Market Forces: Quantifying the Role of Top Credible Ad Servers in the Fake News Ecosystem

Lia Bozarth and Ceren Budak
University of Michigan, School of Information
lbozarth,cbudak@umich.edu

Abstract

Larry Lessig argues that four modes regulate behavior in cyberspace: laws, markets, norms, and architecture. How can these four modes regulate the production and spread of fake news? In this paper, we focus on *markets* and empirically evaluate one particular market-based solution: top ad firms blacklisting fake news producers to eliminate their revenue sources. Our study reveals that fake and low-quality publishers demonstrate a higher tendency to serve more ads and to partner with risky ad servers than traditional news media with similar popularity and age. However, fake news publishers are still strongly reliant on credible ad servers. In fact, the top-10 credible ad servers alone account for 66.7% and 55.6% of fake and low-quality ad traffic respectively. Furthermore, our back-of-the-envelope calculation shows that, at the time of our data collection, the top-10 ad firms were receiving \$985.7K to \$1.15M monthly from web traffic on fake news sites, a negligible fraction of these firms' annual revenue. Overall, our findings suggest that having top ad firms blacklist known fake and low-quality publishers is a low-cost way to combat fake news.

Introduction

The spread of fake news has significant detrimental effects including deteriorating public trust in the established political and media institutions, deepening the suspicion and animosity between populations, and threatening the legitimacy of elections around the world (Silverman 2017; Lazer et al. 2018; Fletcher et al. 2018). Alarmed by its adverse impact, researchers, lawmakers, affected tech firms, and other interested parties have explored various methods to identify and curtail the spread of fake news.

These approaches, according to Larry Lessig's framework of cyberspace regulation, can be broadly categorized into 4 modes: *architecture, law, norms* and *markets* (Lessig 1998, 2006; Verstraete, Bambauer, and Bambauer 2017). Indeed, tech giants such as Facebook and Microsoft have updated the *architecture*, or the code/features, of their platforms to include fake news detectors and to warn users about articles shared from questionable sources (Tian, Zhang, and Peng 2020). Similarly, policymakers propose combating fake news through the rules of *law*, such as requiring platforms to remove false stories with the potential to ignite communal tension (Coyle 2016; Iosifidis and Andrews 2019; Feingold 2017). Many online communities (e.g. the subReddit "r/ElizabethWarren" on Reddit) have imposed or partially imposed community *norms* targeted at fake news (e.g., banning articles from known questionable news publishers). These are all noteworthy endeavors.

In this paper, we focus on the fourth mode of regulation: *markets*. Specifically, we examine whether it is possible to curtail fake news by disrupting its ad revenue pipeline. The success of curbing fake news through markets primarily depends on the incentives of fake news producers and our ability to remove these incentives. Some individuals and organizations create and spread fake news due to deep-rooted partisanship and covert opposition operations (Silverman 2017; Kucharski 2016). These motivations have been at the forefront of fake news discussions. But, financial motivations are just as significant (Mustafaraj and Metaxas 2017; Bakir and McStay 2018; Mills, Pitt, and Ferguson 2019), given the ease with which revenue-seeking parties can set up fake news sites and use them to monetize traffic through ads. The behavior of such agents can be changed by making fake news production less profitable.

There are some ongoing efforts by consumers (Braun, Coakley, and West 2019), retailers (Mills, Pitt, and Ferguson 2019), and platforms (Figueira and Oliveira 2017) to use the power of markets to curb fake news. The policy and legal scholarship provides the theoretical grounding for how market forces, such as top ad firms blacklisting known fake news sites, can disrupt this ecosystem (Verstraete, Bambauer, and Bambauer 2017; Timmer 2016; Tambini 2017; Vasu et al. 2018; Kshetri and Voas 2017; Bakir and McStay 2018; Braun and Eklund 2019; Coyle 2016). Thus far, however, the scholarship lacks empirical evidence. This is the knowledge gap we fill in this paper.

To shed light on this issue, we empirically investigate the extent to which fake and other low-quality news producers rely on display advertising to generate revenue. We further examine—and situate our findings in terms of—traditional news producer behavior. To do so, we tracked the ads served on fake, low-quality, and traditional news outlets over 12 weeks. The resulting dataset includes 1.32M ads served by 565 unique ad servers on 1.6K news sites. We start by examining the similarities and differences between fake and traditional news producer reliance on ad traffic and ask:

RQ1: *To what extent is (i.) traditional, (ii.) fake, and (iii.) other low-quality news producer traffic supported by ad servers? What types of ad servers provide such support?*

We compare and contrast the number and quality of ads and ad servers observed for these three types of news publishers and identify important distinctions. Surprisingly, we find that a smaller fraction of fake and low-quality news sites show fewer ads than traditional news sites. This may come as a surprise given the expectation that fake news publishers are aggressively profit-driven (Braun and Eklund 2019). Yet, ad prevalence is driven by both *ability* and *intention* to profit from ad traffic. Indeed, upon controlling for domain popularity and age—factors that affect the ability to monetize traffic through ads—*fake* domains are revealed to have significantly more ad servers (10 more on average) and ads than traditional publishers. Likewise, on average, ad servers present on fake news sites are also 4% more likely to be risky than those on traditional sites.

While such important distinctions exist, we show that a large fraction of fake news sites—much like traditional news sites—have substantial support from credible ad servers. This finding suggests that the fake news ecosystem can be disrupted if such credible ad firms change behavior. But, convincing *all* ad servers to blacklist fake news publishers is hard—if not impossible. Thus, it is crucial to assess whether convincing *a handful of the most popular* ad servers could work effectively. As such, we ask:

RQ2: *How concentrated is fake and other low-quality news sites' ad reliance on a small number of top credible ad servers?*

Furthermore, as profit-maximizing entities, ad firms will need to trade off the branding benefits of banning problematic sites against the resulting loss in revenue. In other words, our ability to convince ad firms to blacklist fake news sites will depend on how much they are currently benefiting from such a partnership. Therefore, we ask:

RQ3: *What is the cost to ad firms of blacklisting fake and low-quality news sites and how does that cost vary by news publisher type?*

Surprisingly, we see that 66.7% of all ad traffic on fake news domains is delivered by the top-10 credible ad servers compared to 55.6% and 49.6% on low-quality and traditional news sites. That is, top credible ad servers played an even bigger role in generating ad revenue for fake news domains that publish entirely fabricated stories. Additionally, using a back-of-the-envelope calculation, we estimate that top-10 ad firms generate monthly revenue of $985.7K to $1.15M by delivering ads on fake and low-quality news domains—a negligible fraction of the firms' annual revenue.

Finally, deciding whether a content provider is a fake or low-quality news publisher is a challenging task (Tandoc Jr, Lim, and Ling 2018). Therefore, following the guidance of (Bozarth, Saraf, and Budak 2020) who provide a meta-analysis of fake news lists, we use 2 distinct lists of fake

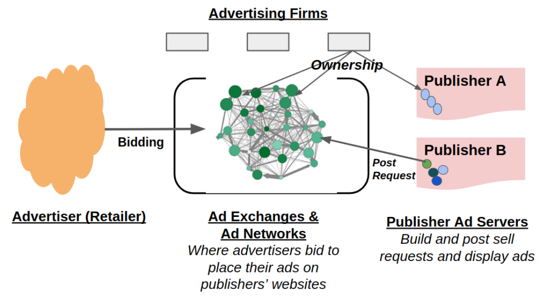


Figure 1: Simplified advertisement ecosystem.

and traditional news sites to show that our results are robust. In sum, our analysis demonstrates that fake news sites are surprisingly dependent on top credible ad firms. Having these firms blacklist such publishers is a simple and effective strategy to combat fake news without hurting the firms' bottom line. While we acknowledge the First Amendment issues and cannot settle what role platforms or ad firms *ought to* play in regulating speech, we address the economics of this policy debate through a large-scale empirical analysis.

