

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

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## 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 adros 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 65.6% and 50.0% of *fake* and *low-quality* ad traffic respectively. Furthermore, our back-of-the-envelope calculation shows that the top-10 ad firms are currently receiving \$1.1 million to \$1.3 million 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.

## 1 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.

Such 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, policy-makers 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 change them. 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 1.8M ads served by 898 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* and *clickbait* domains are revealed to have significantly more ad servers (28 and 10 more respectively) and ads compared to traditional publishers. Likewise, fake news publishers have a higher tendency to partner with at least 1 risky ad server compared to traditional news 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 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 publisher type?*

Surprisingly, we see that 65.6% of all ad traffic on *fake* domains is delivered by the top-10 credible ad servers compared to 50.0% and 38.1% on *low-quality* and *traditional* 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 a monthly revenue of \$1.1 million to \$1.3 million by delivering ads on *fake* and *low-quality* domains—a negligible fraction of the firms’ annual revenue.

Finally, deciding whether a content provider is a fake or low-quality news publisher (Tandoc Jr, Lim, and Ling 2018) is a challenging task. 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 and traditional news sites to show that our results are ro-

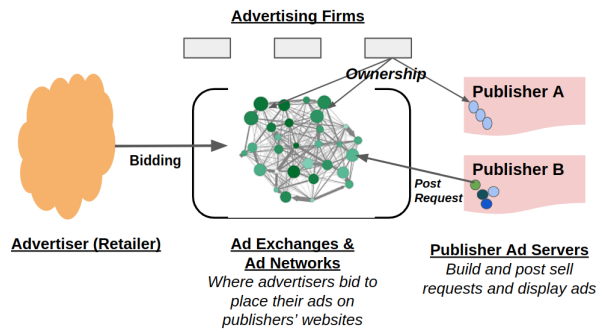


Figure 1: Simplified advertisement ecosystem.

bust. 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 settle the economics of this policy debate through a large-scale empirical analysis.

## 1.1 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)<sup>1</sup> 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 their messages are associated with. 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 in Figure 1), notably the tech giants, commonly own various ad servers and ad exchanges (ad networks).

<sup>1</sup>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).

## 2 Related Work

Given the extensively documented negative impact of fake news on the quality of civic engagement, health and health-care, 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, M 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 (Shao et al. 2017; Allcott, Gentzkow, and Yu 2018; Vargo, Guo, and Amazeen 2018). 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 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 (Timmer 2016). 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 the use of market-based strategies to limit the spread of fake news.

Here, we provide empirical support for this case. In contrast to the aforementioned studies which 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.

## 3 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 et al. (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, M 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 work 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 work that focuses on media bias and fake news (Main 2018; Starbird 2017).

For our paper, we assign these websites into 3 groups: i) *traditional*, ii) *fake* which includes only domains tagged with the subtype *fake*, and iii) *low-quality* for all domains included in Zimdars et al. (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).

Finally, we note that while both *Zimdars* and *Media Bias/Fact Check* 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 of our analysis are presented in Section 4.4.

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

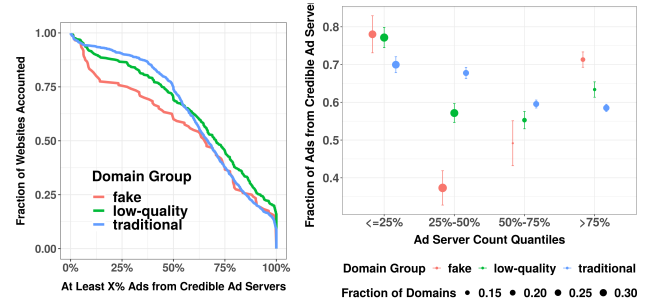
**Known Ad Servers:** We included 22.3K ad servers listed on *Easylist* and *Easylist Privacy* (<https://easylist.to>), the two most comprehensive and commonly used sources for blocking unwanted web content such as ads. While comprehensive, EasyList does not make the distinction between categories of 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. To elaborate, 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 delivered 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 profiles and tweak browser settings. We use an empty profile devoid of any demographics cookies, disabled all cookies and used the private-browsing mode to ensure our analyses were 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 re-focus the mouse on each detected visible iframes. 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. Using these URLs, we then extracted the corresponding domains. For instance, if a given URL is [https://adserver1.co.uk/ad\\_url=123&referrer=cnn.com](https://adserver1.co.uk/ad_url=123&referrer=cnn.com), the domain is `adserver1.co.uk`. We kept the subset of domains that matched one of the known ad servers in our dataset.

