained both a domain and a path or page (e.g., buzzfeed.com/news). In order to cleanly identify direct versus other visits, for these sites we either removed the path and used only the domain, or removed the entry from the list if the domain was already included on the list with a different slant score. Another small subset of sites either functioned as more than just a news site (aol.com, reddit.com) or were simply a sub-site of a portal or social media outlet (facebook.com/cnsnewscom, news.yahoo.com). Again, in order to avoid bias and conflation in our measures, these sites were omitted. All URLs not listed in Table A1 were included as is.

Table A1. Changes in URL Inclusion Compared to Shore et al. (2018)

URL	Issue/Resolution
cnn.com/politics	Includes path. This entry omitted. Separate no-path entry retained.
huffingtonpost.com/black-voices/	
huffingtonpost.com/politics	
rollingstone.com/politics	
wsj.com/opinion	
buzzfeed.com/news	Includes path. This entry used with path removed.
cbc.ca/news/	
nature.com/news	
pbs.org/newshour	
pewresearch.org/fact-tank	
pjmedia.com/instapundit/	
membership.politifact.com	Includes nonrelevant subdomain. Entry used without subdomain.
aol.com	General site containing more than news. Removed.
facebook.com/cnsnewscom	Facebook page, not news site. Removed.
finance.yahoo.com	Subdomain of search/portal site. Removed.
news.msn.com	
news.yahoo.com	
reddit.com	Social media site. Removed from news site list

Table A2. Correlations (1,092,480 User-Periods over 185,548 Users)

	Distinct News Sites	Slant Dispersion	Audience Variety	Reverse Gini	Slant	Cross-Cutting	Direct News Visits	Search Referrals	Email Referrals	Facebook Referrals	Reddit Referrals	Twitter Referrals	Time on Search	Time on Email	Time on Facebook	Time on Reddit	Time on Twitter
Slant Dispersion	0.49																
Audience Variety	0.50	0.62															
Reverse Gini	0.64	0.46	0.78														
Slant	0.07	0.29	0.05	0.06													
Cross-Cutting	0.04	0.16	0.07	0.01	-0.06												
Direct News Visits	0.30	0.07	0.09	0.21	0.09	-0.02											
Search Referrals	0.52	0.19	0.24	0.33	0.00	0.01	0.15										
Email Referrals	0.17	0.06	0.07	0.14	0.02	0.00	0.11	0.12									
Facebook Referrals	0.36	0.18	0.15	0.24	0.04	0.01	0.10	0.15	0.13								
Reddit Referrals	0.21	0.05	0.06	0.07	-0.02	-0.01	0.01	0.04	0.00	0.04							
Twitter Referrals	0.17	0.04	0.04	0.08	0.00	0.00	0.06	0.09	0.07	0.11	0.02						
Time on Search	0.18	0.11	0.14	0.15	0.01	0.02	0.04	0.18	0.10	0.06	0.00	0.02					
Time on Email	0.12	0.09	0.11	0.12	0.02	0.02	0.04	0.08	0.17	0.05	0.00	0.01	0.60				
Time on Facebook	0.13	0.14	0.13	0.12	0.02	0.05	0.00	0.05	0.01	0.25	0.01	0.02	0.08	0.06			
Time on Reddit	0.14	0.05	0.06	0.06	-0.02	-0.01	0.00	0.02	0.00	0.02	0.54	0.01	0.00	-0.01	0.01		
Time on Twitter	0.06	0.02	0.04	0.04	-0.01	0.00	0.00	0.04	0.00	0.02	0.01	0.20	0.02	0.00	0.06	0.02	
Time Online	0.26	0.17	0.22	0.26	0.01	0.04	0.10	0.16	0.09	0.13	0.04	0.04	0.44	0.39	0.35	0.05	0.09

Table A3. Summary Statistics for Users on Panel for at Least 365 Days Across all 4-Week User-Periods Including > 0 News Visits (1,092,480 User-Periods over 185,548 Users)												
	All Users			Liberal Tercile (Users with all-time mean slant < -10.45)			Centrist Tercile (Users with all-time mean slant b/w -10.45 and -3.16)			Conservative Tercile (Users with all time mean slant > -3.16)		
	Median	**Mean**	**SD**	**Median**	**Mean**	**SD**	**Median**	**Mean**	**SD**	**Median**	**Mean**	**SD**
Distinct news sites	2	2.97	3.80	2	2.94	3.81	2	2.90	3.28	2	3.09	4.35
Diversity - Slant dispersion	1.02	6.53	10.46	0.79	5.07	7.93	1.30	5.55	8.75	0.98	9.24	13.66
Diversity - Audience variety	63.09	42.95	40.62	60.84	41.73	40.56	65.10	43.96	39.92	62.64	42.95	41.50
Diversity - Reverse Gini	6.30	19.66	23.35	3.48	19.59	23.65	10.00	19.78	22.56	3.67	19.59	23.98
Slant	-7.58	-4.35	20.75	-16.03	-15.36	11.16	-7.58	-7.03	11.70	-0.44	10.12	27.59
Cross-cutting	0.00	8.59	23.78	0.00	3.87	14.32	N/A			0.00	23.97	35.76
Direct news visits	0	3.26	29.28	0	2.26	20.09	0	2.26	17.34	0	5.51	44.68
Search referrals	0	1.08	3.10	0	0.97	2.74	0	1.20	2.99	0	1.03	3.55
Email referrals	0	0.11	1.18	0	0.15	1.40	0	0.08	1.01	0	0.12	1.14
Facebook referrals	0	0.45	2.40	0	0.58	2.67	0	0.31	1.50	0	0.50	2.94
Reddit referrals	0	0.03	0.55	0	0.07	0.84	0	0.03	0.45	0	0.01	0.20
Twitter referrals	0	0.02	0.33	0	0.02	0.38	0	0.01	0.23	0	0.01	0.38
Time on search	1.56	4.19	10.36	1.36	3.61	9.48	1.81	4.59	10.87	1.49	4.29	10.56
Time on email	0.40	2.61	7.89	0.38	2.39	7.31	0.45	2.68	8.09	0.36	2.74	8.19
Time on Facebook	0.57	4.74	10.78	0.66	4.60	10.22	0.52	4.52	10.41	0.54	5.15	11.74
Time on Reddit	0.00	0.09	1.25	0.00	0.19	1.91	0.00	0.07	0.97	0.00	0.02	0.44
Time on Twitter	0.00	0.13	1.39	0.00	0.14	1.22	0.00	0.16	1.53	0.00	0.09	1.38
Time online	28.91	46.44	57.30	27.18	44.18	54.38	30.80	48.15	57.66	28.38	46.62	59.60
Measures per user												
Age	33	36.94	15.35	32	35.69	15.08	33	36.16	14.84	37	38.98	15.91
Gender	51.55% male			47.39% male			53.60% male			53.65% male		

