Research Article

Trends in the diffusion of misinformation on social media

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Hunt Allcott[1], Matthew Gentzkow[2] and Chuan Yu[3]

Abstract
In recent years, there has been widespread concern that misinformation on social media is damaging societies and democratic institutions. In response, social media platforms have announced actions to limit the spread of false content. We measure trends in the diffusion of content from 569 fake news websites and 9540 fake news stories on Facebook and Twitter between January 2015 and July 2018. User interactions with false content rose steadily on both Facebook and Twitter through the end of 2016. Since then, however, interactions with false content have fallen sharply on Facebook while continuing to rise on Twitter, with the ratio of Facebook engagements to Twitter shares decreasing by 60%. In comparison, interactions with other news, business, or culture sites have followed similar trends on both platforms. Our results suggest that the relative magnitude of the misinformation problem on Facebook has declined since its peak.

Keywords
Misinformation, fake news, social media

Introduction

Although the political process has a long history of misinformation and popular misperceptions, misinformation on social media has caused widespread alarm in recent years (Flynn et al., 2017; Lazer et al., 2018). A substantial number of US adults were exposed to false stories prior to the 2016 election, and post-election surveys suggest that many people who read these stories believed them to be true (Allcott and Gentzkow, 2017; Guess et al., 2018). Many argue that false stories played a major role in the 2016 election (e.g. Gunther et al., 2018; Parkinson, 2016), and in the ongoing political divisions and crises that have followed it (e.g. Azzimonti and Fernandes, 2018; Spohr, 2017). In response, Facebook and other social media companies have made a range of algorithmic and policy changes to limit the spread of false content. In the Online Appendix, we list 12 announcements by Facebook and five by Twitter aimed at reducing the circulation of misinformation on their platforms since the 2016 election.

Evidence of how the scale of the misinformation problem is evolving remains limited.[1] A recent study argues that false stories remain a problem on Facebook even after changes to the platform's news feed algorithm in early 2018 (NewsWhip, 2018). Many articles that have been rated as false by major fact-checking organizations have not been flagged in Facebook's system, and two major fake news sites have seen little or no decline in Facebook engagements since early 2016 (Funke, 2018). Facebook's now-discontinued strategy of flagging inaccurate stories as "Disputed" has been shown to modestly lower the perceived accuracy of flagged headlines (Clayton et al., 2019), though some research suggests that the presence of warnings can cause untagged false stories to be seen as more accurate (Pennycook and Rand, 2017). Media commentators have argued that efforts to fight misinformation through fact checking are "not working" (Levin, 2017) and that misinformation overall is "becoming unstoppable" (Ghosh and Scott, 2018).

In this paper, we present new evidence on the volume of misinformation circulated on social media from January 2015 to July 2018. We assemble a list of 569 sites identified

[1]New York University, Microsoft Research, and NBER, USA
[2]Stanford University and NBER, USA
[3]Stanford University, USA

Corresponding author:
Chuan Yu, Stanford University, 579 Serra Mall, Stanford, CA 94305, USA.
Email: chuanyu@stanford.edu

as sources of false stories in a set of five previous studies and online lists. We refer to these collectively as *fake news sites*. We measure the volume of Facebook engagements and Twitter shares for all stories on these sites by month using data from BuzzSumo (www.buzzsumo.com).[2] As points of comparison, we also measure the same outcomes for stories on (a) a set of major news sites; (b) a set of small news sites not identified as producing misinformation; and (c) a set of sites covering business and culture topics.

The results show that interactions with the fake news sites in our database rose steadily on both Facebook and Twitter from early 2015 to the months just after the 2016 election. Interactions then declined by more than half on Facebook, while they continued to rise on Twitter. The ratio of Facebook engagements to Twitter shares was roughly steady at around 45:1 from the beginning of our period to late 2016, then fell to approximately 15:1 by the end of our sample period. In contrast, interactions with major news sites, small news sites, and business and culture sites have all remained relatively stable over time, and have followed similar trends on Facebook and Twitter both before and after the 2016 election. While this evidence is far from definitive and is subject to important caveats discussed below, we see it as consistent with the view that the overall magnitude of the misinformation problem may have declined, possibly due to changes to the Facebook platform following the 2016 election.

