This paper appears at the 2021 Internet Measurement Conference (IMC).

Polls, Clickbait, and Commemorative $2 Bills: Problematic Political Advertising on News and Media Websites Around the 2020 U.S. Elections

Eric Zeng, Miranda Wei, Theo Gregersen, Tadayoshi Kohno, Franziska Roesner
Paul G. Allen School of Computer Science & Engineering
University of Washington
Seattle, WA, USA
{ericzeng,weimf,theoag,yoshi,franzi}@cs.washington.edu

ABSTRACT

Online advertising can be used to mislead, deceive, and manipulate Internet users, and political advertising is no exception. In this paper, we present a measurement study of online advertising around the 2020 United States elections, with a focus on identifying dark patterns and other potentially problematic content in political advertising. We scraped ad content on 745 news and media websites from six geographic locations in the U.S. from September 2020 to January 2021, collecting 1.4 million ads. We perform a systematic qualitative analysis of political content in these ads, as well as a quantitative analysis of the distribution of political ads on different types of websites. Our findings reveal the widespread use of problematic tactics in political ads, such as bait-and-switch ads formatted as opinion polls to entice users to click, the use of political controversy by content farms for clickbait, and the more frequent occurrence of political ads on highly partisan news websites. We make policy recommendations for online political advertising, including greater scrutiny of non-official political ads and comprehensive standards across advertising platforms.

CCS CONCEPTS

• **Information systems → Online advertising**; • **Social and professional topics → Computing / technology policy**; • **Security and privacy → Human and societal aspects of security and privacy**.

1 INTRODUCTION

The 2020 United States general elections were one of the most important and contentious elections in recent history. Issues facing the U.S. included the COVID-19 pandemic and ensuing economic crisis, controversy surrounding President Donald Trump's first term, and renewed movement for racial justice following the murder of George Floyd and other police violence. During this election season, online political advertising was more prominent than ever: campaigns turned to online ads as the pandemic reduced in-person events and canvassing [89], and spent record sums advertising on Google and Facebook [69]. The misuse of online ads in non-political contexts is a well-known problem, ranging from distasteful clickbait ads to outright scams and malware [47, 58, 95–97]. In this paper, we investigate misleading and manipulative tactics in online political advertising, for purposes such as collecting email addresses and driving traffic to political content websites.

We take a broad view of what constitutes a "political" ad in our work, considering any ad with political content, whether or not the ad was placed by an official political campaign committee. In our investigation, we ask: Who ran political ads during this period? What was the content of these ads, and do they use problematic techniques? Did the number of political ads on different types of websites differ?

To answer these questions, we conducted measurements of online advertising before, during, and after the Nov. 3rd elections. We collected a daily crawler-based sample of ads from 745 online news and media websites from September 2020 to January 2021, providing insight into the ads people saw while reading news during this period. We continued collecting data through several post-election developments: contested vote counting in multiple states, the Georgia U.S. Senate runoff election on January 5, and attack on the U.S. Capitol on January 6. Our crawlers collected data from six locations with varying political contestation: Atlanta, GA; Miami, FL; Raleigh, NC; Phoenix, AZ; Salt Lake City, UT; and Seattle, WA.

Using a combination of qualitative and quantitative techniques, we analyze the political ads in our dataset, including identifying examples of misleading and manipulative techniques, the distribution of political ads across websites of different political biases, and political affiliations and organization types of the advertisers.

Scope. Our crawler-based dataset provides a complementary perspective to the political ad archives from Google and Facebook. Though our dataset is not as complete as the political ad archives, and partially overlaps Google's, our dataset encompasses *all* ads on the pages we crawled — including non-political ads, political-themed ads were not officially classified as political and thus do not appear in Google's archive, and ads served via ad networks outside of Google Ads. Additionally, we capture the URL of the website that each ad appeared on, allowing us to measure contextual targeting of political ads on news and media websites.

Contributions. First, we characterize the quantity and content of online advertising longitudinally during the 2020 U.S. Presidential Election and shortly thereafter, and at scale.

- We observe differences in the number of political ads in different geographical locations.
- We observe shifts in the quantity of political ads through the election, and the effects of political ad bans.
- We characterize the topics of all online advertisements that we collected during this time period.

Through our qualitative analysis, we observed several problematic types of online political advertising, such as:

- The use of misleading and manipulative patterns in political ads. For example, ads that purport to be political polls, but use inflammatory framing, and appear to be used for gathering email addresses.
- Political topics in clickbait and native advertising. These ads imitate the look of links to news articles, but link to external sites. Headlines often imply controversy about candidates, and may fuel disinformation.