An Overview of the Ad Ecosystem

A simplified online advertising ecosystem is shown in Figure 1. Briefly, a news site (salmon-colored shapes in Figure 1), especially one with substantial web traffic, can have many supply-side ad servers (simply referred to as ad servers in our paper) managing separate ad spaces on the site. In Figure 1, ad servers are represented as various blue-colored dots. As shown, Publisher A has a single ad server with 3 dedicated ad spaces; in comparison, publisher B has 4 unique ad servers each with a single ad space. When a user lands on the site, each ad server builds a corresponding ad selling request for each of its ad spaces on the page, and then posts the requests to ad exchanges (or ad networks) [1] where interested advertisers can start bidding for the ad spaces (see Figure 1). After iterations of bids, the highest-bidding advertisers win and their ads are displayed to the user (Choi et al. 2019). The advertisers have limited control over which publishers ultimately display their messages. They can set broad filters in this bidding process (e.g. no porn sites) but cannot specify specific domains to avoid, which can lead to them inadvertently funding or rewarding fake news without ad servers taking action (Tambini 2017). Additionally, ad servers have varied capabilities: some track users, while others are primarily tasked with displaying ads. Further, an ad server can be a built-in module for certain ad networks or ad exchanges (e.g., Google's *DoubleClick For Publishers* is an ad server that is bundled with the firm's own ad exchange). An ad server can also be a standalone supply-side platform with connections to ad exchanges/networks (Choi et al. 2019). Finally, advertising firms (gray-colored shapes

[1] One important distinction is worth noting: On ad exchanges, advertisers can directly buy from publishers. On ad networks, ad spaces are packaged into bundles for wholesale (Mehta et al. 2020).

in Figure 1), notably the tech giants, commonly own various ad servers and ad exchanges/networks.

Related Work

Given the extensively documented negative impact of fake news on the quality of civic engagement, health and healthcare, stock markets, and disaster management (Main 2018; Starbird 2017; Kucharski 2016; Palen and Hughes 2018; Marcon, Murdoch, and Caulfield 2017; Chiou and Tucker 2018; Grinberg et al. 2018), discovering practical and cost-effective methods to curtail its growth has become both a critical research endeavor and a public policy challenge (Coyle 2016; Feingold 2017; Iosifidis and Andrews 2019; Tambini 2017; Lazer et al. 2018).

First, researchers have taken steps to i) define and conceptualize fake news (Tandoc Jr, Lim, and Ling 2018; Kalsnes 2018), ii) annotate and aggregate known deceptive statements, reports, and publishers (Zimdars 2018; Mitra and Gilbert 2015; Leetaru and Schrodt 2013), iii) build automated systems to detect fake news promptly and at scale (Shu et al. 2017; Horne et al. 2018) and iv) examine its longitudinal characteristics and impact (Allcott, Gentzkow, and Yu 2018; Vargo, Guo, and Amazeen 2018; Budak 2019; Bode et al. 2020). These studies are valuable prerequisites for work that aims to combat fake news efficiently.

Next, work that primarily focuses on combating fake news can be categorized into 4 types, according to Larry Lessig's (1998; 2006) framework of cyberspace regulation: i) law (e.g. defamation and obscenity laws), ii) norms (e.g. subreddit community rules), iii) markets (e.g. pricing structures, advertiser preferences), and iv) architecture (e.g. Facebook's report button). Our paper is motivated by this framework and focuses on one of these four modes: markets.

Notably, prior work by Verstraete et al. (2017) assesses Lessig's four modes of regulation to counter fake news and lists market solutions—such as ad servers blacklisting fake news sites—as one of the important tools in the arsenal. Timmer (2016) further argues that market-based solutions will face less scrutiny and fewer legal hurdles compared to a state-sponsored legal solution due to the considerable leeway given to computer service providers to define and block questionable content. Furthermore, as (Mustafaraj and Metaxas 2017) argue, algorithmically allocated financial benefits of online advertising are playing an ever-increasing role in the spread of fake news. More broadly, legal and policy scholarship following the 2016 U.S. presidential elections (Timmer 2016; Tambini 2017; Vasu et al. 2018; Kshetri and Voas 2017; Bakir and McStay 2018; Braun and Eklund 2019; Coyle 2016) has made a strong theoretical case for market-based strategies to limit the spread of fake news.

Here, we provide empirical support for this case. In contrast to the aforementioned studies that focus on the practices of online advertising and public policies to curtail fake news, we focus on empirically assessing the effectiveness of one particular approach: advertising firms ending their partnership with fake news sites.

Data

In this section, we first describe the lists of fake and traditional news domains used as ground truth labels in our work. We then detail our process of identifying all ad servers available on each news site.

Fake and Traditional News Sites: We use the list of fake news sites from (Zimdars 2018) and the list of traditional news sites from *Media Bias/Fact Check*, an independent online media outlet maintained by a small team of researchers and journalists (Van Zandt 2018).

Zimdars list: The researchers (Zimdars 2018) examine domain-level characteristics of news websites, including i) domain name, ii) "about us" page, iii) writing style, iv) aesthetics, and v) social media accounts, to manually label and aggregate fake news sites. Each website is tagged with at most 3 of the following subtypes: *fake, satire, bias, conspiracy, rumor, state, junksci, hate, clickbait*, and *unreliable*. For instance, "sites that entirely fabricate information, disseminate deceptive content, or grossly distort actual news reports" are tagged as *fake* and "sites that provide generally credible content, but use exaggerated, misleading, or questionable headlines, descriptions, and/or images" are tagged as *clickbait*. Using this annotation procedure (please see the original Zimdars manuscript for a detailed description), they identify a total of 786 fake and low-quality news sites. We remove the defunct domains, resulting in 545 active sites.

Many academic works adopt Zimdars's list to study fake news (Shao et al. 2016; Horne et al. 2018; Allcott and Gentzkow 2017; Rini 2017; Koulolias et al. 2018). We use this list in our study too due to its i) transparent annotation and quality evaluation procedure, ii) relative large size compared to various other available lists, and iii) subcategorization (e.g. fake, clickbait), which allows us to determine the ad reliance of different types of problematic news producers.

Media Bias/Fact Check (MBFC) list: The MBFC staff examines a news site's i) wording, ii) source, iii) story selection, and iv) political affiliation to determine whether it is reputable. This list contains 1.3K credible traditional news sites, out of which 1.2K are still active. This list is also widely used in many related works that focus on media bias and fake news (Main 2018; Starbird 2017).

We assign these websites to 3 groups: i) *traditional*, ii) *fake* which includes only domains tagged with the subtype *fake*, and iii) *low-quality* for all problematic domains included in (Zimdars 2018). We also obtain the following additional data for each site: i) *average monthly traffic* using similarweb.com, a popular web analytics platform (Singal and Kohli 2016); and ii) *age* using whois.com, a domain name registrar database (Mueller and Chango 2008).

While both *Zimdars* and *MBFC* are extensively used by the related literature, they are not the only available lists of fake and traditional news domains. As such, we also perform robustness checks by repeating our analysis using different fake and traditional news lists. The description of these lists and the results are presented in Section "*Robustness Check*".

News Site Ad Servers and Ads: We first aggregated a list of known ad servers on the Web. Then, we identified the subset of ad servers present on each news site. Finally, we evaluated the credibility of each ad server in the subset.

Known Ad Servers: We included 22.3K ad servers listed on EasyList and EasyList Privacy (https://easylist.to), the two most comprehensive and commonly used sources for blocking unwanted web content such as ads. While comprehensive, EasyList does not make the distinction between categories of ad servers (e.g., standalone versus bundled). This list includes ad trackers that are used to track and analyze user behavior, in addition to ad servers that deliver ads. Given the focus of our paper, we manually reviewed the top 50 most popular ad servers and removed the domains that merely track users (e.g. Google Analytics).

News Site Ad Servers and Ads: We used Selenium WebDriver API (Avasarala 2014) to identify the subset of ad servers present in fake and traditional news sites and the ads that they serve. Selenium is a tool that simulates the browsing behavior of an ordinary human. Using this tool to regularly "visit" traditional and fake news sites in our dataset, we recorded the set of ads and the ad servers that deliver those ads. Using Selenium has the following advantages over other methods of collecting ad-server-related data: i) it bypasses common anti-scraping techniques such as requiring the "User-Agent" field in the request header or employing honeypot traps; ii) it triggers front-end scripts that fetch ads; and finally, iii) it allows us to set custom user browser settings. We used an empty profile devoid of any demographics cookies, disabled all cookies and enabled the private-browsing mode to ensure our analyses are not impacted by browsing histories.