Our results also reveal that the absolute level of interaction with misinformation remains high and that Facebook continues to play a particularly important role in its diffusion. In the period around the election, fake news sites received about two-thirds as many Facebook engagements as the 38 major news sites in our sample. Even after the post-election decline, Facebook engagements with fake news sites still average roughly 60 million per month.

This research demonstrates how novel data on social media usage can be used to understand important questions in political science around media exposure and social media platforms' content moderation practices. Parallel work released soon after our working paper finds broadly similar results (Resnick et al., 2018).

Data

We compiled a list of sites producing false stories by combining five previous lists: (a) an academic paper by Grinberg et al. (2019; 490 sites); (b) PolitiFact's article titled "PolitiFact's guide to fake news websites and what they peddle" (Gillin, 2017; 324 sites); (c) three articles by BuzzFeed on fake news (Silverman, 2016; Silverman et al., 2017a,. 2017b; 223 sites); (d) an academic paper by Guess et al. (2018; 92 sites); and (e) FactCheck's article titled "Websites that post fake and satirical stories" (Schaedel, 2017; 61 sites). The two lists from academic papers originally derive from subsets of the other three, plus Snopes.com, another independent fact-checking site, and lists assembled by blogger Brayton (2016) and media studies scholar Zimdars (2016). The union of these five lists is our set of fake news sites.

PolitiFact and FactCheck work directly with Facebook to evaluate the veracity of stories flagged by Facebook users as potentially false. Thus, these lists comprise fake news sites that Facebook is likely to be aware are fake. As a consequence, our results may be weighted toward diffusion of *misinformation that Facebook is aware of*, and may not fully capture trends in *misinformation that Facebook is not aware of*. It is difficult to assess how large this latter group might be. Our list almost certainly includes the most important providers of false stories, as Facebook users can flag any and all questionable articles for review. On the other hand, the list likely excludes a large tail of web domains that are small and/or active for only a short period.

Combining these five lists yields a total of 672 unique fake news sites. We report in the Online Appendix the 50 largest sites in terms of total Facebook engagements plus Twitter shares during the sample period. In our robustness checks, we consider alternative rules for selecting the set of fake news sites.

We select three sets of comparison sites based on Alexa (www.alexa.com). Alexa measures web traffic using its global traffic panel, a sample of millions of Internet users who have installed browser extensions allowing their browsing data to be recorded, plus data from websites that use Alexa to measure their traffic. It then ranks sites based on a combined measure of unique visitors and page views. We define *major news sites* to be the top 100 sites in Alexa's News category. We define *small news sites* to be the sites ranked 401–500 in the News category. We define *business and culture sites* to be the top 50 sites in each of the Arts, Business, Health, Recreation, and Sports categories. Some previous research also uses Alexa's lists (e.g. Allcott and Gentzkow, 2017; Flaxman et al., 2016). For each of these groups, we exclude from our sample government websites, databases, sites that do not mainly produce news or similar content,[3] international sites whose audiences are primarily outside the USA,[4] and sites that are included in our list of fake news sites. Our final sample of comparison sites includes 38 major news sites, 78 small news sites, and 54 business and culture sites. Table 1 provides examples of sites in each category. The complete lists can be found in the Online Appendix. We also include a diagram in the Online Appendix summarizing the decisions made during the sample selection to illustrate how we reach the final sample.

