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The agenda-setting power of fake news: A big data analysis of the online media landscape from 2014 to 2016

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Abstract

This study examines the agenda-setting power of fake news and fact-checkers who fight them through a computational look at the online mediascape from 2014 to 2016. Although our study confirms that content from fake news websites is increasing, these sites do not exert excessive power. Instead, fake news has an intricately entwined relationship with online partisan media, both responding and setting its issue agenda. In 2016, partisan media appeared to be especially susceptible to the agendas of fake news, perhaps due to the election. Emerging news media are also responsive to the agendas of fake news, but to a lesser degree. Fake news coverage itself is diverging and becoming more autonomous topically. While fact-checkers are autonomous in their selection of issues to cover, they were not influential in determining the agenda of news media overall, and their influence appears to be declining, illustrating the difficulties fact-checkers face in disseminating their corrections.

Keywords

Big data, computational social science, fact-checking, fake news, intermedia agenda setting, journalism, misinformation, network agenda setting, partisanship

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In late 2016, as the US election day approached, "fake news" gained growing public interest. In November and December, more people Googled the phrase than the combined previous 15 months (Google Trends, 2017). Now, fake news can be "produced purposefully by teenagers in the Balkans or entrepreneurs in the United States seeking to make money from advertising …" (Maheshwari, 2016). Hundreds of websites have popped up around the Internet that appear credible at face value but are fake in nature (Silverman, 2016).

Journalists have little ability to *proactively* fight fake news. Even worse, partisan media can be susceptible to its influence (e.g. Collins, 2016). Other news organizations fight fake news. The BBC, for instance, has announced a commitment to debunk fake news that is shared widely on social media (Jackson, 2017). Fact-checking organizations have become another bulwark against fake news with PolitiFact, FactCheck.org, ABC News, the Associated Press, and Snopes all fighting it on Facebook (Isaac, 2016). However, this *reactive* desire to thwart fake news has required traditional media to divert resources—in the form of time and attention—to fighting it (Easton, 2016). What is worse, by being forced to respond to fake news journalists may be affording fake news websites with the ability to push topics, issues, and even attributes into the public agenda.

What we know about fake news so far is predominantly based on anecdotal evidence. Empirical research is sparse as to the greater effects fake news has had on journalistic practices in different media outlets. Has fake news disrupted the ways *real news* report? Does fake news have the ability to shift journalistic attention—especially those from partisan media—to and from issues? Likewise, while a number of fact-checking organizations are dedicated to publicizing and correcting factual errors (Amazeen, 2013), little is known about the extent to which they quell fake news and influence other media coverage. Do fact-checking activities attract attention from the greater journalism community?

To answer these questions, this article will leverage intermedia agenda-setting theory and the Network Agenda-Setting (NAS) model to assess the relationship fake news, fact-checkers, and online news media—particularly partisan media—have with each other. Based on the Global Database of Events, Language, and Tone (GDELT; Leetaru and Schrodt, 2013), this study takes a computational approach to investigate the role fake news has in the online new media landscape from 2014 to 2016.

Intermedia NAS

Agenda-setting theory originally examined what topics trend in the news and how that affects the opinions of audiences (McCombs, 2014). The first level of agenda setting asserts that the frequency in which news media mention and cover objects (e.g. issues and public figures) largely dictates what objects audiences think are important to society. This is not to say that audiences blindly believe the news. Instead, the news media sets the public *salience* for objects or attributes. When substantial news coverage is dedicated to an issue (e.g. economy), people consider the economy an important issue—even though audiences may have diverging opinions about the issue (e.g. how to fix the economy). This nuance is critical when considering the agenda-setting power of fake news: even if some audience members are aware that fake news is fake, the mere rise in coverage (fake or real) could result in an agenda-setting effect.

The agenda-setting effect is not limited to news and audiences. As an extension of the original theory, *intermedia agenda setting* focuses on the interaction between different media outlets in setting each other's news agenda. Early studies suggested that elite media influenced smaller news organizations (Reese and Danielian, 1989). This occurs partly because journalists validate work by looking at their peers, especially colleagues at established, elite news media (McCombs, 2014). The literature has shown that the *New York Times* and *Washington Post* often set the agenda of newspapers, television, and radio. However, more recent studies show that emerging media (e.g. political blogs and online partisan news websites) are now more powerful in setting the agenda of other media outlets (Vargo and Guo, 2017; Meraz, 2011). These new findings uncover the possibility that fake news may also influence the news coverage of other media outlets. Drawing upon the theoretical framework of intermedia agenda setting, this study seeks to examine how fake news, fact-checking websites, and other online media organizations interplay with each other.

Our investigation approaches agenda-setting effects through a more nuanced perspective: the NAS model, another theoretical advancement of the original theory. The NAS model asserts that the agenda of media is both implicit and explicit (Vargo et al., 2014). Traditional agenda-setting solely measures the explicit mentions of issues and attributes in stories. The NAS model measures the contextual relationships that issues share with each other. For example, an agenda for a news organization is not just how it covers one issue for a certain time. Rather, how often issues are mentioned together during the same news period measures the relationships between different news items. The NAS model further proposes that the salience of these network relationships for issues can be transferred from the news media to the audience's mind (Guo and McCombs, 2016). According to the NAS model, if the US news media recurrently cover the country's energy and its foreign relations problems together, audiences will also consider the two issues interconnected. The NAS model suggests that the news media can construct the public's perceived importance of interconnections among issues, as well as the popularity of such issues.

A number of empirical studies have been conducted to test the model in various sociocultural contexts (see Guo and McCombs, 2016). In addition, the initial NAS model has been extended to examine network agenda *building* (e.g. Neil et al., 2016) and network *intermedia* agenda setting (e.g. Vargo and Guo, 2017). Collectively, this research demonstrates that the network relationships among different news items and messages can be transferred between varied stakeholder agendas: from media to public, from different interest groups to media, as well as from media to media. This study seeks to further contribute to the NAS model by systematically assessing the network intermedia agenda-setting impact of fake news on other media outlets. For this analysis, we focus on different media outlets' network *issue* agenda, that is, how different media organizations associate various issues to portray the social reality and how those issue networks transfer between different media agendas. The following section reviews the limited existing research on fake news, fact-checkers, and the online media landscape to explore the potential direction (i.e. who follows whom) of the NAS effects.