Using this approach, we collected data for 12 weeks (between 09/17/2019 and 12/02/2019) resulting in 898 unique ad servers and 1.8M ad-related URLs.

**Ad Server Credibility Data:** We use 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 malicious. 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 malicious. Otherwise, we marked the ad server as *credible*. Approximately, 82.7% of the 898 ad servers are credible.



(a) Fraction of news sites with (b) Fraction of ads from credible at least X% ads from credible ad servers. Points are scaled proportionally per subtype.

Figure 2: Fraction of ads from credible ad servers. Points are scaled proportionally per subtype.

## 4 Analysis

We first address RQ1 and examine the overall prevalence and quality of display ads across different types of news publishers in Section 4.1. In Section 4.2, we 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 in Section 4.4.

### 4.1 News Producer Display Ad Reliance

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 Server and Ads 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.

Figure 3 presents the distribution of number of unique ad servers for *traditional*, *fake*, and *low-quality* publishers. We observe that 84.8% of all publishers have one or more ad servers displaying ads, comparable to prior observations of

	Model(1)	Model(2)	Model(3)
	ad server count	has at least 1 malicious ad server	dependence on top-10 credible ad servers
domain			
bias	1.533 (3.678)	−0.022 (0.041)	0.041 (0.041)
clickbait	10.084** (5.061)	−0.011 (0.057)	−0.006 (0.056)
conspiracy	−2.679 (3.853)	0.073* (0.043)	−0.045 (0.043)
fake	28.786*** (3.927)	0.129*** (0.045)	−0.101** (0.045)
junksci	−4.417 (6.140)	−0.209*** (0.069)	−0.179** (0.075)
other	2.745 (5.959)	−0.057 (0.067)	−0.082 (0.070)
satire	6.595* (3.880)	0.054 (0.044)	0.128*** (0.043)
unreliable	−2.213 (4.290)	−0.093* (0.048)	−0.016 (0.051)
ad server count		0.005*** (0.0003)	−0.0004 (0.0003)
monthly traffic (log10)	10.990*** (0.677)	0.051*** (0.008)	−0.0004 (0.008)
domain age (years)	0.424*** (0.135)	−0.001 (0.002)	0.001 (0.001)
Constant	−32.194*** (3.633)	0.364*** (0.042)	0.465*** (0.043)
Observations	1,654	1,654	1,394
R <sup>2</sup>	0.213	0.256	0.025

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 result for publisher tendency to include at least one malicious ad server. 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*.

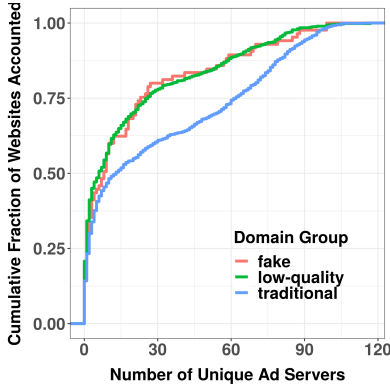


Figure 3: Number of unique ad servers across news publisher types.

ad reliance by news producers (Budak et al. 2016). Surprisingly, *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 7 and 14 respectively. Further, close to two-fifths of *traditional* news sites have 50 or more ad servers, but less than one-fifths for *fake* and *low-quality* publishers fall into that category. Additionally, 17.6% and 21.3% of *fake* and *low-quality* news sites have 0 ad servers (i.e., these sites are ad-free) compared to 13.1% of *traditional* publishers.