For each news site, our automated scripts used Selenium to (i.) initiate a new browsing session, (ii.) navigate to the site's homepage, and (iii.) scroll through the page and refocus the mouse on each detected visible iframe. Iframes are generally used to serve ads, so this process of making iframes visible triggers the ad-serving scripts and populates the URLs that reveal the ad and the ad server delivering it. We scraped all URLs embedded in the webpage and each iframe. We then extracted the corresponding domains from these URLs[2]. We kept the subset of URLs with domains that matched one of the known ad servers in our dataset. Many ad servers track ad-related activities in addition to serving ads. Ad tracking activity does not directly contribute to publisher revenue. Thus, we next filter out such ad tracking links for the top-50 most popular ad servers in our data. These top-50 ad servers account for 83.6% of all likely ads in our data. We manually examined the subdomains and high-frequency substrings for each ad server and identified those that correspond to ad-tracking[3]. We randomly sampled and inspected 10 URLs for each subdomain (and substring) and classified it as ad-tracking if all inspected links were about tracking. Finally, we used these identified elements to filter out ad-tracking URLs through regex matching. Using this approach, we collected data for 12 weeks (between 09/17/2019 and 12/02/2019) resulting in 565 unique ad servers and 1.32M ad-related URLs.

Ad Server Credibility Data: We used 2 sources to determine ad server credibility: i) 10 distinct publicly available malware domain lists (Kuhrer, Rossow, and Holz 2014; Zarras et al. 2014; Zhauniarovich et al. 2018); and ii) VirusTotal (Masri and Aldwairi 2017; Hong et al. 2020), a popular free service that checks whether a given URL is risky. Both sources are commonly used in related work (Kuhrer, Rossow, and Holz 2014; Zarras et al. 2014; Masri and Aldwairi 2017) to identify the trustworthiness of a web domain, or to study the spread of viruses. We marked an ad server as *risky* if it was included in one of the malware domain lists or if at least 1 of the 100 randomly sampled ad URLs for that domain was detected by VirusTotal as risky. Otherwise, we marked the ad server as *credible*. Approximately, 78.8% of the 565 ad servers are credible.

Analysis

We first address RQ1 and examine the overall prevalence and quality of display ads across different types of news publishers. We then address RQ2 by assessing fake and traditional news publishers' dependence on the top-tier credible ad servers. Next, we address RQ3 by estimating the annual ad revenue that top ad firms generate through their partnership with fake and low-quality news sites. Finally, we conduct robustness checks.

News Producer Reliance on Display Ads

The success of a market-based solution to curtail fake news fundamentally depends on fake news sites' reliance on ads to produce revenue. Such an approach would surely be impractical if, for instance, the vast majority of fake news sites are funded by hostile governments. Little empirical work has been done to characterize this ad reliance. To fill this knowledge gap, we first address the following research questions:

RQ1-a: *To what extent is (i.) traditional, (ii.) fake, and (iii.) other low-quality news producer traffic supported by ad servers?*

RQ1-b: *What types of ad servers provide such support?*

Analysis here allows us to not only measure *fake* and *low-quality* news producers' reliance on display ad revenue and examine the characteristics of the ad servers they employ; it also contextualizes these findings by comparing them to *traditional* news publishers.

Ad Servers and Ad Frequency (RQ1-a): News producers are heavily reliant on display ad revenue. (Budak et al. 2016) shows that *news media* is the content provider segment with the highest display-ad reliance—with over 90% of traffic supported by display-ads. Here, we first investigate how different types of news producers (*traditional*, *fake*, and *low-quality*) rely on display advertising to generate revenue.

We observe that 74.2% of all publishers have one or more ad servers displaying ads. In other words, 25.8% of all pub-

[2]For instance, if a given URL is https://adserver1.co.uk/ad_url=123&referrer=cnn.com, the domain is adserver1.co.uk.

[3]As an example, stats.g.doubleclick.net is an ad-tracking subdomain of doubleclick.net. It's a script that collects specific demographic information about visitors. Similarly, the substring "trackimp" in the URL https://ad.doubleclick.net/ddm/trackimp/ also indicates that the URL is not an actual ad.

	Model (1)	Model (2)	Model (3)
	ad server count	likelihood of being a risky ad server	dependence on top-10 credible ad servers
subtype			
bias	0.569 (1.873)	−0.001 (0.051)	−0.035 (0.042)
clickbait	5.208* (2.778)	0.016 (0.0639)	−0.062 (0.056)
conspiracy	−1.587 (1.931)	−0.0729 (0.0579)	−0.053 (0.044)
fake	10.001*** (2.318)	0.1601** (0.0701)	−0.093* (0.051)
junksci	−4.531 (3.320)	0.0533 (0.1003)	−0.242*** (0.077)
other	−7.012** (3.341)	−0.1296 (0.1057)	−0.163** (0.070)
satire	4.822* (2.465)	−0.0686 (0.068)	0.091** (0.042)
unreliable	−1.207 (2.471)	−0.0115 (0.0682)	−0.068 (0.053)
ad server count		−0.0038*** (0.0006)	−0.002*** (0.0004)
monthly traffic (log10)	9.309*** (0.484)	0.0222* (0.0134)	−0.029*** (0.010)
domain age (years)	0.104 (0.082)	0.0049** (0.0022)	0.001 (0.001)
Constant	−30.967*** (2.549)	−0.033 (0.078)	0.570*** (0.051)
Observations	1,847	33,632	1,361
R^2	0.236	0.106	0.056
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 1: Model (1) is the regression result for the number of ad servers across publishers. Model (2) is the likelihood of an ad server being risky modeled using a mixed effect logistic regression. Model(3) is for the fraction of a domain's ads that are delivered by top $N = 10$ credible ad servers. Base publisher type for all models is *traditional*.

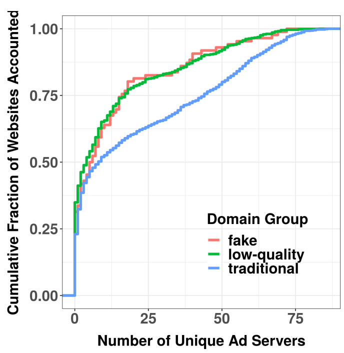


Figure 2: Distribution of the number of unique ad servers across different news publisher types.

lishers are ads-free. Surprisingly, we also see that *fake* publishers have fewer ad servers on average compared to *low-quality* and *traditional*. For instance, the median number of ad servers for *fake* and *traditional* is 6 and 8 respectively (see Figure 2). Further, close to one-fifth of *traditional* news sites have 50 or more ad servers, but less than one-tenth of *fake* and *low-quality* publishers fall into that category. Additionally, 29.6% and 32.8% of *fake* and *low-quality* news sites have 0 ad servers (i.e., these sites are ad-free) compared to 22.9% of *traditional* publishers.

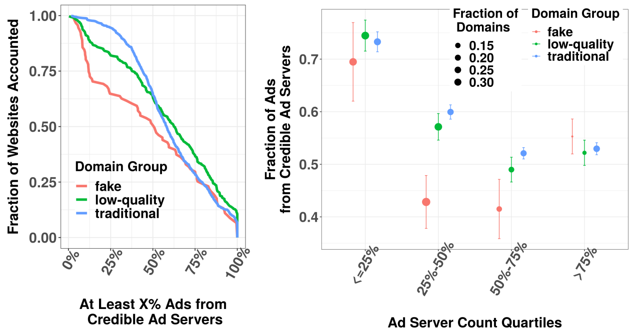
At first sight, results here suggest that news publishers' ad reliance is comparatively less than what's observed in prior research (Budak et al. 2016). Further, findings are also at odds with the claim that fake news publishers are aggressively profit-driven (Braun and Eklund 2019). Yet, explanations and potential confounds are readily available. For instance, past research (Budak et al. 2016) shows that long-tail content providers with a limited audience are less likely to show ads because they have too little traffic to monetize. Indeed, we observe that the combined viewer traffic for ads-free *fake* sites is only 7.5% of the aggregated traffic for all *fake* publishers (comparable results for *low-quality*). Publisher age is likely to play a similar role—newer websites may be preoccupied with other tasks such as Search Engine Optimization instead of expanding their ads pipeline (Kelsey 2017). Finally, past research shows the diversity of motivations for fake news producers (Marwick and Lewis 2017). While many fake news producers are primarily interested in monetizing their traffic, others, such as state-sponsored news, should be less inclined to do so. Here, given publisher i with the number of unique ad servers y_i, we run the following model controlling for average monthly traffic, subtype[4], and website age:

$$y_i = \beta_0 + \beta_1 * monthly\_traffic_i + \beta_2 * subtype_i + \beta_3 * age_i + \epsilon \quad (1)$$

Results are summarized on Table 1 (Model 1). We observe that news publishers labeled *fake* indeed have a significantly higher number of ad servers (10 more ad servers on average) than *traditional* after controlling for web traffic and age. Furthermore, we also observe a marginally-significant higher ad reliance for *clickbait* and *satire* publishers than *traditional*. As a robustness check, we also computed the average number of ads on i's homepage (approximated using the number of unique ad-related URLs) and performed a similar regression task. The results are comparable and the corresponding regression table is omitted for brevity.