Fake news, online media, and fact-checkers

The definition of fake news has been evolving as more knowledge about it has accrued. At its broadest, it has been identified as "news stories that have no factual basis but are presented as news" (Allcott and Gentzkow, 2017: 5). Others narrow the definition to include only "completely false information that was created for financial gain" (Silverman, 2017) and which resembles credible journalism in order to maximize attention (Hunt, 2016, but also see Mustafaraj and Metaxas, 2017). Fake news is different from state- or industry-sponsored disinformation campaigns for political purposes and is also separate from bad reporting and ideologically driven news that is uncongenial to one's views (Silverman, 2017). At its core, "fake news necessitates assumptions about some kind of *authentic* or *legitimate* set of news practices" (Baym, 2005: 261). When readers believe that a website is journalistic in nature, they can be exploited and persuaded to believe untrue things. Fake news evolves from a long line of satire used to hold politicians and media accountable (Painter and Hodges, 2010). While fake news has always been present, recent research suggests that it is now more popular than ever (Dewey, 2016; Silverman, 2016). What has emerged in recent years are websites dedicated solely to propagating fake news. Unlike Painter and Hodges' (2010) notion of press accountability, these fake news websites are financially motivated (Dewey, 2016) and generally fabricate information to stir controversy (Maheshwari, 2016). Content on these sites is sensationalized in intentional ways to drive up the volume of clicks and shares (Mustafaraj and Metaxas, 2017; Silverman and Alexander, 2016). In a meta-analysis, researchers have found over 100 websites that regularly publish false information and remain active today (Shao et al., 2016).

It is unknown whether fake news can set the agendas of other news media. Given that many journalists often pay attention to fake news (IFCN, 2016; Jackson, 2017), in part to address it factually and because fake news is rising in popularity, it stands to reason that fake news websites may possess an agenda-setting power of their own. That is, they may have the ability to affect the popularity of issues simply by introducing misinformation that journalists must address. A network analysis has found that the sites targeted with the most inbound hyperlinks from fake news networks were mainstream media, social networking sites, and Wikipedia. Few of the targeted sites linked back to the fake news sites (Albright, 2016). However, given the lack of empirical evidence so far, we address the subject by posing a research question:

> *RQ1*. Will the network issue agenda of fake news predict the overall news media's agenda online?

Partisan media and fake news

The relationship between fake news and partisan media is worthy of particular attention. Instead of valuing balance, fairness, and objectivity, partisan media often frame stories in a way to advance certain political agendas (Levendusky, 2013b) driven by in-group or tribal identification (Harford, 2017; Roberts, 2017). Traditional partisan media include cable news (e.g. Fox News) and talk radio (e.g. the Rush Limbaugh Show). The Internet has contributed to the proliferation of new forms of partisan media: partisan websites and blogs such as Drudge Report and Daily Kos. With the emergence and popularity of social media services, partisan news coverage is more popular than ever before (Weeks and Holbert, 2013). Moreover, these social media networks facilitate the spread of misinformation via automated, anonymous accounts which target users already engaged in conversation on a particular topic (Mustafaraj and Metaxas, 2017).

When it comes to the interaction between partisan media and fake news, anecdotal evidence suggests that in an extremely polarized political environment, partisan media tend to enable the propagation of fake news. Driven by motivation to attack the opposing party during the 2016 US presidential campaign, fake news site *RealTrueNews*' fictional reporting of Hillary Clinton's leaked speeches to Wall Street banks was soon picked up by *Fox News*. The popularity of the fiction being reported as if it were factual was then extensively reported by conservative-leaning websites such as *The Daily Beast* (Collins, 2016). As this case illustrates, fake news sites can set the issue agenda of partisan media of both sides.

Academic research on partisan media's interplay with fake news is rare. Rojecki and Meraz's (2016) analysis of actors responsible for transmitting factitious information blends (FIBs), a new form of misinformation, sheds some light. Based on the 2004 US presidential election, the study qualitatively analyzed Google search results of two FIBs from a variety of media sources. It found that regarding a political controversy against the Democratic candidate John Kerry, conservative websites and blogs became central gatekeepers in the release and spread of the misinformation. By contrast, both liberal and conservative sites contributed to the growth in covering and propagating an FIB about the Republican candidate George W. Bush. The authors thus concluded that partisan media facilitate the viral spread of partisan misinformation. Considering both anecdotal and empirical evidence, though limited, it seems logical to expect that partisan media follow the agenda of fake news, more so than other types of media outlets:

H1. When compared to the reverse relationship, the agenda of fake news websites will be more likely to predict the network issue agenda of partisan media.

H2. The agenda of fake news websites will be more likely to predict the network issue agenda of partisan media than other types of media outlets.

Revealing that only conservative websites were reactive in both cases, Rojecki and Meraz's (2016) study also indicates a potentially stronger connection between fake news and conservative-oriented partisan media. Relevantly, a recent survey demonstrates that self-reporting Republicans (84%) were significantly more likely to believe fake news headlines than were Democrats (71%; Silverman and Singer-Vine, 2016). Moreover, during the 2016 election, fake news stories favoring Trump were shared on Facebook over three times more often than were fake stories about Hillary Clinton (Allcott and Gentzkow, 2017). It stands to reason that if fake news is more prevalent and widely believed among conservatives, it is also more likely to set the agendas of the media that cater to these audiences:

H3. The network issue agenda of fake news websites will be more likely to predict the agenda of conservative than liberal partisan media.