At first sight, this finding is 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. 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 clickbait 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, and website age:

$$Y = \beta_0 + \beta_1 * \text{monthly\_traffic} + \beta_2 * \text{subtype} + \beta_3 * \text{age} + \epsilon \quad (1)$$

Results are summarized on Table 1 (Model 1). We observe that news publishers labeled as *clickbait* and *fake* indeed have a significantly higher number of ad servers (10 and 28 more respectively) than *traditional* after controlling for web traffic and age. 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 (*fake* publishers has 11 more ads compared to *traditional* sites after controlling for traffic and age) 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. Such producers are clearly supported through other means, and therefore require a different strategy to curb their production. One can turn to the other three forms of regulation—laws, norms or architecture—for this purpose. Yet, it is important to note that this fraction (17.6%), while large 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 being



newer and 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 and clickbait sites are most likely to suffer from a successful market strategy targeting display ad revenue. Overall, we provide empirical evidence for the claim by the policy and legal scholarship (Kshetri and Voas 2017) and journalists (Subramanian 2017) that fake news is at least partially motivated and sustained by ad revenue.

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

*The credibility of Ad Servers Present on News Sites:* Given news producer  $i$ , we model its willingness to expose its readers to *at least some* risky ad content. We let  $y_i = \{0, 1\}$  represent whether  $i$  has at least 1 risky ad server, and we then apply Equation 2:

$$Y = \beta_0 + \beta_1 * \text{monthly\_traffic} + \beta_2 * \text{subtype} + \beta_3 * \text{age} + \beta_4 * \text{ad\_server\_count} + \epsilon \quad (2)$$

As shown in Table 1 (Model 2), *fake* and *conspiracy* domains are 12.9% and 7.3% more likely to have at least 1 risky ad server than *traditional* news sites when we control for i) average monthly traffic, ii) number of total ad servers, and iii) domain age.

Next, we compute the fraction of ads on  $i$  that are delivered through  $\tilde{J}_i$ , the subset of credible ad servers on  $i$ . We write the fraction as  $f_{i, \tilde{J}_i}$ . Figure 2a summarizes the results. We observe that for 37.5% and 29.4% 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 only 25.1% for *traditional* publishers. Further, we also differentiate domains with few ad servers from the ones with a high ad server count. As shown in Figure 2, domains that have very few ad servers (1st quantile) have a significantly higher fraction of credible ads compared to publishers with more ad servers (2nd, 3rd, and 4th quantiles). Further, *fake* and *low-quality* publishers with a moderate number of ad servers (2nd and 3rd quantiles) on average have a considerable 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 quantile), however, possibly because these publishers are more aggressively profit-driven irrespective of domain subtype.

**Implications** Beyond systematic differences in overall reliance on ad revenue, news producers also differ in the *types* of ad servers they partner with. 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

<b>Panel A:</b> The number and fraction of ads of each publisher that are delivered by different ad servers.				<b>Panel B:</b> Monthly traffic for each publisher.	
	P1	P2	P3	P1	90K
AS1	100 (50%)	0	0	P2	9K
AS2	50 (25%)	75 (75%)	0	P3	1K
AS3	50 (25%)	25 (25%)	10 (100%)		

<b>Panel C:</b> Weighted domain share $f(\text{fake}, \text{AS1}) = \frac{0.5 + 0 + 0}{3} = 0.17$ $f(\text{fake}, \text{AS2}) = \frac{0.25 + 0.75 + 0}{3} = 0.33$ $f(\text{fake}, \text{AS3}) = \frac{0.25 + 0.25 + 1}{3} = 0.50$		<b>Panel D:</b> Reliance on top-2 credible ad servers: $f(\text{fake}, \text{AS3}) = 0.5$ , $f(\text{fake}, \text{AS2}) = 0.33$ $f(p1, \tilde{J}_{\text{fake}, 2}) = 0 + 0.25 + 0.25 = 0.5$ $f(p2, \tilde{J}_{\text{fake}, 2}) = 0 + 0.75 + 0.25 = 1$ $f(p3, \tilde{J}_{\text{fake}, 2}) = 0$	
<b>Panel E:</b> Weighted ad share $y(\text{fake}, \text{AS1}) = \frac{0.5 * 90k}{100k} = 0.45$ $y(\text{fake}, \text{AS2}) = \frac{0.25 * 90k + 0.75 * 9k}{100k} = 0.29$ $y(\text{fake}, \text{AS3}) = \frac{0.25 * 90k + 0.25 * 9k + 1 * 1k}{100k} = 0.26$		<b>Panel F:</b> Total ad traffic top-2 credible ad server: $y(\text{fake}, \text{AS3}) = 0.45$ , $y(\text{fake}, \text{AS2}) = 0.29$ $g(\text{fake}, 2) = 0.45 + 0.29 = 0.74$	

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.

polluting consumers news diet but also exposing them to important security risks. Perhaps the fact that fake news sites engage in such risky behavior is not surprising. However, we also observe that sites that are less problematic from an information diet perspective (e.g. satire) have a similar tendency to expose consumers to such security risks. 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.