We also find that problematic political ads are more common on partisan and low-quality news sites.

- More partisan websites have more political ads, on both ends of the political spectrum.
- Problematic categories of ads, such as political products and polls, appear more frequently on right-leaning sites.

We discuss the potential harms from the problematic political ads we observed, and we make recommendations for platform policies, government regulation, and future research. We also release our full dataset of ads and metadata.

2 BACKGROUND AND RELATED WORK

2.1 The 2020-21 U.S. Elections and Ads

Between September 2020 and January 2021, the U.S. held a presidential election, congressional elections, and numerous state and local elections. In the presidential election, Joe Biden, a Democrat, and his running mate, Kamala Harris, ran against Donald Trump, the incumbent Republican president, and his running mate, Mike Pence [8]. We provide more historical background in Appendix A.

Before the election, tech companies faced mounting pressure to address concerns about political advertising spreading misinformation and causing other harms. Some companies had already banned political ads (Pinterest in 2018 [31], Twitter in 2019 [17]), at least in part due to revelations that Russian organizations had purchased political ads during the 2016 presidential election [41]. Google and Facebook allowed political ads in 2020, but implemented several short-term bans. Our dataset of display ads was likely impacted by Google's bans from Nov. 4 through Dec. 10 [25, 78], and again after the storming of the Capitol between Jan. 14 and Feb. 24 [26].

Still, political ads around the 2020-21 elections set new records for ad spending, with overall spending in the billions. On Facebook and Google alone, the Trump campaign spent $276 million and the Biden campaign spent $213 million [69].

2.2 Online Political and Problematic Ads

Prior work studies the online ad ecosystem from various perspectives. In the computer security and privacy community, researchers have often studied the privacy implications of online ads and the tracking enabling them (e.g., [9, 45, 59, 71, 75, 90]). In this work, we focus on the content of ads and contextual targeting that may cause different ads to appear on different types of sites, rather than on the underlying privacy-invasive mechanisms.

Recent work in computer science identifies types of problematic content in ads (e.g., clickbait, distasteful ads, misleading content, manipulative techniques) [96, 97], and types explicitly malicious ads (e.g., spreading malware) [47, 58, 67, 93, 95]. Online ads play a role in spreading mis/disinformation (e.g., during the 2016 and 2018 U.S. elections) [14, 21, 79, 80] as well as in monetizing mis/disinformation websites [15, 27, 40, 60]. Other work has shown that ads (e.g., on Facebook) may be targeted in discriminatory ways [2, 43]. Studies of misleading and manipulative patterns (often called "dark patterns") beyond ads also inform our work (e.g., [51, 57]), particularly a recent study of such patterns in political campaign emails [52].

Significant work in other fields (e.g., political science and marketing) also studies political ads. Kim et al. identified political ads on Facebook purchased by "suspicious" groups, including Russian groups known for spreading disinformation [41]. Stromer-Galley et al. [85] studied U.S. political ads on Facebook in 2016 and 2020, while Ballard et al. [7] characterized political campaign web display ads during the 2012 U.S. elections. Other work considered deceptive political advertising, (not necessarily online) including deceptively formatted "native" ads (e.g., [18, 55]). Van Steenburg provides a systematic literature review of political advertising research and proposes a research agenda, identifying the study of the impact of technology (i.e., the internet) as one key theme and area for future work (but does not discuss the manipulative patterns or non-official political ads that we see in our dataset) [84].

Our work considers ads appearing on websites rather than social media, and we capture all ads (not only those marked as political ads). Prior work has found that Facebook's ad archives are incomplete and use a limited definition of "political" [20, 21, 81]. Indeed, we found many ads that contained political themes but were not placed by an official campaign.

3 METHODOLOGY

In this section, we describe our methodology for measuring ads throughout the 2020 U.S. elections. In summary, we selected a group of popular mainstream and alternative news websites and scraped ads from these sites using crawlers in different locations. We collected 1.4 million ads in total from September 2020 to January 2021. We analyzed the content of our ads dataset using a combination of natural language processing, to automate tasks like identifying which ads were political, and manual qualitative analysis techniques, to provide greater context such as the party affiliation of the advertiser. See Figure 1 for a summary of our analysis pipeline.