No research has examined the intermedia agenda-setting relationship between fake news and other, nonpartisan media. Right-wing media have been shown to set the election coverage agenda of mainstream media (Benkler et al., 2017). However, it is not clear to what degree fake news stories were involved in this coverage. Thus, it remains a question whether traditional, elite media such as the *New York Times* and *Washington Post*, news agencies, or other nonpartisan, emerging news sites such as *CNET* and *Gawker* respond to fake news. Therefore, we ask

> *RQ2*. Will the network issue agenda of fake news predict other, nonpartisan media's agenda?

Aside from news media, the practice of fact-checking has drawn interest as a means to counter the impact of fake news. This study also examines the role these fact-checking organizations have played in this evolving online media landscape.

Fact-checking

Fact-checking aspires to the normative standard first espoused by Lippmann (2009 [1922]) of making the unintelligible facts known to the masses so as to foster informed decision making. Lippmann's position has theoretical grounding in the social responsibility of the press paradigm, formalized by Siebert et al. (1956). These perspectives formed the basis for the modern fact-checking model of journalism, which emerged out of the concern that traditional reporting had ceased to hold political figures accountable for the accuracy of their claims (Graves and Konieczna, 2015). What distinguishes contemporary fact-checkers such as PolitiFact and FactCheck.org from traditional journalistic conventions are their focus on determining and drawing attention to whether a claim is factually accurate rather than eliminating errors or falsehoods in reporting (Amazeen, 2013; Graves and Glaisyer, 2012). Specifically, fact-checkers decide what to check based on whether or not a statement is factually verifiable. In the context of this analysis, it would be reasonable to expect that

> *H4*. When compared with the reverse relationship, the network issue agenda of fact-checking websites will be more likely to follow the agenda of fake news websites.

Ultimately, the objectives of fact-checkers are threefold: informing the public, improving political rhetoric, and influencing other journalists (Amazeen, 2013; Graves and Glaisyer, 2012). To achieve these goals, fact-checkers are highly reliant on other news organizations to increase the spread and impact of their reporting through the media ecosystem (Amazeen, 2013; Graves and Konieczna, 2015). Although fact-checkers are frequently cited by other journalists (Amazeen, 2013), what is unknown is whether fact-checkers have the ability to alter the agendas of news media coverage. While journalists cite fact-checking, they may do so in a reactive nature, for instance, only when they need to refute fake news. Conversely, it could be fact-checking organizations that give light to fake news. If this were the case, fact-checkers themselves could possess significant agenda-setting power among media.

When it comes to the predictive power of fact-checkers and partisanship, research shows that compared with conservative media, liberal media were more attentive to fact-checking activities (Graves and Glaisyer, 2012). In addition, liberals have been found to be more receptive to fact-checking than conservatives (Barthel et al., 2016). Although conversations around fact-checking tend to be politically polarized, some of it is apolitical. Indeed, a network analysis study revealed the fact-checker that was the most influential in terms of total links from other sites was the general interest site, Snopes. The three, national fact-checkers, FactCheck.org, PolitiFact, and the *Washington Post*'s Fact Checker, have all engaged in highly political conversations yet still receive relatively high attention from centrist outlets (Graves and Glaisyer, 2012). It then stands to reason that the agenda-setting power of fact-checking websites may still be high for nonpartisan media outlets. Given the lack of literature on the agenda-setting power of fact-checkers, we chose to pose a research question:

> *RQ3*. Will the network issue agenda of fact-checking websites predict the overall news media agendas of various types of media online?

Fact-checkers may influence the agenda of partisan media like discussed above or follow partisan media's coverage by checking their statements. The manner in which fact-checkers select claims to evaluate has been a point of contention for critics, with some claiming they use biased selection methods that are driven by partisanship (Amazeen, 2013; Davis, 2012). Compared with other media, partisan media are more likely to frame news in a way to advance certain political agendas (Levendusky, 2013a) and, therefore, more likely to contain statements that are rooted in verifiable facts that could be misleading—and rife for selection by fact-checkers. However, no empirical research has followed the attention of fact-checking coverage at the level of media type (e.g. partisan, emerging, and traditional). As an initial analysis, this study broadly attempts to assess the degrees to which fact-checkers follow different types of media:

> *RQ4*. Will the network issue agenda of fact-checking websites follow the overall news media agendas of various types of media online?

Method

This article uses GDELT's Global Knowledge Graph (GKG) as its data source (Leetaru, 2012a, 2015a). On a daily basis, GDELT monitors news globally and employs a computer-assisted content analysis that identifies people, locations, themes, emotions, narratives, and events (Leetaru, 2015).[1] The dataset has given researchers the ability to computationally analyze news content of all sorts: real, fake, and fact-checking oriented (Abbar et al., 2015; Vargo and Guo, 2017).

Coding for issues

GDELT offers themes that represent core topics of discussion.[2] Themes cover a broad range of issues, topics, and attributes,[3] many of which are similar to those studied in agenda-setting studies (e.g. "Econ_Bankruptcy," "Econ_Cost of living," "Military_Cooperation," and "Refugees."). With almost 300 themes, GDELT offers a higher level hierarchy to arrange the data in a way that makes it comparable to other agenda-setting research. This analysis of intermedia agenda setting relied on Vargo and Guo's (2017) theme categorization and sorted the data by themes that have been thought to broadly encompass major issues in US news coverage (Neuman et al., 2014). The themes are composed of 16 issues: taxes, unemployment, economy, international relations, border issues, health care, public order, civil liberties, environment, education, domestic politics, poverty, disaster, religion, infrastructure, and media and Internet.[4]

News media types

Fake news. GDELT ingests all news-like content from online sources including Google News. It does not have any type of quality control system, so as a result, it—like many other media sources—contains content from fake news websites. Shao et al. (2016) created and maintain a meta-analysis of fake news websites for use with their service Hoaxy, which tracks fake news media from nine different sources such as US News and World Report, CBS News, and Snopes Field Guide.[5] For this study, we included a fake news website in the analysis if it was identified by more than one of the nine sources. In all, 96 fake news websites were searched for in the GDELT database. In total, 60 fake news websites and 171,365 stories from fake news websites were found in the GDELT data from 2014 to 2016.[6]