We gather monthly Facebook engagements and Twitter shares of all articles published on both fake news sites and comparison sites from January 2015 to July 2018 from BuzzSumo. BuzzSumo is a commercial content database that tracks the volume of user interactions with internet content on Facebook, Twitter, and other social media platforms. It then uses Facebook APIs to get Facebook engagements for each URL and purchases data on share counts for

Table 1. Examples of sites in each category.

Category	Site		
Major News Sites	cnn.com	nytimes.com	theguardian.com
	washingtonpost.com	foxnews.com	huffingtonpost.com
	usatoday.com	wsj.com	cnbc.com
	reuters.com	time.com	nypost.com
	usnews.com	cbsnews.com	chron.com
Small News Sites	aspentimes.com	bakersfield.com	bendbulletin.com
	bnd.com	broadcastingcable.com	charlestoncitypaper.com
	chicagomaroon.com	collegian.psu.edu	columbian.com
	dailynebraskan.com	dailynexus.com	dailynorthwestern.com
	dailypress.com	dailyprogress.com	dailytexanonline.com
Business and Culture Sites	imdb.com	ign.com	rottentomatoes.com
	forbes.com	shutterstock.com	businessinsider.com
	webmd.com	psychologytoday.com	who.int
	9gag.com	jalopnik.com	timeout.com
	espn.com	cricbuzz.com	nba.com
Fake News Sites	dailywire.com	ijr.com	dailycaller.com
	occupydemocrats.com	express.co.uk	redstatewatcher.com
	thepoliticalinsider.com	thefederalistpapers.org	truthfeed.com
	bipartisanreport.com	rightwingnews.com	qpolitical.com
	madworldnews.com	yournewswire.com	uschronicle.com

Notes: This table lists examples of comparison sites and fake news sites. *Major News Sites* include 38 sites selected from the top 100 sites in Alexa's News category. *Small News Sites* include 78 sites selected from the sites ranking 401–500 in the News category. *Business and Culture Sites* include 54 sites selected from the top 50 sites in each of the Arts, Business, Health, Recreation, and Sports categories. *Fake News Sites* include 569 sites assembled from five lists. For each comparison group, we omit from our sample government websites, databases, sites that do not mainly produce news or similar content, international sites whose audiences are primarily outside the USA, and sites that are included in our list of fake news sites.

each URL from Twitter. BuzzSumo data has been used in prior research (e.g. Allcott and Gentzkow, 2017; Mehta and Guzman, 2018; Waszak et al., 2018).

We use BuzzSumo's data on total Facebook engagements and total Twitter shares by originating website and month. Facebook engagements are defined as the sum of shares, comments, and reactions such as "likes." BuzzSumo does not provide a decomposition of Facebook engagements at the site level, so we cannot directly compare Facebook shares with Twitter shares. Ideally, we would measure exposure to fake articles using data on views, but such data are not publicly available. We sum the monthly Facebook engagements and Twitter shares of articles from all sites in each category and then average by quarter.

We are able to obtain BuzzSumo data for 569 of our 672 fake news sites, and for all of our major news, small news, and business and culture sites. This set of sites comprises our main sample. Supplemental data from other web measurement companies suggests that the 103 fake news sites for which we could not obtain BuzzSumo data are likely small. According to Alexa, the sum of the average daily reach of the 103 missing sites is 0.0232%, compared with 0.9012% for the other 569 sites in our sample. None of the missing sites are indexed by ComScore, and only 22% are indexed by SimpleWeb (www.simpleweb.com). Those that are indexed by SimpleWeb have an average global traffic rank of 16,344,129. Only one of the 103 missing sites was in active operation as of July 21, 2018, according to Alexa. Together, these facts suggest that the omission of these sites should have limited influence on our total counts of engagements, although we cannot rule out the possibility that it introduces meaningful bias.