Implications Our analysis shows that a larger fraction of fake news sites are ad-free than traditional news sites. Yet, it is important to note that this fraction, 29.6%, while large

[4]When a publisher has multiple subtypes (see detailed description of subtypes in Section "*Data*"), we create separate datapoints for i for each subtype.



(a) Fraction of news sites with at least $X\%$ ads from credible ad servers.

(b) Fraction of ads from credible ad servers. Points are scaled proportionally per news publisher type.

Figure 3: Fraction of ads from credible ad servers.

compared to traditional news sites, is still rather small compared to other content provider segments (Budak et al. 2016). Further, we show that this unexpected difference between fake and traditional news sites can be explained by fake news sites having smaller audiences. This also has important implications. As fake news sites become more popular over time, they can improve their display ad capabilities. Therefore, it is crucial to respond to this crisis as soon as possible. Finally, we identify the differing degrees to which different publisher subtypes benefit from display ads. Our analysis suggests that fake, clickbait, and satire sites are most likely to suffer from a successful market strategy targeting display ad revenue. Overall, we provide empirical evidence for the claim by experts (Kshetri and Voas 2017) and journalists (Subramanian 2017) that fake news is at least partially motivated and sustained by ad revenue.

Ad Servers and Ad Credibility (RQ1-b) In this section, we compare and contrast the difference in quality between ad servers in different groups of domains (*fake*, *low-quality*, *traditional*).

First, for a given publisher i, we model i's ad servers' riskiness using a mixed effect logistic regression. Specifically, the number of risky ad servers on i is modeled as the number of *successes* and the total number of ad servers as the number of Bernoulli trials in a binomial distribution. Let J_i denotes i's ad servers, and P(is_risky) be the binomial probability. We apply the following model:

$$T_i = Binomial(P(is\_risky), |J_i|) \quad (2)$$

$$P(is\_risky) = logit(\beta_0 * i + \beta_1 * monthly\_traffic_i + \beta_2 * subtype_i + \beta_3 * age_i + \beta_4 * ad\_server\_count_i + \epsilon) \quad (3)$$

Note that we also include a random effect for the domain i when modeling P(is_risky). As shown in Table 1 (Model 2), ad servers on *fake* sites are, on average, 4% ($\beta_{fake} = 0.16$) more likely to be risky than those on *traditional*. Finally, as a robustness check, we write y_i as the number of risky ad servers on i, and run a simple regression controlling for i's subtype, average monthly traffic, and age. Results are consistent with our prior observation (i.e., *fake* sites have more risky ad servers on average).

Next, we compute the fraction of ads on i that are delivered through $\widetilde{J_i}$, the subset of credible ad servers on i. We write the fraction as $f_{i,\widetilde{J_i}}$. As shown in Figure 3a, we observe that for 44.6% and 35.7% of *fake* and *low-quality* publishers, respectively, the majority of ads present on their websites are in fact delivered by risky ad servers. In comparison, that figure is 34.1% for *traditional* publishers. Further, we also differentiate domains with few ad servers from the ones with a high ad server count. Results are summarized in Figure 3b. Publishers are separated by type (color) and into quartiles based on their ad server counts (x-axis). Additionally, the y-axis values indicate the average fraction of ads delivered by credible ad servers across domains. Finally, datapoint size is scaled per news publisher type. As shown, domains that have very few ad servers (1st quartile) have a significantly higher fraction of credible ads compared to publishers with more ad servers (2nd, 3rd, and 4th quartiles). Further, *fake* and *low-quality* publishers with a moderate number of ad servers (2nd and 3rd quartiles) on average have a considerably higher fraction of ads delivered by risky ad servers than *traditional* publishers. The difference is insignificant for domains with a high ad server count (4th quartile), however. This is possibly because these publishers are more aggressively profit-driven regardless of domain type.

Implications Beyond systematic differences in overall reliance on ad revenue, news producers also differ in the *types* of ad servers with which they partner. Overall, our results here suggest that fake and low-quality news sites partner more with risky ad servers. This has important implications for news consumers. These low-quality news producers are not only polluting consumers' news diet but also exposing them to potential privacy and security risks. Perhaps the fact that fake news sites engage in such risky behavior is not surprising. However, this highlights the importance of tools and regulations to protect news consumers online. Finally, while fake and low-quality news sites have a higher tendency to partner with risky ad servers compared to traditional news sites, they are still highly reliant on credible ad servers to monetize their traffic. In the next section, we will delve deeper into that reliance and determine whether it can be leveraged to combat fake news.

Fake News Publishers' Dependence on Top Credible Ad Servers

Thus far, we showed that *fake* sites have significantly higher ad reliance than *traditional* news sites of comparable viewer traffic and age. Further, the majority of ads for 55.4% and 64.3% of *fake* and *low-quality* domains with at least 1 ad server are delivered through credible ad servers. Both observations suggest promise for a market-based solution. Nevertheless, convincing *all* credible ad servers to blacklist known fake news sites is nontrivial. This leads us to address the following research question:

RQ2: *How concentrated is fake and other low-quality news publishers' ad reliance on a small number of top credible ad servers?*

This research question can help us determine the effectiveness of pressuring top-tier credible ad servers to black-

Panel A: The number and fraction of ads of each publisher that are delivered by different ad servers.

	P1	P2	P3
AS1	100 (50%)	0	0
AS2	50 (25%)	75 (75%)	0
AS3	50 (25%)	25 (25%)	10 (100%)

Panel B: Monthly traffic for each publisher.

P1	90K
P2	9K
P3	1K

Panel C: Weighted domain share

$f(fake,, AS1) = \frac{0.5+0+0}{3} = 0.17$

$f(fake, AS2) = \frac{0.25+0.75+0}{3} = 0.33$

$f(fake, AS3) = \frac{0.25+0.25+1}{3} = 0.50$

Panel D: Reliance on top-2 credible ad servers: $f(fake, AS3) = 0.5$, $f(fake, AS2) = 0.33$

$f(p1, \widetilde{J}_{fake,2}) = 0 + 0.25 + 0.25 = 0.5$

$f(p2, \widetilde{J}_{fake,2}) = 0 + 0.75 + 0.25 = 1$

$f(p3, \widetilde{J}_{fake,2}) = 0$

Panel E: Weighted ad share

$y(fake, AS1) = \frac{0.5*90k}{100k} = 0.45$

$y(fake, AS2) = \frac{0.25*90k + 0.75*9k}{100k} = 0.29$

$y(fake, AS3) = \frac{0.25*90k+0.25*9k+1*1k}{100k} = 0.26$

Panel F: Total ad traffic top-2 credible ad server: $y(fake, AS3) = 0.45$, $y(fake, AS2) = 0.29$

$g(fake, 2) = 0.45 + 0.29 = 0.74$

Figure 4: A simple example using 3 fake news publishers and 3 credible ad servers to summarize the two measures of ad reliance. Note that i) panel A and B contain data; ii) panel C and D are an example of weighted domain share; and iii) panel E and F are an example of weighted ad share.

list fake and low-quality news producers. Owners of these ad servers are likely to be more motivated to ban *fake* and *low-quality* domains from using their services given their brand safety concerns (Mills, Pitt, and Ferguson 2019).

We evaluate the dependence on top credible ad servers for each cluster of domains (*fake*, *low-quality*, *traditional*) using 2 measurements: i) weighted domain share, and ii) weighted ad traffic share. These measures are summarized in Figure 4 through a toy example and described in detail below. We note that only domains with at least 1 ad server are included in the analysis.

Weighted Domain Share The *fake* and *low-quality* new sites whose reliance on top-k credible ad servers exceeds their profit margin are particularly vulnerable to the market-based strategy studied in our paper. For instance, approximately 33.3% of ads on realnewsrightnow.com are served by DoubleClick—one of the top-10 credible ad servers according to our analysis described below. If this site's profit margin is lower than 33.3%, being blacklisted by DoubleClick would wipe out all its profits and likely lead to its demise—assuming ads are similarly priced. As this example demonstrates, this measure allows us to estimate the fraction of fake news sites that is likely to perish under different profit margin assumptions if top-k credible ad servers are pressured into blacklisting them.