Fact-checking websites. The selection of fact-checkers for this study derived from multiple sources. The Duke Reporter's Lab at Duke University maintains a list which includes fact-checkers that (1) examine all political parties and ideological sides, (2) examine discrete claims and reach conclusions, (3) track political promises, (4) are transparent about sources and methods, (5) disclose their funders and affiliations, and/or (6) are primarily driven by a mission of news and information (Adair and Stencel, 2016). Other fact-checkers are signatories of the Poynter Institute's International Fact-Checking Network (IFCN), a forum for fact-checkers that reviews statements by public figures, major institutions, and other widely circulated claims that are of interest to society (About the International Fact-checking Network, n.d.). Members of the IFCN commit to the following principles: (1) nonpartisanship and fairness, (2) transparency of sources, (3) transparency of funding and organization, (4) transparency of methods, and (5) open and honest corrections (International Fact-checking Network Fact-checkers' Code of Principles, n.d.). Fact-checkers that do not derive from these two sources yet abide by the spirit of these general principles were also considered for inclusion. Of these websites, only those fact-checking organizations that were solely dedicated to fact-checking and available in the GDELT dataset were included: Climate Feedback, FactCheck.org, Gossip Cop, Health News Review, PolitiFact, Snopes, and Wafflesatnoon.com. Overall, GDELT contained 13,036 stories for the seven sources from 2014 to 2016.

News media websites. The study also drew upon Vargo and Guo (2017) for online news media categorization. The study identified the top 2760 US news media websites in GDELT. Their analysis further sorted media into five different categories: (1) elite media (i.e. the *New York Times* and the *Washington Post*), (2) news agencies, (3) traditional media, (4) online partisan media, and (5) emerging media (i.e. nonpartisan and online media). This study updated the list of online partisan media for 2016 by including the National Review, Vox, ThinkProgress.org, CounterPunch, Veterans Today, and Truthdig.com in the analysis.[7]

To address hypotheses in this study, we further updated the existing list of partisan media by delineating between liberal and conservative slant. In total, two coders coded the 70 partisan media sites as liberal or conservative. Coders studied each site, searching the Internet for claims from credible news organizations or media watchdogs asserting that a given site was indeed partisan or to see whether a site self-identified as partisan. After an initial review and discussion of each site, the coders agreed that 62 ($\alpha = 1$) of the media sites were partisan. In total, 31 sites were liberal and 31 were conservative in nature. Across the 3 years, there were 594,634 stories from liberal sources and 625,295 articles from conservative outlets. In total, three sources were not deemed to be news media, and five media outlets were nonpartisan in nature and as such were added to the "emerging media" category. The emerging category comprised 14,120,889 stories from 767 outlets.

Overall, nine media groups were considered in the analysis: (1) fake news websites, (2) fact-checking websites, (3) online partisan media, (3a) liberal media, (3b) conservative media, (4) elite media ($n = 2$, stories = 549,009), (5) news agencies ($n = 2$, stories = 539,841), (6) traditional media ($n = 1911$, stories = 25,719,311) and (7) all news media (i.e. groups 3–6). A graph depicting the rising number of fake news and fact-checking articles can be seen in Figure 1.

Computer-assisted NAS analysis

GDELT CKG data can be downloaded freely from GDELT's website in tab-separated values format. The data are structured by news events. Each event is a row of data. News events are defined as collection of news stories from various sources that contain the same set of themes. Using Python, each row of data was scanned to see whether each event contained any media or issues of interest in this study. When an event contained a media source that was identified in one of the media types above, the themes in that event were inspected to see any matched the 16 issue constructs previously noted. If an event matched a media source and themes that corresponded with multiple issues, all possible unordered pairs of issues were identified and considered as ties (Wasserman and Faust, 1994). For example, if an article mentioned economy, border issues, and civil liberties, it was determined that the article had three ties: (1) economy and border issues, (2) economy and civil liberties, and (3) border issues and civil liberties. All ties were then summed by day and media type. Each tie's corresponding weight (i.e. strength) was a summation of the number of stories that mentioned that issue pair (e.g. economy and foreign policy).

Eigenvector centrality is a measure of influence in a network (Ruhnau, 2000). A higher centrality score refers to a greater number of connections between a node (an issue in the analysis here) and all the other nodes in the network. The more ties an issue has with other issues, the higher centrality value the issue has, and the more centrally it is located in the resulting networks. Eigenvector centrality was the key unit of analysis. As such, it was calculated for each media type. For instance, fake news websites had 16 centrality scores, one for each issue. This score relates to how central each issue was in

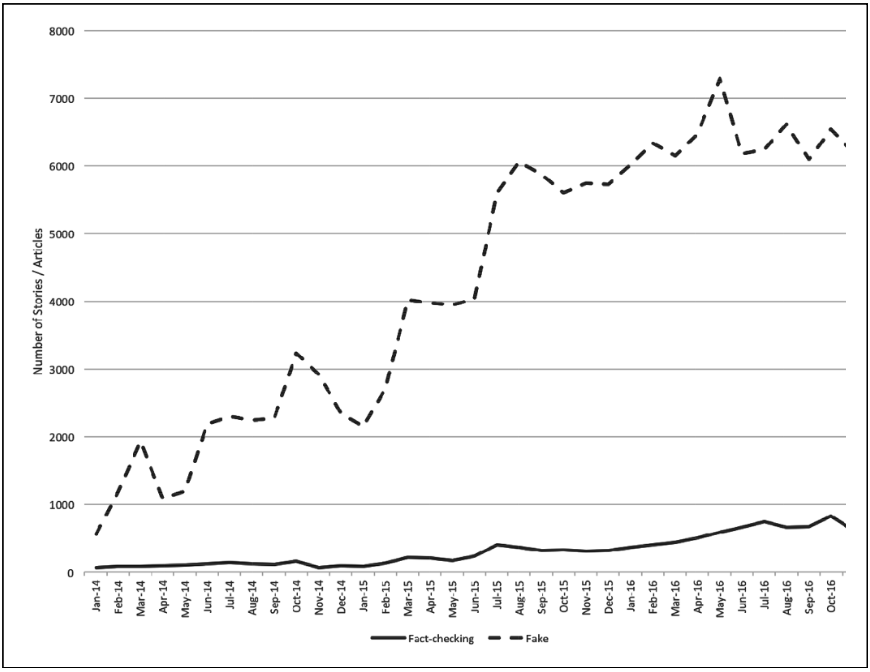

Figure 1. The number of fake news stories and fact-checking articles by month (2014–2016).

its coverage. This was done for each day in the 3-year sample, and the data were treated as time series.