3.1 Ad Crawling

3.1.1 Seed Websites. To collect ads, we crawled news and media websites that spanned the political spectrum and information ecosystem. We identified 6,144 mainstream news websites in the Tranco Top 1 million [44], using categories provided by the Alexa Web Information Service [4]. These mainstream sites included national newspapers, local newspapers, TV stations, and online digital media. We also compiled a list of 1,344 websites which we refer to as "misinformation websites". Websites in this list were identified as "fake news", alternative news, mis/disinformation, highly partisan, propaganda, or conspiracy websites by fact checkers (Politifact [83], Snopes [42], Media Bias/Fact Check [54], and others [23, 36, 61]).

To ensure that our crawlers could complete the crawl list in one day, we truncated the list to 745 sites by picking all sites with a ranking higher than 5,000 (411 sites), and then sampling from the remaining tail (334 sites) by choosing 1 site per bucket of 10,000 site rank, to ensure that lower ranked sites were represented. In

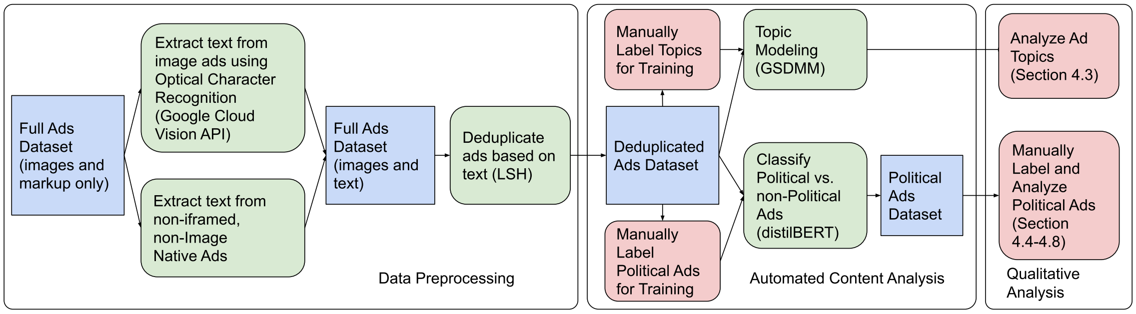


Figure 1: Overview of our analysis methodology. We used NLP techniques to preprocess and organize our dataset, and then conducted manual content analyses to explore political ads in greater detail, and to validate automated outputs. Blue boxes represent data, green boxes represent automated processes, and red boxes represent manual and qualitative analyses.

Site Bias	# Sites	Examples
Mainstream News and Media Websites		
Left	63	jezebel.com, salon.com
Lean Left	57	miamiherald.com, theatlantic.com
Center	46	npr.org, realclearpolitics.com
Lean Right	18	foxnews.com, nypost.com
Right	44	dailysurge.com, thefederalist.com
Uncategorized	376	adweek.com, nbc.com
News Websites Labeled as Misinformation		
Left	13	alternet.org, dailykos.com
Lean Left	6	greenpeace.org, iflscience.com
Center	1	rferl.org
Lean right	11	rt.com, newsmax.com
Right	60	breitbart.com, infowars.com
Uncategorized	50	globalresearch.ca, vaxxter.com

Table 1: Summary of our seed sites, by misinformation label and political bias (sources in Section 3.1.1).

Table 1, we show the number of sites in our crawl list by misinformation label and political bias. The political bias of websites were aggregated from Media Bias/Fact Check [54] and AllSides [3].

3.1.2 Crawler Implementation. We built a web crawler to scrape ads based on Puppeteer [28], a Chromium-based browser automation library. Each crawler node crawls the seed list once per day, crawling 6 domains in parallel in random order. For each seed domain, the crawler loads the root page and detects ads using CSS selectors from EasyList [19], a filter list used by ad blockers. Elements smaller than 10 pixels in width or height (like tracking pixels) were ignored. The crawler scrolls to each ad, takes a screenshot, and collects the HTML content. Then, the crawler clicks the ad, and collects the URL and content of the landing page. Because ads may differ on site homepage vs. subpages, for each seed domain, the crawler also visits and collects ads from an article on the site.

To minimize behavioral ad targeting, we crawled each seed domain using a clean browser profile (similar to prior work [96]). For each domain we visited, we ran separate browser instances inside a new Docker container, so that no tracking cookies or other state persisted across domains (though fingerprinting may be possible).

3.1.3 Crawler Nodes and Locations. We crawled ads using 4 nodes from geographical locations where we predicted the political landscape could result in different ads.