To estimate this fraction for each news site, we first define the weighted domain share of an ad server j on a news site i as the fraction of ads on i delivered by j (denoted as $f_{i,j}$). This is presented in panel (A) in Figure 4. Given this measure, we next define the weighted domain share of an ad server j for all publishers in G (*fake*, *low-quality* or *traditional*) by simply averaging $f_{i,j}$ for all $i \in G$ (denoted as $f_{G,j}$, example given in panel (C) in Figure 4). This measure can be used to rank all credible ad servers and identify top-k for each $G \in \{traditional, fake, low\text{-}quality\}$ (denoted as $\widetilde{J}_{G,k}$). Having identified the top credible ad servers ($\widetilde{J}_{G,k}$), we denote the dependence of each publisher i on this set of ad servers as $f_{i,\widetilde{J}_{G,k}}$ (example given in panel (D) in Figure 4). We provide an overview of the top-10 ad servers and their weighted domain share in Table 2.

How does this reliance vary across publisher types? To answer this question, we examine reliance on the top-10 credible ad servers ($y_i = f_{i,\widetilde{J}_{G,10}}$) by applying the regression characterized by the following Equation:

$$y_i = \beta_0 + \beta_1 * monthly\_traffic_i + \beta_2 * subtype_i + \beta_3 * age_i + \beta_4 * ad\_server\_count_i + \epsilon \quad (4)$$

As shown in Table 1 (Model 3), we see *fake*, and *junksci* sites are significantly less dependent on the top-10 than *traditional* news sites. For instance, a *fake* news site has 9.3% ($\beta_2 = -0.093$) less dependence on the top-10 credible ad servers than a *traditional* news site of a similar age, popularity, and server count. We also repeat the process for $k = \{5, 15\}$ and reach comparable results.

Next, we group each publisher i according to its reliance on the top-k credible ad servers ($f_{i,\widetilde{J}_{G,k}}$). We consider four levels: i) $\leq 33\%$, largely independent; ii) $(33\%, 66\%]$, moderately dependent; iii) $(66\%, 99\%]$, significantly dependent; or iv) 100%, completely dependent. We then plot the 4 levels of dependence in Figure 5a. The x-axis gives the top-k credible ad servers (e.g. $\widetilde{J}_{fake,k}$ for the first facet) and the y-axis gives what fraction of the domains in that group (e.g. *fake*) has a given level of reliance. We see that 6.7% of all *fake* domains are completely dependent on the top-10 ad servers. In other words, if the top-10 credible ad servers are no longer available, 6.7% of *fake* publishers will have 0 ad servers left. Additionally, we also see that close to half of all *fake* domains are at least moderately dependent on top-10 ad servers. The patterns observed for *fake* are rather comparable to *low-quality* and *traditional*—especially when focusing on reliance on a small number of top ad servers (small x-values). The distinctions, however, become more apparent when considering all ad servers (max x-value) and lower reliance levels (e.g. $(33\%, 66\%]$). The increased distinction is due to a higher reliance on risky ad servers by *fake* publishers than *traditional* ones

Implications We show that the top credible ad servers play a substantial role in delivering ad revenue to a large fraction of fake news sites. For instance, 6.7% of all *fake* domains are *completely* dependent on the top-10 ad servers. Such sites are almost sure to perish if those ad servers are pushed to blacklist them. This already demonstrates the potential of our proposed market-based solution. However, we expect the effect to be much larger depending on the profit margins of news publishers. To determine the fraction of sites that is likely to lose all profits, we turn to profit margin estimates shared for news and online media organizations. Past work shows that the profit margins of news media organizations have been on the decline, with best performing organizations' profit margins hovering around 10% (Nee 2011). Tra-

	weighted domain share			weighted ad traffic share		
	fake	**low-quality**	**traditional**	**fake**	**low-quality**	**traditional**
1	doubleclick.net (0.31)	doubleclick.net (0.3)	doubleclick.net (0.27)	doubleclick.net (0.4)	doubleclick.net (0.28)	doubleclick.net (0.22)
2	googlesyndication.com (0.05)	googlesyndication.com (0.04)	addthis.com (0.06)	googlesyndication.com (0.05)	adfox.ru (0.08)	googlesyndication.com (0.02)
3	projectwonderful.com (0.01)	addthis.com (0.03)	googlesyndication.com (0.03)	lockerdome.com (0.05)	googlesyndication.com (0.02)	gannett-cdn.com (0.02)
4	content.ad (0.01)	lockerdome.com (0.01)	gannett-cdn.com (0.02)	zemanta.com (0.04)	libertycdn.com (0.01)	addthis.com (0.01)
5	earnify.com (0.01)	pubmine.com (0.01)	casalemedia.com (0.01)	lockerdome-cdn.com (0.03)	casalemedia.com (0.01)	casalemedia.com (0.01)
6	outbrain.com (0.01)	revcontent.com (0.01)	everesttech.net (0.01)	outbrain.com (0.02)	connatix.com (0.01)	serving-sys.com (0.01)
7	serving-sys.com (0.01)	shopify.com (0.01)	ownlocal.com (0.004)	adrta.com (0.01)	adrta.com (0.01)	gumgum.com (0.01)
8	acuityplatform.com (0.01)	lockerdome-cdn.com (0.01)	gumgum.com (0.004)	udmserve.net (0.01)	fastly.net (0.01)	betrad.com (0.01)
9	sekindo.com (0.01)	adblade.com (0.01)	serving-sys.com (0.004)	posst.co (0.01)	revcontent.com (0.01)	company-target.com (0.01)
10	lockerdome.com (0.01)	sekindo.com (0.01)	rfihub.com (0.004)	ezoic.net (0.004)	yimg.com (0.01)	everesttech.net (0.01)

Table 2: Top-10 credible ad servers ranked by i) weighted domain share and ii) weighted ad share.

ditional news media employ a large body of trained journalists and are likely to have higher costs compared to fake and low-quality news publishers. Therefore, to provide a more conservative estimate of the proposed method, we identify profit margins across different sectors and find that even the most profitable sectors have a net profit margin lower than 20% [5]. While we do not know the profit margins of the new sector of fake and low-quality news, using even the most conservative estimates leads us to conclude that *fake* and *low-quality* publishers with at least moderate dependence ($> 33\%$) stand to become unprofitable. This amounts to more than half of all *fake* news sites and two-thirds of all *low-quality* sites.

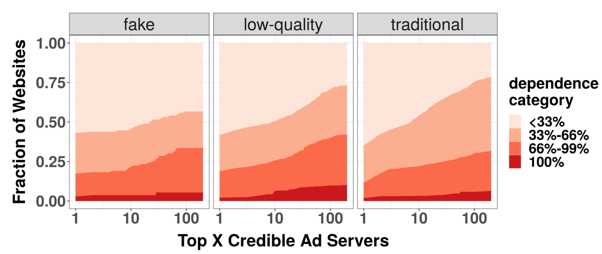
Weighted Ad Traffic Share Web traffic is considerably different from domain to domain: top-tier publishers garner millions of viewers a week, whereas lower-tier news sites have only thousands of visitors a month. A fake news site with millions of views has a more detrimental effect on our society than one that has only thousands. To account for this, we next reweight ad server significance by taking into account the ad/web traffic of the publishers they serve.

Given publisher $i \in G$ and ad server j, we define j's weighted ad traffic share on i as $y(i, j) = f_{i,j} * s_i$, where s_i is the average monthly web traffic of i. We then calculate j's aggregated weighted ad traffic share for group G as $y(G, j) = \frac{\sum_{i \in G} y(i,j)}{\sum_{k \in J} \sum_{i \in G} y(i,k)}$ (panel E in Figure 4). We then denote $\widetilde{G}_{G,k}$ as the top-k credible ad servers serving domains in G according to weighted ad traffic. The top-10 credible ad servers ranked by weighted ad share are listed on Table 2.

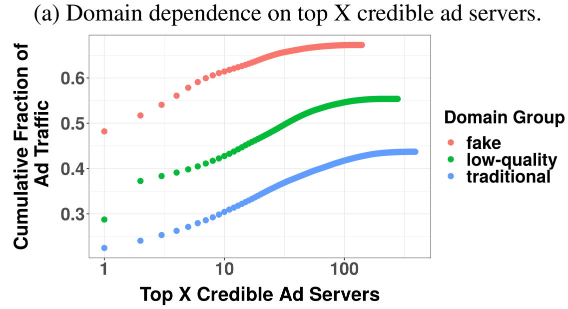
Next, given $\widetilde{G}_{G,k}$, we compute the total ad traffic accounted for by $\widetilde{G}_{G,k}$ as $\sum_{j \in \widetilde{G}_{G,k}} y(G, j)$ (panel F in Figure 4).