Time series modeling

The centrality scores (issue centrality score × media type × day) were treated as a time series. This analysis was performed for each year of data. Granger causality models were constructed for each issue and for each media type. Time series X is said to "Granger cause" another time series Y if regressing for Y in terms of past values of both X and Y results in a better model for Y than regressing only on past values of Y. Running F-tests provided values of significance in which Granger causality could be determined. All tests were run at five lags, that is, 1-day lag, 2-day lag, 3-day lag, 4-day lag, and 5-day lag, respectively. While ordinary least squares (OLS) models can assign best fit for one lag, including lags of multiple days allows the research at present to address different types of agenda-setting relationships that differing stories can have.

A significant fake news effect was operationalized in this article as having a significant effect for at least 9 of the 16 issues studied here. This threshold gives us the power to say that the majority of an *entire media agenda* was explained by a given relationship. In theory, any one issue with a significant test means a significant effect was observed. However, given the large number of causality tests performed here, any one test comes with a significant probability of type I and type II errors. Second, the sheer number of issue to issue tests from one media type to another is "big data" itself. Aside from majority rule, this analysis looks at patterns across years. If a media relationship fell below the majority threshold, but the same issue was significantly predicted across all 3 years, an effort was made to call out this relationship in this article. However, one-off relationships that fell below the majority thresholds were not addressed here due to the large number and potential spuriousness of the result.

Results

Table 1 provides a summary of the Granger causality tests run for this analysis. The number of significant tests are displayed for each relationship of interest. Table 2 shows the detailed Granger causality results for one of the most important relationships investigated in this study: the ability of fake news websites to predict the agenda of all news media.

Fake news and online media

RQ1 asked whether the network issue agenda of fake news would predict the overall news media's agenda online. The results showed that the fake news websites Granger caused the agenda of all news media as a group in terms of seven issues in 2014 and 2015 and four issues in 2016 for at least one lag (see Table 1). Given that we consider nine issues as a cutoff for significant NAS effect, it appeared that fake news did not set the overall online media agenda for the 3 years examined; instead, its NAS power turned out to be shrinking over time. However, our results did suggest fake news was successful in transferring the centrality salience of certain issues to the news media agenda (see Table 2). For example, in each of the 3 years, whenever fake news fabricated stories about international relations, the news media would react in <5 days.

With respect to the relationship between fake news and partisan media (H1), the results showed that the fake news websites Granger caused the agenda of all online partisan media in terms of 8 issues in 2014 and 2015 and 12 issues in 2016 for at least one lag. Reversely, online partisan media predicted the network agenda of fake news in terms of 13 issues in 2014, 13 issues in 2015, and 9 issues in 2016 for at least one lag. As such, we concluded that partisan media were more likely to predict—rather than follow—the agenda of fake news in 2014 and 2015. In 2016, the relationship between the two media groups was reciprocal, but fake news was indeed more likely to influence the agenda of partisan media compared with the reverse relationship. The two media groups responded to each other in covering issues of environment, unemployment, economy, international relations, civil liberties, and religion. Fake news also unidirectionally predicted the issue agenda of partisan media in reporting infrastructure, disaster, border issues, domestic politics, health care, and public order. Notably, many of these issues were under heated debate in the 2016 US presidential campaign season. Given the evidence, H1 was supported with respect to the online media landscape in 2016 but not in the previous 2 years.

H2 hypothesized that fake news would be more likely to predict the network agenda of partisan media than other types of media. The results showed that the fake news websites significantly set the network agenda of liberal-oriented partisan media ($n=9$) and

Table 1. Number of significant Granger causality tests, by year.

Independent variable	Dependent variable	2014	2015	2016
Fake	NYT/WaPo	8	9	6
Fake	News agencies	6	4	2
Fake	Traditional	7	8	7
Fake	Liberal	9	10	9
Fake	Conservative	4	11	7
Fake	All online partisan	8	8	12
Fake	Emerging	9	7	9
Fake	Fact-checking	6	3	5
Fake	All fact-based media	7	7	4
All online partisan	Fake	13	11	9
Conservative	Fake	10	9	11
Fact-checking	Fake	4	5	3
NYT/WaPo	Fake	9	10	8
News agencies	Fake	11	10	7
Traditional	Fake	11	12	10
Emerging	Fake	10	12	10
All fact-based media	Fake	12	13	11
Liberal	Fake	13	11	8
Fact-checking	NYT/WaPo	5	4	4
Fact-checking	News agencies	3	3	4
Fact-checking	Traditional	7	2	3
Fact-checking	Liberal	4	5	5
Fact-checking	Conservative	3	4	4
Fact-checking	All online partisan	4	4	4
Fact-checking	Emerging	10	6	5
Fact-checking	Fake	4	5	3
Fact-checking	All fact-based media	6	4	2
All online partisan	Fact-checking	6	8	6
Conservative	Fact-checking	8	6	6
NYT/WaPo	Fact-checking	5	6	4
News agencies	Fact-checking	6	0	4
Traditional	Fact-checking	8	4	5
Fake	Fact-checking	6	3	5
Emerging	Fact-checking	8	6	6
All fact-based media	Fact-checking	7	6	7
Liberal	Fact-checking	7	8	4

Number of significant Granger causality tests, maximum number possible is 16, one for each issue.

emerging media ($n=9$) in 2014; elite media ($n=9$), liberal-oriented partisan media ($n=10$), and conservative-oriented partisan media ($n=11$) in 2015, and liberal-oriented partisan media ($n=9$), all online partisan media ($n=12$), and emerging media in 2016 ($n=9$). The pattern did show that fake news influenced the agenda of various partisan

Table 2. Granger test of causality of fake news on all news media's network issue agendas.