- *Sep. 25, 2020 – Nov. 12, 2020*: We first crawled from two cities in states predicted to be contested (Miami, FL; Raleigh, NC) and two uncompetitive (Seattle, WA; Salt Lake City, UT).
- *Nov. 13, 2020 – Dec. 8, 2020*: Due to contested election results, we switched two crawlers to Phoenix, AZ and Atlanta, GA. The other two crawlers alternated between the 4 previous locations (Seattle, Salt Lake City, Miami, Raleigh).
- *Dec. 9, 2020 – Jan. 19, 2021*: After the presidential election was resolved, we crawled from Atlanta, GA and Seattle, WA to observe the Georgia special election. Due to the Capitol insurrection, we continued crawling for 2 weeks.

To simulate crawling from these locations, we tunneled our traffic through the Mullvad VPN service. Mullvad's VPN servers ran on rented servers in local data centers (100TB, Tzulo, and M247). We verified that the VPN servers were located in the advertised locations using commercial IP geolocation services.

In sum, we ran 312 daily crawls, on 4 machines, using Chromium 88.0.4298.0, on a Debian 9 Docker image. The hardware was: Intel Core i7-4790 3.6GHz 32GB RAM, Intel Core i7-7740X 4.3 GHz 64GB RAM, and Intel Core i5-6600 3.30GHz, 16GB RAM (2x).

3.1.4 Data Collection Errors. No data was collected globally from 10/23–10/27 (VPN subscription lapsed), nor 12/16–12/29 and 1/15–1/19 in Seattle (VPN server outage). Some individual crawls also sporadically failed. In total, 33 of 312 daily crawl jobs failed.

3.2 Preprocessing Ad Content

3.2.1 Extracting Text from Ads. To enable large-scale analysis of the content of our dataset, we extracted the text of each ad. For ads where 100% of the visual content is contained in an image, we used the Google Cloud Vision API to perform optical character recognition (OCR). We extracted text from 877,727 image ads (62.6%) using this method. For native ads (i.e., sponsored content headlines), the text is contained in the HTML markup, so we automatically extracted the text from these ads using JavaScript. We extracted text from 524,518 native ads (37.4%) using this method.

3.2.2 *Ad Deduplication.*

Many ads in our dataset appeared multiple times, some appearing tens of thousands of times. To reduce redundancy during qualitative coding and the runtime of machine learning tasks, we de-duplicated ads using the extracted text. We grouped our dataset by the domain of the landing page of the ad, and for each group, we used MinHash-Locality Sensitive Hashing[1] (LSH) to identify ads with a Jaccard similarity > 0.5. We maintained a mapping of unique ads to their duplicates, which we used later to propagate qualitative labels for unique ads to their duplicates, enabling analysis of the whole dataset. After deduplication, we obtained a subset of 169,751 unique ads.

3.3 Analyzing Ad Content with Topic Modeling

To help us broadly understand the content of the ads in our dataset, we used topic modeling to automatically create groups of semantically similar ads, allowing us to qualitatively analyze those groups. We experimented with several topic modeling and text clustering algorithms, and selected Gibbs-Sampling Dirichlet Mixture Model (GSDMM) [94], which performed best on our dataset (see our experimental methodology in Appendix B). Second, we automatically generated qualitative descriptions of each ad cluster, by using c-tf-idf to extract the most significant words from the text cluster [33]. We applied GSDMM & c-tf-idf to describe the topics in our overall ads dataset (Sec. 4.3) and political product ads (Sec. 4.7).

3.4 Analyzing Political Ads In-Depth

Our main focus is the content of political ads in our dataset. We defined a political ad broadly: any ad with political content, whether or not the advertiser was a political campaign. This includes ads with incidental political content, such as ads for products incorporating election imagery or ads promoting political news articles.

Our analysis of political ads consisted of three phases. First, we used machine learning to automatically identify political ads in our overall ads dataset. Second, we manually labeled the attributes of each political ad, such as the purpose of the ad, and the advertiser's political affiliation. Lastly, we performed quantitative analyses of the labeled political ad data.

3.4.1 *Political Ads Classifier.*

To analyze political ads, we first needed to isolate political ads from the overall ads dataset. We implemented a binary text classifier based on the BERT language model, to classify our ads as political or non-political.