[5]https://www.forbes.com/sites/sageworks/2015/09/06/these-industries-generate-the-highest-profit-margins

We can then plot this measure, which characterizes the fraction of ad traffic in each group G accounted for by top-k credible ad servers.



(a) Domain dependence on top X credible ad servers.



(b) Fraction of total ad traffic delivered by credible ad servers

Figure 5: The reliance of different types of publishers on credible ad servers.

The results are given in Figure 5b. We observe that 67.5% and 56.6% of all ad traffic on *fake* and *low-quality* sites are delivered by credible ad servers, compared to 46.4% of *traditional* sites. Further, the top-10 credible ad servers alone accounted for 61.1% of all ad traffic on *fake* sites and 43.4% on *low-quality* sites, suggesting that the distribution of ad traffic across all credible ad servers is highly unequal. Indeed, the normalized Gini coefficients (Gini 1921) for the distribution $y(G, J)$ are 0.83 and 0.81 for *fake* and *low-quality* sites respectively (i.e., a substantial fraction of total ad traffic is concentrated on a handful of credible ad servers). Also note that Figure 5b shows a clearer divide between *fake*, *low-quality*, and *traditional* domains' reliance on top-k (e.g., when k=10) ad servers compared to Figure 5a. This is due to the long tail of small publishers (*fake*, *low-quality*, and *traditional*) with comparatively less web traffic behaving more similarly.

Implications The weighted ad traffic analysis reiterates the significant role top credible ad servers play in providing revenue streams for problematic news producers. A striking amount—61%—of fake news web traffic is estimated to be supported by only 10 credible ad servers. Using the earlier measure, we were able to show that 50.0% of fake news sites are at least moderately reliant on top-10 ad servers and stand to become unprofitable if blacklisted. The weighted ad traffic analysis paints a similar picture, with a comparable dent when accounting for publisher popularity.

Top Ad Firms Profiting From Fake News Ad firms are profit-maximizing entities. As such, the ability to convince even the most contentious ad firm to blacklist fake news sites depends on the revenue they would lose through such an action. Therefore, here we address the following question:

RQ3: *What is the cost to ad firms of blacklisting fake and low-quality news sites and how does that cost vary by publisher type?*

To achieve this, we first match each ad server to its advertising firm using Whois[6]. Then, we determine each firm's aggregated weighted ad traffic for each group G, and use a back-of-the-envelope calculation to estimate ad revenue. Given a firm m and its ad servers J_m, we calculate m's weighted ad traffic for each group G as $y(G, J_m) = \sum_{j \in J_m} y(G, j)$. We observe that 48.0% and 32.0% of all weighted ad traffic on *fake* and *low-quality* sites are delivered through Google alone. Or, in the words of Craig Silver, "[Google is the] financial engine for fake news". Aggregated ad traffic for the remaining firms us more modest. Notably, MGID, Lockerdome, Outbrain, and Yandex each has above 5.0% weighted ad traffic in *fake* or *low-quality* domains.

Next, ad revenue is most commonly generated through ad impressions. The number of ad impressions is defined as the total number of ads displayed when a user lands on a webpage. Based on the 2018-2019 Google advertising rates (Aribarg and Schwartz 2020; Volovich 2019), 1K impressions, or 1 CPM (cost-per-mile), typically generates \$2.40 to \$2.80 in ad revenue for a news site. We first obtained the 2018 revenue information for each advertising firm from: i) its own press release or financial report; ii) statia.com, a market and statistics research company; or iii) owler.com, a website specialized in building company profiles. Next, we compute the normalized annual ad revenue through news sites in group G for each ad firm m as:

[6]Whois (Mueller and Chango 2008) provides domain ownership information. For instance, various ad servers (e.g. doubleclick.net, alooma.com, gvt1.com, 2mdn.net) are all registered under Google.

	ad firm	weighted ad share	monthly revenue upper bound
top ad firms working with fake news publishers			
1	google	0.48	11.4 K (0.000008%)
2	mgid	0.08	1.9 K (0.002347%)
3	lockerdome	0.08	1.8 K (0.039764%)
4	outbrain	0.06	1.3 K (0.000146%)
5	criteo sa	0.02	0.5 K (0.000021%)
top ad firms working with low quality news publishers			
1	google	0.32	652.9 K (0.000477%)
2	yandex	0.08	174.5 K (0.007969%)
3	criteo sa	0.04	73.0 K (0.003176%)
4	pubmatic	0.03	55.5 K (0.103937%)
5	tmrg	0.02	47.9 K (0.011419%)

Table 3: Top-10 ad firms' monthly ad revenue by partnering with *fake* and *low-quality* news publishers. Ad firms are ranked by the weighted ad share. Table includes each firm's monthly revenue in i) absolute dollar amount, and ii) normalized by the firm's 2018 annual revenue in parentheses.

$$r_m = \frac{y(G, J_m) * T_G * CPM}{R_m} \tag{5}$$

where the upper and lower bound for CPM is set at $CPM = \{\$2.40, \$2.80\}$; T_G is the aggregated viewer traffic, in thousands, for all publishers in group G; and, R_m is m's total annual revenue for 2018.

In terms of absolute dollar amount, we estimate that top-10 firms, in aggregate, generate \$24,500 to \$28,600 monthly ad revenue through *fake* new sites, and \$985,700 to \$1.15 million through *low-quality* publishers. Additionally, for the top-10 high ad traffic firms in the *fake* or *low-quality* categories, we depict the corresponding r_m in Table 3. As shown, even for the smaller advertising firms (e.g., Lockerdome, Pubmatic), ad traffic through fake news sites only contributes 0.1% to 1.0% to their total annual revenue. For tech giants like Google, r_m is a mere millionth of a fraction. Finally, ad firms and publishers can also opt to use the pay-by-click revenue model instead of the pay-by-impression model. As such, for robustness check, we repeat our estimation using the current benchmark cost-per-click (CPC) rates, which ranges from \$0.35 per-click to \$0.74 per-click. We observe comparable results.

Implications Overall, we observe that revenue generated through *fake* and *low-quality* sites contributes little to the top ad firms' total annual revenue. The findings in previous sections and here collectively make a compelling case: convincing a handful of top ad management firms (Google, MGID, Lockerdome, Yandex, Pubmatic, and Outbrain) to blacklist fake and low-quality news sites can be cost-effective and is therefore, a financially reasonable path to follow.

Robustness Check

Prior research shows that the choice of which fake news list to use as ground truth can impact downstream results (Bozarth, Saraf, and Budak 2020). In this section, we introduce two new datasets—one for defining fake news and another for defining traditional news—and repeat our analysis to inspect robustness. The two datasets are given below:

Alternative fake news list—PolitiFact: The PolitiFact list (Gillin 2017) deviates from *Zimdars* in various important ways: (i.) it is much smaller—there are approximately $\frac{3}{10}$ as many domains listed as fake; (ii.) its primary creation goal was to identify the most-shared fake news sites on Facebook during the 2016 presidential election, so it more narrowly focuses on political fake news; and (iii.) unlike Zimdars (2018), this list has not been updated since its creation.

Alternative traditional news list—Vargo: This list of traditional news (Vargo, Guo, and Amazeen 2018) differs from *Media Bias/Fact Check* in that i) the data is collected through GDELT's global knowledge graph, ii) the list is twice as large with 2.3K traditional news domains in total.

We conducted robustness checks using ground truth pairs (*PolitiFact, Vargo*), (*Zimdars, Vargo*), and (*PolitiFact, MediaBias/Fact Check*). The results are largely consistent across analyses. Below, we provide more detailed information for (*PolitiFact, Vargo*) and omit the other two for brevity.

First, we observe that *fake* sites still have a higher ad reliance than *traditional*; but the difference is not statistically significant (see the regression in Table 1 for our original analysis). A likely explanation is that *PolitiFact* has few *fake* domains which lead to the differences not being significant. Next, for ad credibility, we see that *fake* and *low-quality* publishers rely more on risky ad servers: 40% of *fake* and 39.8% of *low-quality* domains have the majority of their ads delivered by risky ad servers compared to 37.2% of *traditional*. This is consistent with our prior observations.