In practice, the fake news sites in our data carry some combination of true news and clickbait in addition to misleading and false content. To more precisely focus attention on the latter, besides the site-level data described above, we also gather a list of specific URLs spreading misinformation. We scrape all claims on the fact-checking site Snopes.com that are classified as "false" or "mostly false." In late 2015, Snopes began to provide permanent URLs for the sources of these false claims through a web-archiving site, archive.is. We collect all these URLs for articles published in 2016 or later, yielding an intermediate sample of 1535 article URLs. We then extract keywords from the titles of these articles and capture all articles in the BuzzSumo database published in 2016 or later that contain these keywords and have at least 100 Facebook engagements or 10 Twitter shares. This yields a sample of 11,351 URLs. Finally, a research assistant manually screened out those that are not in fact asserting the claim associated with the original Snopes article, leading to a final sample of 9540 false stories URLs. The Online Appendix provides more detail on this procedure.

Results

Figure 1 shows trends in the number of Facebook engagements and Twitter shares of stories from each category of sites. Note that the scales of the y-axis are different between different categories. Interactions for major news sites, small news sites, and business and culture sites have remained relatively stable during the past two years, and follow similar trends on Facebook and Twitter. Both platforms show a modest upward trend for major news and small news sites, and a modest downward trend for business and culture sites. In contrast, interactions with fake news have changed more dramatically over time, and these changes are very different on the two platforms. Fake news interactions increased steadily on both platforms from the beginning of 2015 up to the 2016 election. Following the election, however, Facebook engagements fell sharply (declining by more than 50%), while Twitter shares continued to increase.

Figure 2 shows our main result: trends in the ratios of Facebook engagements to Twitter shares. The ratios have been relatively stable for major news, small news, and business and culture sites. For fake news sites, however, the ratio has declined sharply, from around 45:1 during the election to around 15:1 two years later.

While these results suggest that the circulation of misinformation on Facebook has declined, it is important to emphasize that the absolute quantity of interactions with misinformation on both platforms remains large and that Facebook in particular has played an outsized role in its diffusion. Figure 1 shows that Facebook engagements fell from a peak of roughly 160 million per month at the end of 2016 to roughly 60 million per month at the end of our sample period. As a point of comparison, the 38 major news sites in the top left panel—including the *New York Times, Wall Street Journal, CNN, Fox News*, etc.—typically garner about 200–250 million Facebook engagements per month. On Twitter, shares of false content have been in the 3–5 million per month range since the end of 2016, compared to roughly 20 million per month for the major news sites.

Figure 3 presents the results for our list of false story URLs. Since the number of URLs we capture starts close to zero in 2016 and grows from month to month, there is a steeper increase in Facebook and Twitter interactions with these URLs than that in the site-level analysis. Similar to the site-level analysis, the ratio of Facebook engagements to Twitter shares has declined by half or more after the 2016 election. For this set of URLs, we have both Facebook engagements and Facebook shares and they are highly correlated. We report the same figure using Facebook shares in the Online Appendix. The median ratio of Facebook engagements to Facebook shares in this set of false stories URLs is around 6.

Interpretation and robustness checks

Our evidence is subject to many important caveats and must be interpreted with caution. This is particularly true for the raw trends in interactions. While we have attempted to make our database of false stories as comprehensive as possible, it is likely far from complete, and many factors could generate selection biases that vary over time. The raw decline in Facebook engagements may partly reflect the under-sampling of sites that could have entered or gained popularity later in our sample period, as well as efforts by producers of misinformation to evade detection on Facebook by changing their domain names. It may also reflect changes over time in demand for highly partisan political content that would have existed absent efforts to fight misinformation, and could reverse in the future; for example, in the run-up to future elections. Actions by policymakers and civil society organizations to improve media literacy could have also affected the observed trends, independently of actions by the platforms (Strauss, 2018; Zubrzycki, 2017).