Lag	Tax	Unemployment	Economy	International relations	Border issues	Health care	Public order	Civil liberties	Environment	Education	Domestic politics	Poverty	Disaster	Religion	Infrastructure	Media and Internet
2014																
1. $F(1, 351)$	2.32	1.36	4.27*	13.56**	14.33**	4.76*	2.74	0.54	0.14	2.78	2.03	0.23	0.05	3.51	4.23*	0.36
2. $F(2, 352)$	1.69	0.96	3.45*	4.97**	7.98**	3.24*	1.75	0.34	0.18	1.86	1.42	0.05	2.63	1.42	1.81	0.3
3. $F(3, 353)$	1.37	1.31	3.78*	3.39*	4.96**	1.48	0.97	0.18	3.15*	2.21	0.91	0.4	1.79	1.52	0.99	0.56
4. $F(4, 344)$	1.75	1.17	3.42**	2.72*	4.65**	0.92	0.75	0.63	2.28	2.24	1.41	0.41	1.21	2.91*	1.09	0.57
5. $F(5, 345)$	1.3	0.95	3.29**	2.84*	2.98*	0.84	0.78	0.63	2.39*	1.72	1.25	0.4	1.12	2.09	1.06	0.46
2015																
1. $F(1, 361)$	1.29	0.35	8.57**	12.57**	1.01	2.22	0.01	6.19*	0.69	8.82**	0.78	9.05**	2.69	7.30**	2.13	0.38
2. $F(2, 352)$	2.49	0.46	5.67**	5.41**	0.34	6.05**	1.53	2.23	1.33	3.69*	0.25	5.09**	1.44	5.27**	0.59	0.39
3. $F(3, 353)$	1.86	0.76	4.24**	5.95**	0.51	3.80*	1.9	1.03	1.96	3.46*	0.24	2.83*	1.17	3.46*	0.31	0.91
4. $F(4, 354)$	1.38	0.58	2.50*	4.85**	0.84	2.97*	1.46	0.84	1.3	2.68*	0.21	2.44*	1.16	2.65*	0.29	0.78
5. $F(5, 345)$	1.03	0.62	1.72	3.01*	0.79	2.39*	1.24	2.46*	1.13	2.30*	0.62	2.35*	0.98	1.71	0.35	1.13
2016																
1. $F(1, 361)$	0.01	0.19	0.45	6.72**	0.62	2.27	1.78	10.79**	2.53	0.01	0.74	1.87	11.39**	2	0.78	0.98
2. $F(2, 352)$	0.1	0.65	0.18	3.91*	0.51	1.22	1.49	7.00**	1.33	0.44	0.54	0.88	7.68**	3.03*	0.58	0.42
3. $F(3, 353)$	0.64	1.52	1.37	3.25*	1.01	0.73	1.04	4.12**	1.12	0.33	1.49	0.59	4.96**	2.72*	0.35	0.28
4. $F(4, 354)$	0.7	1.14	0.95	2.22	0.85	0.6	0.92	2.76*	0.67	0.61	1.28	0.74	3.67**	2.83*	0.29	1.61
5. $F(5, 355)$	0.49	0.87	1.18	1.63	0.82	0.57	0.71	2.26*	1.17	0.73	1.01	0.81	2.73*	2.42*	1.36	1.21

All lag times are in days (e.g. 2 = 2 days).
$^*p < 0.05$; $^{**}p < 0.01$.

media in each year, but it also demonstrated that some other media outlets, especially emerging media, were also reactive to the fake news coverage. Therefore, H2 was supported but to a limited extent.

Contrary to what we expected, the results also revealed that fake news was more likely to influence the issue agenda of liberal media than their conservative counterparts. Thus, H3 was rejected. However, fake news appeared to be significantly influenced *by* both liberal and conservative media. Remarkably, in 2016, conservative media were found to Granger cause the network issue agenda of fake news in terms of 11 issues for at least one lag. The same significant agenda-setting effect was not found for liberal media. Taken all together, the results seem to suggest that conservative media transferred the issue salience to the fake news websites, which then affected what issues liberal media decided to report.

In answering RQ2, fake news was also powerful in influencing the network issue agenda of emerging and elite media in certain years, as mentioned above. When considering the reverse relationship, the fake news websites were found to be reactive to all types of media. In particular, fake news significantly followed the network issue agenda of emerging media and traditional media throughout 2014–2016.

The role of fact-checkers in the online mediascape

As Table 1 illustrates, fact-checking websites appeared to be largely autonomous from other online media agendas. Surprisingly, a significant NAS effect was found in only one Granger causality test considering all possible relationships: in 2014, fact-checking websites Granger caused the issue agenda of emerging news websites in terms of 10 issues for at least one lag. Furthermore, the connection between fact-checkers and other media outlets appeared to be diminishing over time. While the findings provided little evidence to support our hypothesis, a brief discussion of results related to it and our research questions are offered below.

In testing H4, our results showed that the fact-checking organizations did not necessarily follow the issue agenda of fake news. In 2015, they were even found to be more likely to transfer the issue salience *to* fake news: fact-checkers and fake news were reciprocal in reporting border issues and civil liberties. Moreover, the fake news websites also followed the fact-checking websites for producing stories about the environment, unemployment, and public order. Ironically, fact-checkers, originally with the intention to correct fake news, may provide ideas for fake news to "cover" under some circumstances.