We started by generated a training set of political and non-political ads by labeling a random sample of ads in our dataset, obtaining 646 political ads and 1,937 non-political ads. We supplemented this data by crawling 1,000 political ads from the Google political ad archive [30] to balance the classes. We implemented the classifier by fine-tuning the DistilBERT model [76] for a binary classification task. We trained our model with a 52.5% / 22.5% / 25% Train / Validation / Test split. Our model achieved an accuracy of 95.5%, and an F_1 score of 0.9. We ran the classifier on our deduplicated dataset (169,751 unique ads) and it classified 8,836 unique ads as political (5.2%).

[1]We used the MinHash LSH implementation from the datasketch Python library: http://ekzhu.com/datasketch/lsh.html.

3.4.2 *Qualitative Analysis of Political Ads.*

Next, we we qualitatively coded the 8,836 unique political ads in our dataset to build a systematic categorization of the ads' content and characteristics [74]. Prior work in computer science and political science has also analyzed ad content using qualitative coding [85, 96]. We describe the development of our qualitative codebook and coding methods in detail in Appendix C.

Codebook Summary. We describe the high level categories of our codebook; a full list of subcodes is presented in Table 2, and a full set of definitions in Appendix C. We identified three mutually exclusive categories at the top level. **(1) Campaigns and Advocacy** ads explicitly addressed a political candidate, election, policy, or call to action. We further coded the *Election Level*, *Ad Purpose*, *Political Affiliation*, and *Organization Type*. We coded Election Level based on the level of government, and Purpose based on the desired action in the ad. We coded Organization Type by first identifying the advertiser, using "Paid for By..." labels and the landing page content, and then looking up the legal registration of the advertiser. We coded Affiliation if the advertiser was officially associated with a political party, or indicated alignment with words such as "conservative". We were able to attribute an organization type and advertiser affiliation for 96.5% of the campaigns and advocacy ads. **(2) Political News and Media** ads promoted political news articles, videos, news sources, or events. We further demarcated two subcategories. *Sponsored Articles / Direct Links to Articles* included ads which promoted a specific article or piece of content. *News Outlets, Programs, Events, and Related Media* contained all other types of political news and media. **(3) Political Products** ads centered on selling a product or service by using political imagery or content. We labeled political product ads as either *Political Memorabilia*, *Nonpolitical Products Using Political Topics*, or *Political Services*. Ads were labeled as **(4) Malformed/Not Political** if the classifier identified the ad as political, but the content was occluded, incorrectly cropped, or contained multiple ads, in a way that made it impossible to analyze the ad. False positives (ads incorrectly labeled as political by the classifier) were also given this label.

3.5 Ethics

Our data collection method had two types of impacts on the web. First, our crawler visited web pages and scraped their content. We believe this had a minimal impact: all sites we visited were public-facing content websites, contained no user data, and were visited by our crawlers no more than 4 times per day.

Second, our crawler clicked on ads to scrape the landing page of the ads. By clicking on the ads, we may cause the advertiser to be charged for the clickthrough (unless our click is detected as illegitimate), which is paid to the website and various middlemen.

We determined that clicking on ads was necessary because it was the only way for us to obtain the content and URL of the landing page for each ad. Many ads obscure their landing page through nested iframes and redirect chains. This data was needed for automatically determining the identity of the advertiser and for manually investigating the landing pages during qualitative coding (when the ad itself did not have sufficient context).

It is difficult to estimate the costs incurred to advertisers as a result of our crawls, but we believe the amount was low enough to be inconsequential. We cannot precisely determine the cost because the bid for each ad is not visible, and we do not know if advertisers pay using a cost-per-impression model or cost-per click model. For advertisers who pay based on impressions, we estimate the amount charged to be $3.00 per thousand impressions [87]. If all advertisers paid by impression, we estimate the total cost to *all* advertisers to be approximately $4,200. For the average advertiser, the mean number of ads we crawled was 63, and the median was 3, resulting in a mean cost of $0.19, and median cost of $0.009. If advertisers instead paid per click, we estimate a cost of approximately $0.60 per click [39]: in this case, the the mean advertiser would have been charged $37.80, and the median would have paid $1.80. The outlier advertisers in our dataset who received the most clicks were predominantly intermediary entities, such as Zergnet (36k ads), mysearches.net (26k ads), and comparisons.org (9k ads). These intermediaries place ads on other websites on behalf of advertisers on their platform, meaning that costs incurred for these intermediaries were spread among many individual sub-advertisers.