We see the comparison of Facebook engagements to Twitter shares as potentially more informative. If the design of these platforms and the behavior of their users were stable over time, we might expect sample selection biases or demand changes to have similar proportional effects, and thus leave the ratio of Facebook engagements to Twitter shares roughly unchanged. For example, we might expect producers changing domain names to evade detection to produce similar declines in our measured interactions on both platforms. The fact that Facebook engagements and Twitter shares follow similar trends prior to late 2016 and for the non-fake-news sites in our data, but diverge sharply for fake news sites following the election, suggests that some factor has slowed the relative diffusion of misinformation on Facebook. The suite of policy and algorithmic changes made by Facebook following the election is one plausible candidate, though we have no direct evidence on this or other possible causes.

We stress that even the relative comparison of the platforms is only suggestive. Both Facebook and Twitter have made changes to their platforms, and so this measure at best captures the relative effect of the former compared to the latter. Engagements on Facebook affect sharing on Twitter and vice versa. The selection of stories into our database could for various reasons differentially favor the kinds of stories likely to be shared on one platform or the other, and this selection could vary over time. Demand changes need not have the same proportional effect on the two platforms. Some of these factors would tend to attenuate changes in the Facebook–Twitter ratio, leading our results to be conservative, but others could produce a spurious decrease over time.

Finally, it is important to keep in mind the potential limitations of our engagement data from BuzzSumo. Since the BuzzSumo data are obtained directly from the Facebook API and from Twitter, we expect them to be reasonably accurate. However, we do not have independent validation of their accuracy, and there may be reasons why the engagements they record do not exactly match what would be recorded internally by the platforms. In addition, it is possible that our results could be affected by the 103 sites for which BuzzSumo has no data. The evidence above suggests