Further, focusing on the most popular ad servers, we observe that approximately three-fifths of all *fake* domains listed in PolitiFact are at least *moderately dependent* on the top-10 credible ad servers. Similarly, 42% and 61% of total weighted ad traffic in *low-quality* and *fake* sites are delivered by the top-10 credible ad servers (compared to 56.6% and 67.5% obtained when using *Zimdars* and *MBFC*). In other words, we again find that *fake* domains are heavily reliant on the top credible ad servers, both in terms of the fraction of publishers with heavy reliance and the fraction of total traffic across all *fake* publishers supported by these ad servers.

Finally, focusing on advertising firms and ad revenue, we observe that Google still dominates the advertising ecosystem—30% and 62% of all weighted ad traffic on *low-quality* and *fake* domains are delivered by Google ad servers compared to 32% and 48% when using (Zimdars 2018). However, we observe a shift in top ad firms ranked 2-9 (e.g., Nielsen Company has rank=2 opposed to Yandex, and TMGR has rank=3 opposed to rank=5) collaborating with *fake* publishers listed in *PolitiFact*. We also estimate much lower revenue for top ad management firms: $16,500 to $19,300 in monthly ad revenue through *fake* publishers, and $334,200 to $390,000 through *low-quality* sites. This can be explained by the fact that *PolitiFact* is a much smaller list than *Zimdars*.

Conclusion and Discussion

In this paper, we provided the first large-scale examination of the existing advertising ecosystem on fake and low-quality news websites and contrast it against that of traditional news media. We demonstrated that fake news domains have far more ad servers and ads. Further, ad servers on fake news site are also significantly more likely to be risky. But, top-tier credible ad servers (and the tech giants that own them) are responsible for delivering a substantial fraction of ads on fake and low-quality news sites. Further, based on our estimation, top-tier firms make negligible ad revenue through these sites. Given these considerations, an effective way to combat fake news is to have ad tech giants blacklist known fake and low-quality news sites.

Granted, there are several obstacles to implement this measure. First, platforms are historically reluctant to take up editorial duties, such as deciding which publishers are fake news sites, for fear of backlash (Farkas and Schou 2018). Some critics and political pundits, however, suggest that this responsibility could be passed on to policy-makers or public news media associations who would then assist platforms in ensuring online news publishers meet a minimum quality standard (Coyle 2016). In fact, policies regulating broadcasting networks in the past can be adopted here (Iosifidis and Andrews 2019). Next, tech executives also point out that profit-driven fake news sites banned by top-tier advertising firms can simply move on to the less reputable ones (Braun and Eklund 2019). Conversely, opponents argue that top-tier ad firms also own the lion's share of ad inventories, which would become unavailable to fake and low-quality news sites. Further, by partnering with risky ad firms, fake news sites are likely to lose access to high-profile, brand-conscience retailers, and high-quality ads. Having more low-quality advertisers and ads present on fake news sites can then provide additional visual cues to viewers that they are untrustworthy (Tambini 2017).

The effectiveness of this measure may also be hindered by profit-driven owners of blacklisted websites migrating to new domains. As such, effective fake news detection systems are necessary to ensure these problematic publishers are identified promptly. The strategy of blocking fake news producers would only be as effective as our ability to detect such sites. There are various commendable efforts in this space, including both manual (Zimdars 2018; Van Zandt 2018; Mitra and Gilbert 2015; Leetaru and Schrodt 2013) and automated approaches (Shu et al. 2017; Horne et al. 2018). Nonetheless, there is still a lot left to do. For instance, researchers should include additional validation archetypes and bias assessment steps to ensure model performance is robust (Bozarth and Budak 2020).

We observe the following limitations to our work. First, approximately 40% to 60% of all fake news included under the original *Zimdars* and *PolitiFact* lists were already defunct before our study. Defunct domains potentially differ from the still active ones. Were the defunct domains blacklisted by Google and other popular ad firms? If so, did this loss of revenue lead to their demise? Unfortunately, Google does not release a list of news sites it has blacklisted. As such, we cannot address this question here. Additionally, we only collected ad-related data from each site's homepage; future work should scrape subpages to ensure a more comprehensive dataset. Furthermore, our current work is limited to ad servers; future work should also examine the types of advertisers and ads frequently present on fake and low-quality news sites to further map out these websites' advertising ecosystems. Additionally, the CPM and CPC rates used in this paper are industrial benchmark rates set by the largest ad firms. Similarly, profit margin measures used are informed by sector averages. These measures are likely different for fake and low-quality news sites. However, we note that we use conservative estimates in order not to overestimate the impact of the proposed approach to curb fake news.

Lastly, relying on ad firms to curtail fake news has important consequences. Should ad firms be used to regulate speech online? We cannot address this question and, as such, do not make a policy recommendation. Instead, we focus primarily on the monetary implication of such an approach. We believe that the policy discussion should include—but not be limited to—the analysis presented in this paper. Indeed, because fake news producers have varied motivations, interventions that target only one may be unsuccessful (Verstraete, Bambauer, and Bambauer 2017). As mentioned before, market forces are only one of the four modes that constrain behavior. While we provide evidence for the feasibility of using market forces to affect the fake news ecosystem, we cannot settle whether this approach should be preferred over the other three forms of regulation. Future work is needed to further examine both theoretical and empirical support for different ways to curtail fake news, especially considering the ever-changing strategies employed by fake news producers.

Acknowledgments

This research was supported by the National Science Foundation (Grant IIS-1815875 and GCR-1934494).

References

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

Allcott, H.; Gentzkow, M.; and Yu, C. 2018. Trends in the Diffusion of Misinformation on Social Media. *arXiv preprint arXiv:1809.05901* .

Aribarg, A.; and Schwartz, E. M. 2020. Native Advertising in Online News: Trade-Offs Among Clicks, Brand Recognition, and Website Trustworthiness. *Marketing Research* .

Avasarala, S. 2014. *Selenium WebDriver practical guide*. Packt Publishing Ltd.

Bakir, V.; and McStay, A. 2018. Fake News and The Economy of Emotions. *Digital Journalism* 6(2): 154–175.

Bode, L.; Budak, C.; Ladd, J.; Newport, F.; Pasek, J.; Singh, L.; Soroka, S.; and Traugott, M. 2020. *Words that Matter: How the News and Social Media Shaped the 2016 Presidential Election*. Brookings Institution Press.

Bozarth, L.; and Budak, C. 2020. Toward a better performance evaluation framework for fake news classification. In *Proceedings of the international AAAI conference on web and social media*, volume 14, 60–71.

Bozarth, L.; Saraf, A.; and Budak, C. 2020. Higher ground? How groundtruth labeling impacts our understanding of fake news about the 2016 US presidential nominees. In *International AAAI Conference on Web and Social Media*.

Braun, J. A.; Coakley, J. D.; and West, E. 2019. Activism, advertising, and far-right media: The case of sleeping giants. *Media and Communication* 7(4).

Braun, J. A.; and Eklund, J. L. 2019. Fake News, Real Money: Ad Tech Platforms, Profit-Driven Hoaxes, and the Business of Journalism. *Digital Journalism* 7(1): 1–21.

Budak, C. 2019. What happened? The Spread of Fake News Publisher Content During the 2016 U.S. Presidential Election. In *The World Wide Web Conference on - WWW '19*, 139–150. San Francisco, CA, USA: ACM Press.

Budak, C.; Goel, S.; Rao, J.; and Zervas, G. 2016. Understanding Emerging Threats to Online Advertising. In *Proceedings of the 2016 ACM Conference on Economics and Computation*, EC '16, 561–578. ACM.

Chiou, L.; and Tucker, C. 2018. Fake news and advertising on social media: A study of the anti-vaccination movement. Technical report, National Bureau of Economic Research.

Choi, H.; Mela, C. F.; Balseiro, S.; and Leary, A. 2019. Online display advertising markets: A literature review and future directions. *Columbia Business School Research Paper* .

Coyle, D. 2016. Making the most of platforms: a policy research agenda. *Available at SSRN 2857188* .

Farkas, J.; and Schou, J. 2018. Fake news as a floating signifier: Hegemony, antagonism and the politics of falsehood. *Javnost-The Public* 25(3): 298–314.

Feingold, R. 2017. Fake News & Misinformation Policy Practicum.