Stepping back, as we discuss further in Section 5, because of the distributed nature of the web ad ecosystem and the complex incentives of different stakeholders, we believe it is critical that external audits investigate the content and practices in this ecosystem, as we do in this study. Towards that end, we believe that the (small) costs of our study were justified. It is only through the process of clicking on ads, and evaluating the resulting landing pages, that can one fully understand the impact to users if they were to click on the ads. This is akin to the observation that malware websites may be linked from ads, potentially requiring search engine companies aiming to develop lists of known malware sites to engineer their crawlers to click on ads [63]. Moreover, similar methodologies have been used in prior works studying ads [67, 93].

3.6 Limitations

Our crawling methodology provided an incomplete sample of political advertising on the web. Our crawlers only visited a finite set of news and media websites, excluding other places that political ads appear, e.g., Facebook. Because we only visited each site once, we only saw a fraction of all ad campaigns running at that time. Our crawlers also only see political ad campaigns that were served to them — ongoing political ad campaigns may not have been shown to the crawler e.g. because of targeting parameters. We may have failed to load landing pages for ads because of detection and exclusion of our crawler by ad platforms. Due to VPN outages and crawler bugs, some days are missing from the data (Sec. 3.1.4).

We relied on categorizations from the fact checkers AllSides [3] and Media Bias/Fact Check [54] to identify the political bias of our input websites. 42% of our input sites had a rating: some uncategorized sites were non-political news websites (e.g., espn.com), while others may not have been popular enough to be rated.

Our automated content analyses were based on text extracted with OCR and did not use visual context from images. Some ads contained text artifacts, which negatively impacted downstream analyses. Based on the sample we labeled, we estimate that 18% ads in our dataset were malformed, i.e., impossible to read the ad's content. This was typically caused by modal dialogs (such as newsletter signup prompts) occluding the ad, which are difficult to automatically and consistently dismiss.

For the majority of ads, our data did not allow us to identify the ad networks involved in serving the ads. Though our crawler collected the HTML content of each ad (including iframes), this alone was rarely sufficient to identify ad networks.

Despite the above limitations, our dataset presents a unique and large-scale snapshot of political (and other) web ads surrounding the 2020 U.S. election. These include ads that do not appear in Google's (or others') political ad transparency reports. To support future research and auditing of this ecosystem, we will release our full dataset along with the publication of this paper, including ad and landing page screenshots, OCR data, and our qualitative labels.

4 RESULTS

In this section, we present an analysis of the ads in our dataset. We begin by providing an overview of the dataset as a whole, including: How many ads appear overall, and how many of these are political ads of different types (Sec. 4.1)? How did the number of ads (political and non-political) change over time and location (Sec. 4.2)? Overall, what ad topics were common (Sec. 4.3)?

Then, we dive more deeply into our analysis of political ads. We investigate and characterize the sites political advertising appeared on (Sec. 4.4), advertisers running official campaign and advocacy ads (Sec. 4.5), misleading/manipulative campaign ads (Sec. 4.6), and political product ads (Sec. 4.7) and news and media ads (Sec. 4.8).

4.1 Dataset Overview

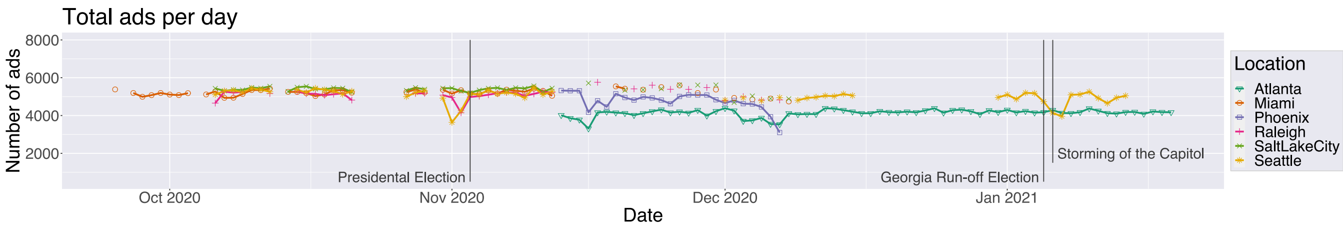
Between September 26, 2020 and January 19, 2021, we collected 1,402,245 ads (169,751 unique ads) from 6 locations: Atlanta, Miami, Phoenix, Raleigh, Salt Lake City, and Seattle. Our political ad classifier and qualitative coding, detected 67,501 ads (8,836 unique) with political content, or 3.9% of the overall dataset. During our qualitative analysis of political ads, we removed 11,558 false positives and malformed ads (3,201 unique), resulting in 55,943 political ads. In Tab. 2, we show the number of political ads, across our qualitative categories. About a third of ads were from political campaigns and advocacy groups; over half advertised political news and media, and the remainder political products.