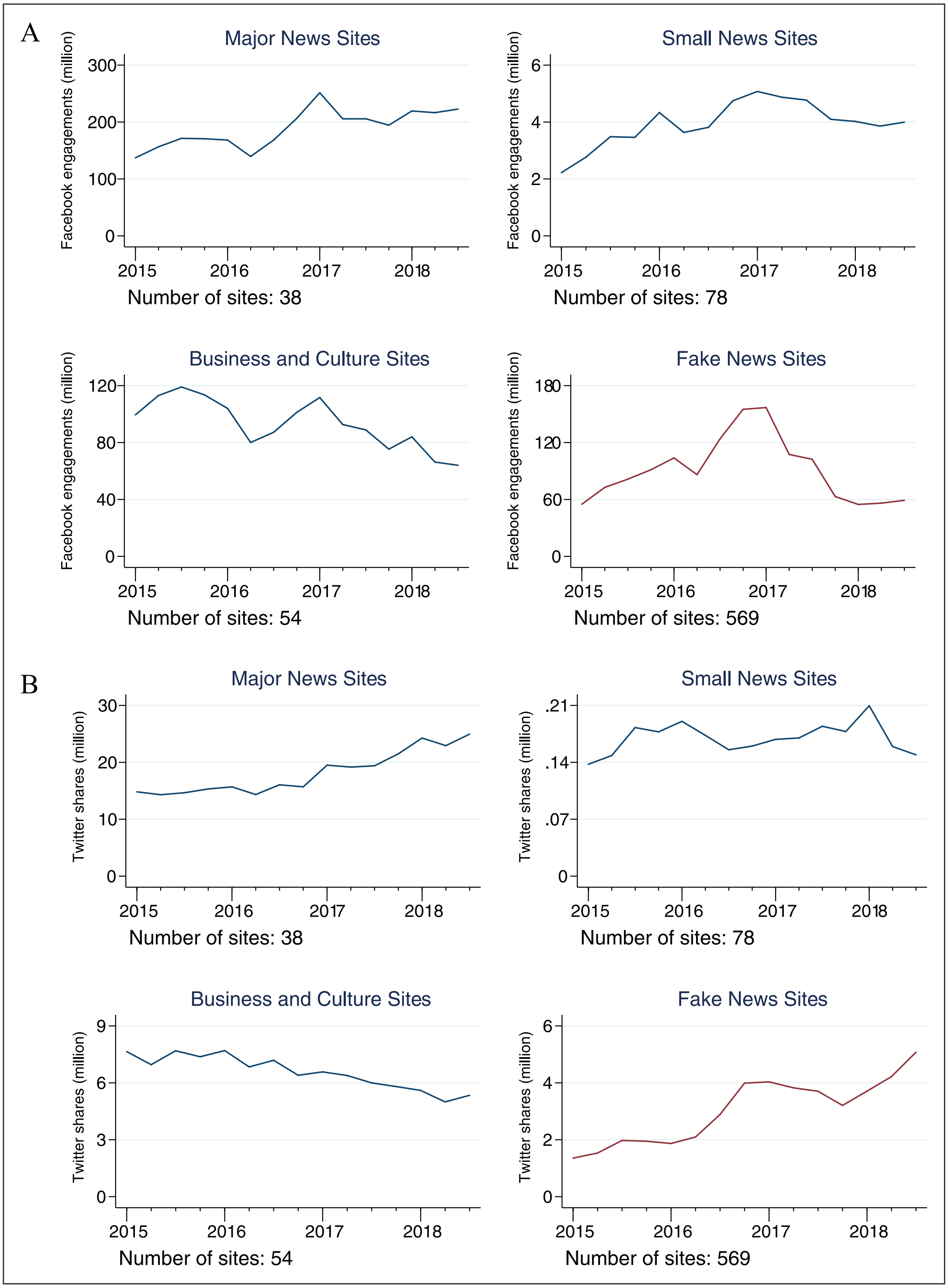

Figure 1. Engagement on Facebook and Twitter.
Panel A: Facebook Engagements.
Panel B: Twitter Shares.
Notes. This figure shows monthly Facebook engagements and Twitter shares of all articles published on sites in different categories averaged by quarter. Data comes from BuzzSumo. Major News Sites include 38 sites selected from the top 100 sites in Alexa's News category. Small News Sites include 78 sites selected from the sites ranking 401–500 in the News category. Business and Culture Sites include 54 sites selected from the top 50 sites in each of the Arts, Business, Health, Recreation, and Sports categories. Fake News Sites include 569 sites assembled from five lists. The complete lists can be found in the Online Appendix.