## 4.2 Fake News Publishers' Dependence on Top Credible Ad Servers

Thus far, we have show that one-fifth of *fake* and *low-quality* publishers is not reliant on ads revenue at all. Further, the remaining four-fifth also demonstrate a higher tendency than *traditional* publishers to rely on risky ad servers. Nevertheless, we observe that the *fake* and *low-quality* publishers without any ad servers are small sites with little viewer traffic (e.g., the combined web traffic for *fake* sites without ads is only 3.0% of the aggregated web traffic for all *fake* publishers). In other words, the general public is rarely exposed to this subset of new sites. Further, we also see that the majority of ads for 62.5% and 70.6% of *fake* and *low-quality* domains with at least 1 ad server are delivered through credible ad servers. Both of these 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—those that may be more motivated to ban *fake* and *low-quality* domains from using their services given their brand-safety concerns (Mills, Pitt, and Ferguson 2019)—to blacklist fake and low-quality news producers.

More specifically, 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** Here, our goal is to identify the degree to which each *fake* and *low-quality* news site relies on top- $k$  credible ad servers to produce ad revenue. The sites whose reliance on this subset of ad servers is higher than their profit margin are particularly vulnerable to the market-based strategy studied in our paper. For instance, roughly 50% of ads on *davidduke.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 a 50% profit margin, being blacklisted by DoubleClick would wipe out all its profits and likely lead to its demise. 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, we first define the weighted domain share of an ad server  $j$  on a news publisher 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  $G \in \{\text{traditional}, \text{fake}, \text{low-quality}\}$  (denoted as  $\tilde{J}_{G,k}$ ). Having identified the top credible ad servers ( $\tilde{J}_{G,k}$ ), we denote the dependence of each publisher  $i$  on this set of ad servers as  $f_{i,\tilde{J}_{G,k}}$  (example given in panel (D) in Figure 4). We provide an overview of this set 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 ( $f_{i,\tilde{J}_{G,10}}$ ) by applying the regression characterized by Equation 2. As shown in Table 1 (Model 3), compared to *traditional* news sites, *fake*, and *junksci* sites are significantly less dependent on the top-10 than *traditional* news sites. For instance, a *fake* news site has 10.1% ( $\beta_2 = -0.101$ ) less dependence on the top-10 credible ad servers compared to a *traditional* news site with 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 ( $f_{i,\tilde{J}_{G,k}}$ ). 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.  $\tilde{J}_{\text{fake},k}$  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 15.5% 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, 15.5% 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 become more apparent when considering all ad servers (max  $x$ -value) and lower reliance levels (e.g.  $(33\%, 66\%]$ ) due to a higher reliance by *fake* publishers than *traditional* one.

**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, 15.5% 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 promise of our proposed market-based solution. However, we expect the effect to be much larger depending on the profit margins on 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). Traditional news media employ a large body of trained journalists and are likely to have higher costs compare 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 lower than 20% net profit margin<sup>2</sup>. While we do not know the profit margins of the new sector of fake and low-quality news, using even the most conservative estimates lead us to conclude that *fake* and *low-quality* publishers with at least moderate dependence ( $> 33\%$ ) stand to become unprofitable. This amounts to half of all *fake* news sites and 60% 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,