To answer RQ3, the results showed that, again, the fact-checking websites did not predict the overall news media agenda online. Granger causality tests indicated a declining influence over the issue agenda of all fact-based media from a high of six in 2014, to four in 2015, declining to two in 2016. The two issues that fact-checkers were able to transfer the salience of to the overall online media agenda in 2016 were disaster and international relations. Finally, in addressing RQ4, fact-checkers did predict the network issue agenda of emerging media in 2014 but not in the following years.

Overall online mediascape 2014–2016

Overall, Table 3 provides a look at how influential and autonomous each media's news agendas were from 2014 to 2016 when considering the entire media landscape. This

Table 3. Weighted indegree and outdegree scores by media type.

Media type	Indegree[a]			Outdegree[a]		
	2014	2015	2016	2014	2015	2016
All fact-based media	88	72	66	119	104	104
All online partisan	95	89	95	103	93	82
Conservative	95	103	86	98	82	84
Emerging	103	89	96	106	97	104
Fact-checking	61	47	47	46	37	34
Fake	93	93	77	64	67	61
Liberal	103	87	84	99	83	76
NYT/WaPo	97	92	95	103	70	80
News agencies	97	55	68	81	69	69
Traditional	96	73	77	109	98	97

Indegree scores can be thought of as the degree to which other media predicted that media type. Outdegree can be thought of as the degree to which that media predicted other media types.
[a]All scores here are weighted by number of significant issue relationships (e.g. Granger causality tests) observed.

table presents weighted indegree and outdegree measures, with lower indegree scores denoting more agenda autonomy and higher outdegree scores denoting more agenda influence. Put another way, indegree measures the ability for all other media to explain that media, and outdegree measures the ability that media has to control other media agendas.

Thankfully, fake news media do not appear to be gaining agenda-setting power across the entire mediascape (from 64 in 2014 down to 61 in 2016). This finding stands despite the increased attention partisan media gave to fake news in 2016. This suggests that just as partisan media tuned in more to fake news, other nonpartisan media began to tune out. However, fake news does appear to be diverging from the entire mediascape. Their agendas are becoming more autonomous (from a score of 97 in 2014 down to 77). This is particularly worrisome given fake news' relatively stable ability to influence the entire mediascape. Taken together, while fake news is approximately as powerful as it was in 2014, it appears to be more topically independent than in 2014.

Fact-checkers appear to be the most autonomous group studied here. Their agendas are least explainable by the mediascape. However, this autonomy seems to come at a price. The news mediascape as a whole seems to be paying less attention to them. In particular, the outdegree scores here suggest that fact-checking websites had approximately half (34 compared to 61) of the influence that fake news did in 2016.

Discussion

Fake news spreads on social media and is perhaps more popular than ever (Dewey, 2016; Silverman, 2016). Previous research has shown that American adults are susceptible to fake news headlines (Silverman and Singer-Vine, 2016). Thus, fake news distorts breaking news (Hermann et al., 2016) and may even disrupt global politics (Frenkel, 2016). Our study confirms that content generated from fake news sites is on the rise (see Figure 1) and furthers our understanding of fake news by assessing its ability to "push" or "drive" the popularity of issues in the broader online media ecosystem. Such a rapid rise in fake news content generation is problematic. It remains unclear just why fake news websites now generate more content than ever. Have recent advances in algorithmic content creation allowed fake news to automate news stories?[8] This question begs for further research.

By studying an exhaustive collection of media types across 3 years, a picture of fake news—and the fact-checkers who fight them—has emerged. Fake news did not appear to control the agenda of the whole media landscape from 2014 to 2016. If anything, the NAS power of fake news across all media seems to be steady or slightly declining. This is particularly heartening news for the journalism industry and consumers alike. However, when considering the entire mediascape, the agendas of fake news websites appear to be diverging and becoming more autonomous. This finding is concerning and suggests that fake news has more freedom than ever. Across all 3 years, fake news was able to set the agenda for the key issue of international relations. Moreover, for 2 years, it set the agenda on the issues of the economy and religion. Further study is warranted to examine why these types of fake news stories were so successful in their agenda-setting ability.

Our analysis here also reveals that partisan media are intricately entwined with fake news. On one hand, fake news is particularly responsive to the agendas of partisan media across many issues. For all 3 years studied here, fake news seemed to take cues from the partisan media when it came to stories that mentioned the economy, education, environment, international relations, religion, taxes, and unemployment. If fake news is to be better understood, fought, and ultimately stopped—further study of these issues and what makes them so tempting will ultimately allow journalists to know when the conditions for partisan fake news skimming is ripe.

On the other hand, in 2016, our data suggest that partisan media were far more responsive to the agendas of fake news than in years past. Fake news had the ability to control the popularity for a shocking 12 of the 16 issues studied here. This increased responsiveness could be due to the fact that partisan media were more driven by their motivation to attack the candidates in 2016. When looking at all 3 years studied, partisan media seemed attentive to fake news coverage of border issues, international relations, and religion. While the data presented here cannot offer clear reasons as to why these issues are consistently brought from fake news to the partisan media agenda, we believe that these issues paint an intuitive picture. Partisan media are known largely for their controversial stances on these topics. It could be that partisan media use fake news to not only support their claims but also use the increased Internet "buzz" around these issues as an excuse to continue the discussion with their own fake reportage. As Amazeen (2014) has observed, "Partisan media can be considered a guerilla marketing approach in pursuit of building an agenda that makes a particular ideology seem commonsensical" (p. 287). Thus, further study of the relationship between partisan media and fake media is warranted. Furthermore, in light of recent findings showing the success of partisan media in influencing the news coverage of other media outlets, including mainstream media (Vargo and Guo, 2017; Meraz, 2011), future research should test this potential two-step flow: fake news → partisan media → all online media.

Emerging media, which is also online-only, appears to be responsive to the agendas of fake news, as well. The online nature of emerging media may make it more attentive to all online information, including fake news. Taken all together, online partisan and nonpartisan media were closely intertwined with fake news websites, producing an extremely complicated and uncertain online mediascape.