Figueira, A.; and Oliveira, L. 2017. The current state of fake news: challenges and opportunities. *Procedia Computer Science* 121: 817–825.

Fletcher, R.; Cornia, A.; Graves, L.; and Nielsen, R. K. 2018. Measuring the reach of "fake news" and online disinformation in Europe. *Reuters Institute Factsheet* .

Gillin, J. 2017. PolitiFact's guide to fake news websites and what they peddle. *PolitiFact* .

Gini, C. 1921. Measurement of inequality of incomes. *The Economic Journal* 31(121): 124–126.

Grinberg, N.; Joseph, K.; Friedland, L.; Swire-Thompson, B.; and Lazer, D. 2018. Fake news on Twitter during the 2016 US presidential election. Technical report, Working Paper. Available from the authors.

Hong, J.; Kim, T.; Liu, J.; Park, N.; and Kim, S.-W. 2020. Phishing url detection with lexical features and blacklisted domains. In *Adaptive Autonomous Secure Cyber Systems*.

Horne, B. D.; Dron, W.; Khedr, S.; and Adali, S. 2018. Assessing the News Landscape. In *Companion of the The Web Conference 2018*, 235–238. Lyon, France: ACM Press.

Iosifidis, P.; and Andrews, L. 2019. Regulating the internet intermediaries in a post-truth world: Beyond media policy? *International Communication Gazette* .

Kalsnes, B. 2018. Fake news. In *Oxford Research Encyclopedia of Communication*.

Kelsey, T. 2017. *Introduction to search engine optimization: a guide for absolute beginners*. Apress.

Koulolias, V.; Jonathan, G. M.; Fernandez, M.; and Sotirchos, D. 2018. Combating Misinformation: An ecosystem in co-creation.

Kshetri, N.; and Voas, J. 2017. The economics of "fake news". *IT Professional* 19(6): 8–12.

Kucharski, A. 2016. Post-truth: Study epidemiology of fake news. *Nature* 540(7634): 525.

Kuhrer, M.; Rossow, C.; and Holz, T. 2014. Paint It Black: Evaluating the Effectiveness of Malware Blacklists. In Stavrou, A.; Bos, H.; and Portokalidis, G., eds., *Research in Attacks, Intrusions and Defenses*, volume 8688, 1–21. Cham: Springer International Publishing.

Lazer, D. M.; Baum, M. A.; Benkler, Y.; Berinsky, A. J.; Greenhill, K. M.; Menczer, F.; Metzger, M. J.; Nyhan, B.; Pennycook, G.; Rothschild, D.; et al. 2018. The science of fake news. *Science* 359(6380): 1094–1096.

Leetaru, K.; and Schrodt, P. A. 2013. Gdelt: Global data on events, location, and tone, 1979–2012. In *ISA annual convention*, volume 2, 1–49. Citeseer.

Lessig, L. 1998. The new Chicago school. *The Journal of Legal Studies* 27(S2): 661–691.

Lessig, L. 2006. *Code: Version 2.0*. Shoeisha Co., Ltd.

Main, T. J. 2018. *The Rise of the Alt-Right*. Brookings Institution Press.

Marcon, A. R.; Murdoch, B.; and Caulfield, T. 2017. Fake news portrayals of stem cells and stem cell research. *Regenerative medicine* 12(7): 765–775.

Marwick, A.; and Lewis, R. 2017. Media manipulation and disinformation online. *Data and Society Research Institute* .

Masri, R.; and Aldwairi, M. 2017. Automated malicious advertisement detection using VirusTotal, URLVoid, and TrendMicro. In *2017 8th International Conference on Information and Communication Systems (ICICS)*. Irbid, Jordan: IEEE.

Mehta, S.; Dawande, M.; Janakiraman, G.; and Mookerjee, V. 2020. Sustaining a Good Impression: Mechanisms for Selling Partitioned Impressions at Ad Exchanges. *Information Systems Research* 31(1): 126–147.

Mills, A. J.; Pitt, C.; and Ferguson, S. L. 2019. The relationship between fake news and advertising: brand management in the era of programmatic advertising and prolific falsehood. *Journal of Advertising Research* 59(1): 3–8.

Mitra, T.; and Gilbert, E. 2015. Credbank: A large-scale social media corpus with associated credibility annotations. In *Ninth International AAAI Conference on Web and Social Media*.

Mueller, M.; and Chango, M. 2008. Disrupting global governance: the Internet whois service, ICANN, and privacy. *Journal of Information Technology and Politics* 5(3): 303–325.

Mustafaraj, E.; and Metaxas, P. T. 2017. The fake news spreading plague: was it preventable? In *Proceedings of the 2017 ACM on web science conference*, 235–239. ACM.

Nee, R. C. 2011. The role of digitally native, nonprofit news media in the future of American journalism: An exploratory study. *UMI Dissertation Publishing* .

Palen, L.; and Hughes, A. L. 2018. Social Media in Disaster Communication. In *Handbook of Disaster Research*. Springer.

Rini, R. 2017. Fake news and partisan epistemology. *Kennedy Institute of Ethics Journal* 27(2): E–43.

Shao, C.; Ciampaglia, G. L.; Flammini, A.; and Menczer, F. 2016. Hoaxy: A Platform for Tracking Online Misinformation. *WWW '16 Companion* .

Shu, K.; Sliva, A.; Wang, S.; Tang, J.; and Liu, H. 2017. Fake news detection on social media: A data mining perspective. *ACM SIGKDD Explorations Newsletter* 19(1): 22–36.

Silverman, C. 2017. The fake news watchdog - 50 ideas blowing up American politics and the people behind them. https://www.politico.com/interactives/2017/politico50/craig-silverman/. Accessed: 2018-09-30.

Singal, H.; and Kohli, S. 2016. Trust necessitated through metrics: estimating the trustworthiness of websites. *Procedia Computer Science* .

Starbird, K. 2017. Examining the Alternative Media Ecosystem Through the Production of Alternative Narratives of Mass Shooting Events on Twitter. In *ICWSM*, 230–239.

Subramanian, S. 2017. Meet the Macedonian Teens Who Mastered Fake News and Corrupted the US Election. *Wired* ISSN 1059-1028. URL https://www.wired.com/2017/02/veles-macedonia-fake-news/.

Tambini, D. 2017. Fake news: public policy responses. *Media Policy Brief* .

Tandoc Jr, E. C.; Lim, Z. W.; and Ling, R. 2018. Defining "Fake News": A typology of scholarly definitions. *Digital Journalism* 6(2): 137–153.

Tian, L.; Zhang, X.; and Peng, M. 2020. FakeFinder: Twitter Fake News Detection on Mobile. In *Companion Proceedings of the Web Conference 2020*, 79–80.

Timmer, J. 2016. Fighting Falsity: Fake News, Facebook, and the First Amendment. *Cardozo Arts and Ent. LJ* 35: 669.

Van Zandt, D. 2018. Media Bias/Fact Check (MBFC News) About. https://mediabiasfactcheck.com/about/. Accessed: 2018-09-30.

Vargo, C. J.; Guo, L.; and Amazeen, M. A. 2018. The agenda-setting power of fake news: A big data analysis of the online media landscape from 2014 to 2016. *new media and society* 20(5): 2028–2049.

Vasu, N.; Ang, B.; Teo, T.-A.; Jayakumar, S.; Raizal, M.; and Ahuja, J. 2018. *Fake news: National security in the post-truth era*. RSIS.

Verstraete, M.; Bambauer, D. E.; and Bambauer, J. R. 2017. Identifying and countering fake news. *Arizona Legal Studies* .

Volovich, K. 2019. What's a Good Clickthrough Rate? New Benchmark Data for Google AdWords. https://blog.hubspot.com/agency/google-adwords-benchmark-data. Accessed: 2020-05-24.

Zarras, A.; Kapravelos, A.; Stringhini, G.; Holz, T.; Kruegel, C.; and Vigna, G. 2014. The Dark Alleys of Madison Avenue: Understanding Malicious Advertisements. ACM.

Zhauniarovich, Y.; Khalil, I.; Yu, T.; and Dacier, M. 2018. A survey on malicious domains detection through DNS data analysis. *ACM Computing Surveys (CSUR)* 51(4): 1–36.

Zimdars, M. 2018. False, Misleading, Clickbait-y, and/or Satirical "News" Sources. https://docs.google.com/document/d/1zhaZooMfcJvk_23in201nviWJN1-LhRvGlPXJWBrPRY/. Accessed: 2019-09-30.