<sup>2</sup><https://www.forbes.com/sites/sageworks/2015/09/06/these-industries-generate-the-highest-profit-margins>

	weighted domain share			weighted ad share		
	fake	low-quality	traditional	fake	low-quality	traditional
1	doubleclick.net(0.21)	doubleclick.net(0.23)	doubleclick.net(0.19)	doubleclick.net(0.31)	googlesyndication.com(0.19)	googlesyndication.com(0.16)
2	googlesyndication.com(0.12)	googlesyndication.com(0.13)	googlesyndication.com(0.15)	googlesyndication.com(0.21)	doubleclick.net(0.17)	doubleclick.net(0.15)
3	revcontent.com(0.02)	addthis.com(0.02)	addthis.com(0.05)	lockerdome.com(0.03)	adfox.ru(0.08)	gannett-cdn.com(0.01)
4	addthis.com(0.01)	revcontent.com(0.02)	gannett-cdn.com(0.02)	revcontent.com(0.02)	postrelease.com(0.02)	postrelease.com(0.01)
5	googleadservices.com(0.01)	bluekai.com(0.01)	postrelease.com(0.02)	zemanta.com(0.02)	revcontent.com(0.01)	addthis.com(0.01)
6	pubmine.com(0.01)	lockerdome.com(0.01)	bluekai.com(0.01)	lockerdomecdn.com(0.02)	rs-stripe.com(0.01)	bluekai.com(0.01)
7	marfeel.com(0.01)	googleadservices.com(0.01)	ads-twitter.com(0.01)	outbrain.com(0.01)	casalemedia.com(0.01)	casalemedia.com(0.01)
8	agkn.com(0.01)	pubmine.com(0.01)	googleadservices.com(0.01)	getclicky.com(0.01)	libertycdn.com(0.01)	tribalfusion.com(0.01)
9	yimg.com(0.01)	rs-stripe.com(0.01)	casalemedia.com(0.005)	adrt.com(0.01)	connatix.com(0.01)	serving-sys.com(0.01)
10	sekindo.com(0.01)	vimeocdn.com(0.01)	vimeocdn.com(0.005)	atdmt.com(0.01)	bluekai.com(0.005)	betrad.com(0.01)

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

we next reweight ad server significance by taking into account the ad/web traffic of the publishers they serve.

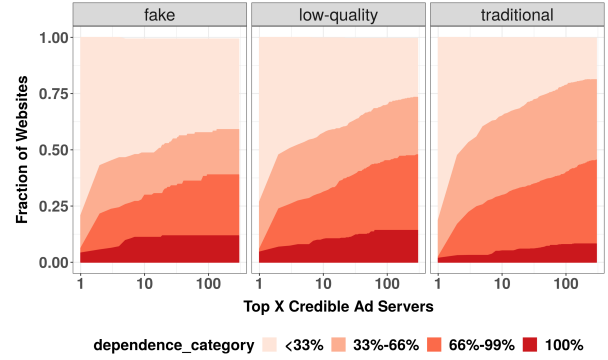
Specifically, given publisher  $i \in G$  and ad server  $j$ , we define  $j$ 's weighted ad traffic share on  $i$  as  $y(i, j) = f_{i,j} * s_i$ , where  $s_i$  is the average monthly web traffic of  $i$ . We then calculate  $j$ 's aggregated weighted ad traffic share for group  $G$  as  $y(G, j) =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

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

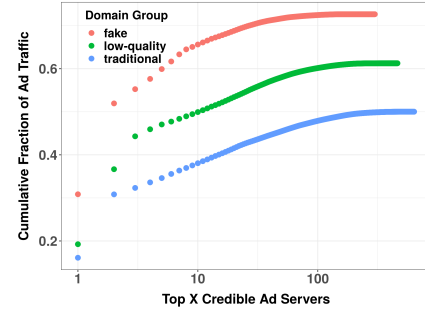
The results are given in Figure 5b. We observe that 72.7% and 61.2% of all ad traffic on *fake* and *low-quality* sites are delivered by credible ad servers, compared to 50.0% of *traditional* sites. Further, the top-10 credible ad servers alone accounted for 65.6% of all ad traffic on *fake* sites and 50.0% 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 0.97 and 0.95 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 are playing in providing revenue streams for problematic news producers. A striking amount—66%—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 60% of fake news sites are at least moderately reliant on top-10 ad servers and stand to become unprofitable if they are blacklisted. The weighted ad traffic analysis paints a similar picture, with a

comparable dent when accounting for publisher popularity.



(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.