4.2 Longitudinal and Location Analysis

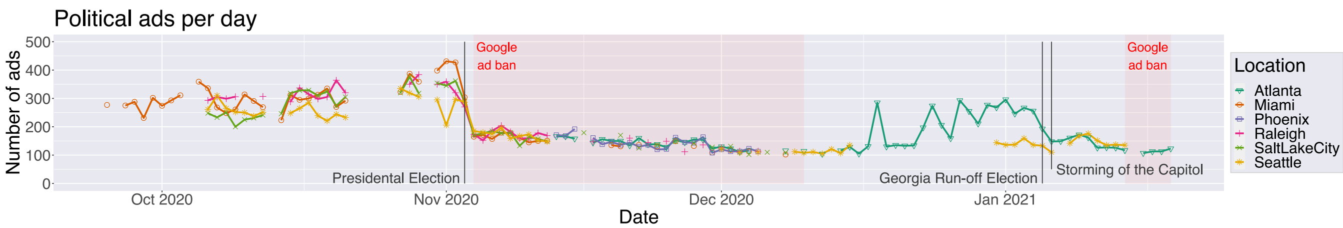
4.2.1 Ads Overall. We show the quantity of ads collected by location in Fig. 2a. The number of ads per day stayed relatively stable in each location: consistently around 5,000 ads per day. The stability in ad counts indicates that changes in demand for ad space before and after the election had little impact on websites' ad inventory.

We collected about 1,000 fewer ads per crawler day in Atlanta than other locations. We do not know if this was due to differences in location-based targeting or an artifact of our crawling (e.g., limitations of the Atlanta VPN provider).

4.2.2 Political Ads. The amount of political ads over time and locations is visualized in Fig. 2b. Leading up to the presidential election on Nov. 3, 2020, the number of ads per day in each location increases from less than 250 to peaks of 450. After election day, the number of political ads seen by crawlers sharply decreases, to below 200 ads/day. This decrease could be a natural consequence



(a) The number of ads collected in each crawler location. We collected a relatively constant number of ads for each location.



(b) The number of political ads, classified as political by our text classifier, collected in each crawler location. The number of political ads was higher prior to the elections in November and January, were lower in the period after the elections.

Figure 2: Longitudinal graphs showing the number of total ads and political ads, collected in six locations from Sept. 2020 to Jan. 2021. Salient U.S. political events, as well as ad bans implemented by Google, are superimposed for context. Gaps from mid-Nov. to mid-Dec. are because we scheduled crawls on nonconsecutive days. Other gaps are due to VPN outages (see Sec. 3.1.4).

of less political attention following election day; it likely was also due to Google's first ad ban, from Nov. 4 to Dec. 10. We believe Google's ad bans help contextualize our results, given Google's large presence in web ads — but because we did not determine the ad networks used by each ad, we cannot prove a causal connection.

During Google's first ban, we collected 18,079 political ads. 76% of these ads were political news ads and political product ads. In the 4,274 campaign and advocacy ads during this period, 82% were from nonprofits and unregistered groups, such as Daily Kos, UnitedVoice, Judicial Watch, and ACLU. The remaining 18% (783 ads) were from registered committees, some from candidates in special elections (e.g., Luke Letlow, Raphael Warnock), but others from PAC groups specifically referencing the contested Presidential election. For example, an ad from the Democratic-affiliated Progressive Turnout Project PAC reads: "DEMAND TRUMP PEACEFULLY TRANSFER POWER – SIGN NOW".

Google lifted their political ad ban on Dec. 11. At this time, we only collected data from Seattle and Atlanta, and observed a rise in the number of political ads per day in Atlanta until the Georgia run-off election on Jan. 5, 2021, but no corresponding rise in Seattle. The increase in Atlanta came almost entirely from Republican-affiliated committees — Democratic-affiliated advertisers seem to have bought very little online advertising for this election (Fig. 3).

Following the Georgia election, we again observed a sharp drop in ads per day from the Atlanta crawler, matching the Seattle crawler at less than 200 political ads per day.

Though we observe that the volume of political advertising generally fell after elections, Google's ban on political advertising did not stop all political ads — other platforms in the display ad ecosystem still served political advertising.