Fact-checkers appeared to be largely autonomous (see Table 1). Their decisions on what issues to cover did not appear to be dictated by fake news or any other type of news. On one hand, this evidence serves to undermine the accusations of critics who claim fact-checkers display a partisan bias in claim selection (Amazeen, 2013; Davis, 2012). On the other hand, this lack of consistent bias in attention suggests that fact-checking websites are not aggressively refuting certain media. Indeed, due largely to resource-driven constraints, early fact-checking conventions were to correct a claim and move on. Even when patterns of deception were evident, fact-checkers saw "little point in repeating ourselves … we didn't run a new story every time" (the same inaccurate claim emerged; Amazeen, 2012: 43). Fact-checkers have only begun to pivot toward an "ongoing story structure" that facilitates connecting fact-checks to claims that persist (Amazeen, 2013: 27). The previously mentioned initiative by Facebook to algorithmically include fact-checkers as third-party network agents is one example of this necessary convention.

The results of this study also suggest that fact-checkers were not influential in predicting the agenda of news media overall. This is consistent with other research indicating that corrections do not spread as widely as misinformation (Friggeri et al., 2014; Zollo et al., 2015). It also illustrates the difficulties fact-checkers face in achieving their goal of influencing other journalists (Amazeen, 2013; Graves and Konieczna, 2015). However, this analysis only collected data from independent fact-checkers unaffiliated with media organizations. Had the study included news sites that offered fact-checking in addition to other reporting (e.g. the *Washington Post*'s Fact Checker), the results may have differed. Nonetheless, this is a networked problem that must be solved collectively, particularly as new evidence suggests the spread of misinformation is facilitated by nonhuman "bots" that give the illusion a topic is popular (Flam, 2017).

In all, this analysis shows that fake news can influence the issue agendas of partisan and emerging news media coverage. While the influence that fake news had on partisan media grew in 2016, the overall influence of fake news on the entire mediascape appears unchanged. This suggests that just as partisan media adopted fake news agendas, other media began to resist. Further research should study the increasing link between partisan media and fake news. One possible explanation for this finding is that partisan media have begun to leverage fake news to bolster and selectively support their own agendas. If this is indeed the case, it is yet another cause for concern regarding the effects of partisan media on a healthy society.

It is important to reiterate: the agenda-setting effect does not mean media coverage was littered with the same factual errors. In many cases, news media likely adopted fake news agendas to refute claims. A notable limitation of this study is that it stops short of measuring the agenda-setting power of specific false claims that fake news generates, a direction future research should consider pursuing.

Still, the power of altering issue salience is not one to be taken lightly. As Donald Trump himself once said in his book *The Art of the Deal* (Trump and Schwartz, 2009, p. 57):

I'm not saying that [journalists] necessarily like me. Sometimes they write positively, and sometimes they write negatively. But from a pure business point of view, the benefits of being written about have far outweighed the drawbacks. It's really quite simple. If I take a full-page ad in the New York Times to publicize a project, it might cost $40,000, and in any case, people tend to be skeptical about advertising. But if the New York Times writes even a moderately positive one-column story about one of my deals, it doesn't cost me anything, and it's worth a lot more than $40,000…. the point is that we got a lot of attention, and that alone creates value.

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Notes

1. Global Database of Events, Language, and Tone (GDELT) indexes news stories from Associated Press, United Press International, *Washington Post*, the *New York Times*, and all national and international news from Google News with the exception of sports, entertainment, and strictly economic news.
2. GDELT researchers create themes by training a computer system. The system recognizes keywords in text that are associated with a theme. Leetaru (2012b) lays out the structure of the underlying algorithms. To validate a theme, the manual review of randomly selected articles is conducted to ensure external validity. GDELT maintains that theme detection is accurate and on par with leading computer-assisted classification systems (Leetaru, 2012b).
3. To establish a theme, a machine learning algorithm is trained to recognize keywords in text that is associated with that theme. Leetaru (2012b) outlines the process, but in general, a theme is trained through feeding the system articles identified by humans. Humans review randomly selected articles to verify the final algorithm's accuracy. The results show that GDELT's CKG system performs well (Leetaru, 2012b).
4. Vargo and Guo (2017) tasked human coders to match GDELT themes to the 16 issue constructs. Coders agreed on 271 of the 285 theme assignments ($\alpha = 0.841$).
5. The full list of sources, as well as the fake news websites themselves, is hosted by Indiana University here: https://docs.google.com/spreadsheets/d/1S5eDzOUEByRcHSwSNmSqjQMpaKcKXmUzYT6YlRy3UOg
6. An important distinction here is that we are not asserting that each and every story in our database of fake news websites is fake. Instead, we are looking more broadly at the agendas of websites that are known to create fake news. Previous studies have looked at the individual influence that specific fake news articles have on society. Here, we take a look at the entire body of work that a fake news website creates. This allows us to see whether fake news agendas have broader effects on the journalism industry.
7. In the previous list, partisan allegations on Wikipedia served as a basis for paritisanship (Vargo and Guo, 2017). At the time of this analysis, some pages had clearer Wikipedia (or other sources) mentions denoting or accusing of partisan behavior.
8. Ultimately, this study did not identify who the actors behind these fake news websites are. While previous research has suggested that most fake news is monetarily driven (Maheshwari, 2016), the specific methods by which stories are created is largely unknown. Is fake news computerized and algorithmic? While our study did not tackle this question, our research shows that fake news appears to be more autonomous than ever. This means that fake news is not simply amplifying agendas of existing media but creating their own original agendas.

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Michelle A Amazeen (PhD, Temple University) is an assistant professor at Boston University. Her research examines misinformation and the blurred lines between advertising, journalism, and politics. A multi-method researcher, she explores how various types of consumer and political misinformation affect public perceptions and the effectiveness of correction efforts. Her research on fact-checking has been funded by the American Press Institute as is her current research on studying the effects of native advertising disclosure transparency on publisher reputations.