### 4.3 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?



	ad firm	weighted ad share	monthly revenue lower bound
<b>top ad firms working with fake news publishers</b>			
1	google	0.55	17.7 K (0.000013%)
2	mgid	0.06	1.8 K (0.002266%)
3	lockerdome	0.05	1.6 K (0.035232%)
4	outbrain	0.03	1.1 K (0.000122%)
5	revcontent	0.02	0.8 K (0.000416%)
<b>top ad firms working with low quality news publishers</b>			
1	google	0.39	690.4 K (0.000505%)
2	yandex	0.08	138.3 K (0.006313%)
3	pubmatic	0.04	64.8 K (0.121324%)
4	appnexus	0.02	41.4 K (0.013813%)
5	amazon	0.02	39.5 K (0.000017%)

Table 3: Top-10 ad firms’ monthly ad revenue by collaborating 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 as well as ii) normalized by the firm’s 2018 annual revenue in parentheses.

To achieve this, we first match each ad server to its advertising firm using Whois<sup>3</sup>. 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. More specifically, 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 55.0% and 39.0% 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 are more modest. Notably, MGID, Lockerdome, 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. Then, letting  $r_m$  represent  $m$ ’s normalized annual ad revenue through news sites in group  $G$ , we calculate  $r_m$ :

$$r_m = \frac{y(G, J_m) * T_G * CPM}{R_m} \quad (3)$$

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 currently generate \$25,300 to \$29,500 monthly ad revenue through *fake* new sites, and \$1.1 million to \$1.3

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, Adroll), ad traffic through fake news sites only contributes 0.1% to 1.0% to their total annual revenue. For tech giants like Amazon and 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, while may be significant to certain individuals such as the Macedonian teens involved in creating and spread fake news in the 2016 presidential election (Subramanian 2017), contributes little to the top ad firms’ total annual revenue. The findings in Section 4.2 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 reasonable path to follow.

#### 4.4 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 nar-

<sup>3</sup>Whois (Mueller and Chango 2008) provides domain ownership information. For instance, various ad servers (e.g. doubleclick.net, aloom.com, gvt1.com, 2mdn.net) are all registered under Google.

rowly focuses on political fake news; and (iii.) unlike Zimdars (2018), this list has not been updated since its creation. **Alternative traditional news list: Vargo** Vargo’s 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, Media-Bias/Fact Check*). The results are consistent across analyses. Below, we provide more detailed information for (*PolitiFact, Vargo*) and omit the other two for brevity.

First, we again observe that *fake* domains have heavier ad-reliance. For instance, *fake* domains have 24.0 more ad servers than *traditional* publishers (see the regression in Section 4.1 for our original analysis). Further, *fake* and *low-quality* publishers also rely more on risky ad servers: 38.5% of *fake* and 35.0% of *low-quality* domains have the majority of their ads delivered by risky ad servers compared to 17.8% of *traditional* news sites.

Next, focusing on the most popular ad servers, we observe that approximately half of all *fake* domains listed in *PolitiFact* are at least *moderately dependent* on the top-10 credible ad servers. Similarly, 72.8% and 73.2% of total weighted ad traffic in *low-quality* and *fake* sites are delivered by the top-10 credible ad servers (compared to 50.0% and 65.6% obtained when using *Zimdars* and *Media Bias/Fact Check*). 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 dominated the advertising ecosystem—47.5% and 47.8% of all weighted ad traffic on *low-quality* and *fake* domains are delivered by Google ad servers compared to 39% and 55% when using (*Zimdars, M 2018*) (Section 4.3). 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=6) collaborating with *fake* publishers listed in *PolitiFact*. We also estimate much lower revenue for top ad management firms: \$12,750 to \$14,900 in monthly ad revenue through *fake* publishers, and \$396,400 to \$462,400 through *low-quality* sites. This can be explained by the fact that *PolitiFact* is a much smaller list than *Zimdars*.

## 5 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 contrasted it against that of traditional news media. We demonstrated that fake news domains have far more ad servers and ads, and are also significantly more likely to partner with at least 1 risky ad server. 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-tiers 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 suffer 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 the 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. Finally, 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, M 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 to do.

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 ecosystem. 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. But, because fake news producers have varied motivations, interventions that target only one may be unsuccessful (Verstraete, Bambauer, and Bambauer 2017). We believe that the policy discussion should include—but not be limited to—the analysis presented in this paper. Indeed, 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 is needed, especially considering the ever-changing strategies employed by fake news producers.

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