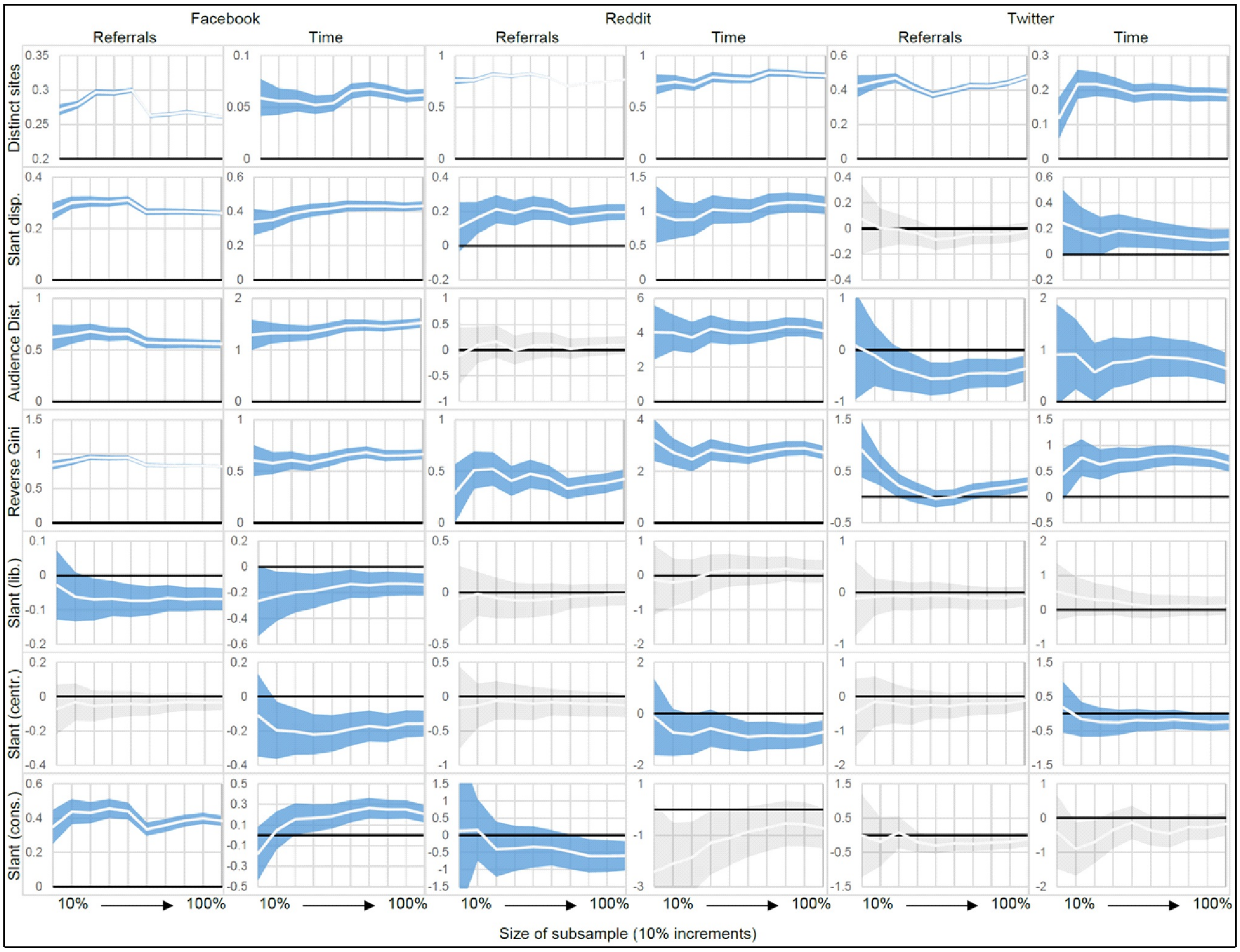

Figure A1. 95% CI Plots for Coefficients Estimated Using Random Subsamples