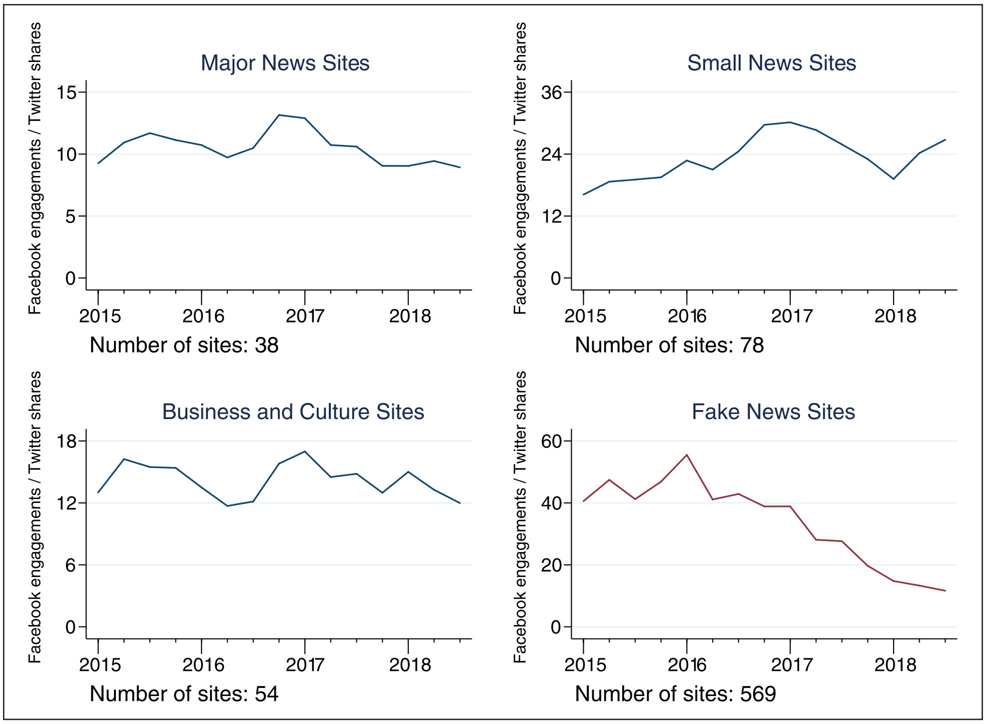

Figure 2. Relative engagement on Facebook.
Notes. This figure shows the monthly ratio of Facebook engagements to Twitter shares of all articles published on sites in different categories averaged by quarter. Data comes from BuzzSumo. Major News Sites include 38 sites selected from the top 100 sites in Alexa's News category. Small News Sites include 78 sites selected from the sites ranking 401–500 in the News category. Business and Culture Sites include 54 sites selected from the top 50 sites in each of the Arts, Business, Health, Recreation, and Sports categories. Fake News Sites include 569 sites assembled from five lists. The complete lists can be found in the Online Appendix.

that these sites are small, but we cannot rule out the possibility that including them would increase or decrease the relative decline in fake news we observe on Facebook.

We report a number of robustness checks in the Online Appendix, most of which are designed to address concerns about selection into our sample of sites. First, as Lim (2018) points out, the inter-rater reliability between fact-checking organizations may be relatively low due to ambiguity. One single fact-checking organization may incorrectly include sites that should not be counted as fake news sites. So we restrict to sites that are identified as fake news sites by at least two or three of our original five lists, which leaves 116 and 19 sites, respectively. Second, given that people might disagree with any one particular study's list of fake news sites, we run five additional analyses, each excluding fake news sites identified exclusively by one of our five lists. Third, we focus on sites that started active operations after November 2016, sites that were still in active operation as of July 2018, and sites that were in active operation from August 2015 to July 2018, which leaves 152, 140, and 81 sites respectively. (Active operation is defined to have a global traffic rank reported by Alexa of at least one million.) Fourth, we exclude the five largest sites in terms of total interactions to ensure the trend is not driven solely by outliers. We also look at sites in the first decile and sites in the bottom nine deciles separately to see if the trend holds for both large sites and small sites. Fifth, Grinberg et al. (2019) provide three lists of sites classified by different likelihoods to publish misinformation. We look at each of these lists separately. Sixth, we present an alternative comparison group: a small set of politically focused sites such as Politico and The Hill. These sites do see a decline in engagements on Facebook relative to Twitter, but it mainly occurred in late 2015. Finally, we present results using only the count of Facebook shares instead of engagements, which includes shares, comments, and reactions such as "likes." Our main qualitative conclusions remain consistent across all these checks, though the exact size and shape of the trends vary.

Conclusion

The diffusion of misinformation through social media is a potential threat to democracy and broader society. While its potential effects have been much discussed, there is little evidence on how the scale of the problem has evolved in recent years. We show that user interactions with false content rose steadily on both Facebook and Twitter through the end of 2016. Since then, interactions have fallen sharply on Facebook while continuing to rise on Twitter. These results suggest that

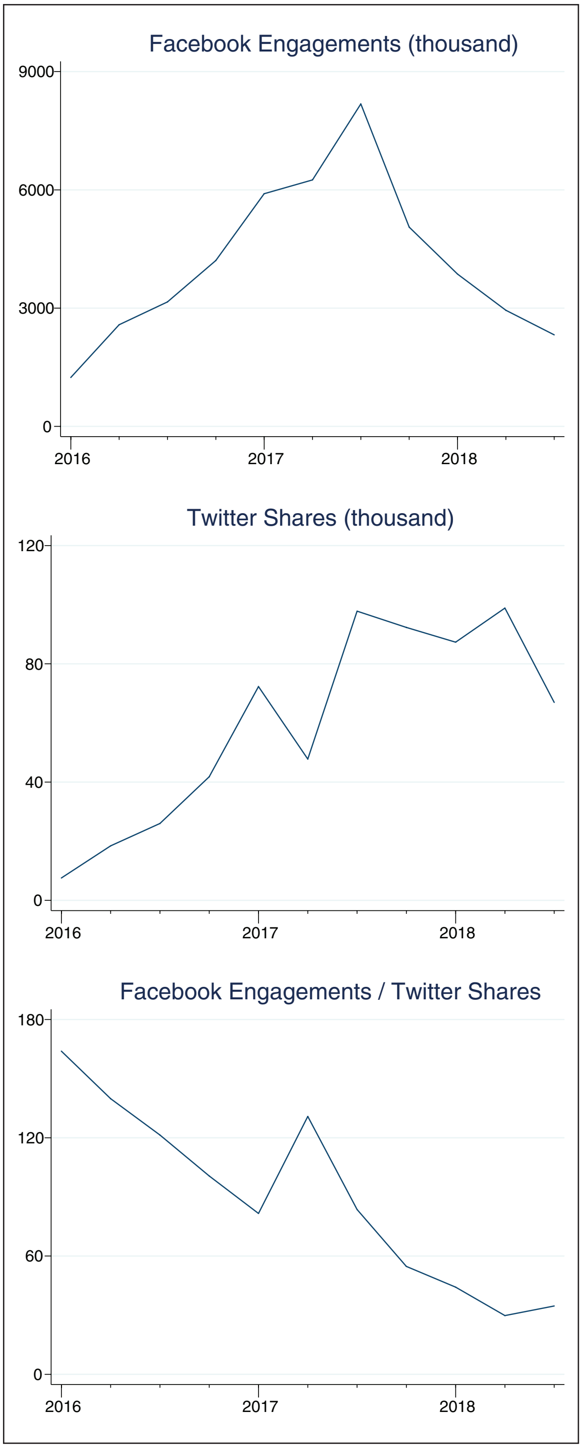

Figure 3. Engagement on Facebook and Twitter for fake news URLs.
Notes. This figure shows Facebook engagements, Twitter shares, and the ratio of Facebook engagements to Twitter shares of a set of 9,540 URLs spreading misinformation. See the "Data" section for details on how the set of URLs is constructed. We sum the Facebook engagements and Twitter shares of all URLs by month and average by quarter.

the relative magnitude of the misinformation problem on Facebook has declined since its peak. One hypothesis is that these trends reflect changes to the Facebook platform implemented since the 2016 election, which were designed to combat misinformation, although directly testing the ultimate cause is beyond the scope of our study. Our findings are consistent with contemporaneous work by Resnick et al. (2018) and contribute to the broader literature on misinformation (e.g. Allcott and Gentzkow, 2017; Grinberg et al., 2019; Guess et al., 2018; Lazer et al., 2018).

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The replication files are available at https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/YAR9FU

Notes

1. Lazer et al. (2018) write, "There is little research focused on fake news and no comprehensive data-collection system to provide a dynamic understanding of how pervasive systems of fake news provision are evolving … researchers need to conduct a rigorous, ongoing audit of how the major platforms filter information" (p. 1096).
2. We describe the BuzzSumo data in detail in the "Data" section below. We discuss important caveats associated with these data in the "Interpretation and robustness checks" section below.
3. Examples include chase.com, booking.com, xfinity.com, spotify.com, and target.com.
4. Examples include bbc.co.uk, indiatimes.com, news.com.au, chinadaily.com.cn, and dw.com.

ORCID iD

Chuan Yu https://orcid.org/0000-0003-0112-3611

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