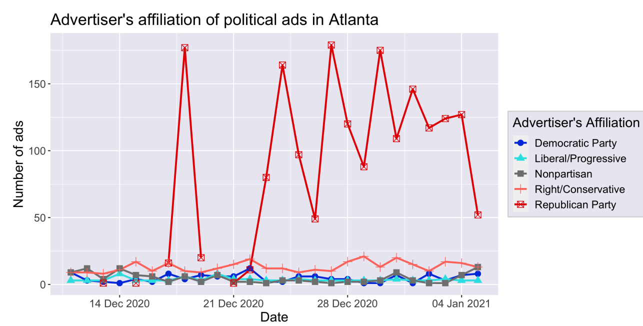


Figure 3: Campaign ads observed in Atlanta in Dec 2020–Jan 2021, prior to the Georgia special elections. Almost all ads during this time period were run by Republican groups.

4.3 Topics of Ads in Overall Dataset

To provide context before diving into political ads (Sec. 4.4-4.8), we present results from a topic model of the entire dataset. Tab. 3 displays the 10 largest topics in the data, each with a manually assigned topic description, the top c-TF-IDF terms, and the number of ads assigned to the topic.

The largest topic regarded "enterprise" ads, e.g., a Salesforce ad to "empower your partners to accelerate channel growth with external apps." The second largest topic included "tabloid" ads, e.g., "the untold truth of Arnold Schwarzenegger," as well as many clickbait and native advertisements. The model's fourth largest topic, "politics", contained 71,240 ads: a 64.8% overlap with the 55,943 political ads identified by our classifier and qualitative coding.

These topics give us a sense of the context within which political ads were embedded. Like the web ad content studied in prior

Ad Categories	**Count**	**%**
Political News and Media	29,409	52%
Sponsored Articles	25,103	45%
News Outlets, Programs, Events	4,306	7%
Campaigns and Advocacy	22,012	39%
Level of Election		
Presidential	5,264	9%
Federal	5,058	9%
State/Local (including initiatives/referenda)	2,320	4%
No Specific Election	2,150	4%
None	7,220	13%
Purpose of Ad (not mutually exclusive)		
Promote Candidate or Policy	10,923	20%
Poll, Petition, or Survey	7,602	14%
Voter Information	4,145	7%
Attack Opposition	3,612	6%
Fundraise	2,513	4%
Advertiser Affiliation		
Democratic Party	5,108	9%
Right/Conservative	5,000	9%
Republican Party	4,626	8%
Nonpartisan	4,628	8%
Liberal/Progressive	1,673	3%
Unknown	781	1%
Independent	172	<1%
Centrist	24	<1%
Advertiser Organization Type		
Registered Political Committee	12,131	22%
News Organization	4,249	8%
Nonprofit	2,736	5%
Business	931	2%
Unregistered Group	913	2%
Unknown	781	1%
Government Agency	241	<1%
Polling Organization	30	<1%
Political Products	4,522	8%
Political Memorabilia	3,186	6%
Nonpolitical Products Using Political Topics	1,258	2%
Political Services	78	<1%
Political Ads Subtotal	55,943	100%
Political Ads - False Positives/Malformed	11,558	
Non-Political Ads Subtotal	1,347,810	
Total	1,402,245	

Table 2: Summary of the types of ads in our dataset.

Topic	c-Tf-IDF Terms	Ads	%
enterprise	cloud, data, business, software, marketing	93,475	6.7
tabloid	look, photo, star, upbeat, celebrity, celeb, truth	90,596	6.5
health	fungus, trick, fat, try, cbd, dog, doctor, knee, tinnitus	73,240	5.2
politics	vote, trump, biden, president, election, yes, sure	71,240	5.1
sponsored search	search, senior, yahoo, living, car, might, visa	70,613	5.0
entertainment	stream, original, music, watch, listen, tv, film	50,248	3.6
shopping (goods)	boot, shipping, jewelry, newchic, mattress, rug	49,457	3.5
shopping (deals/sales)	friday, black, deal, sale, cyber, review, monday	45,022	3.2
shopping (cars/tech)	suv, luxury, phone, common-search, deal, net, auto	44,179	3.2
loans	loan, mortgage, payment, rate, apr, fix, nml	43,629	3.1

Table 3: Top Topics in the Overall Ad Dataset.

work [96, 97], political ads were surrounded by ordinary or legitimate ads for products and services, as well as low-quality and potentially problematic ads.

4.4 Distribution of Political Ads On Sites

Next, we examine how political ads were distributed across sites by political bias, misinformation label, and popularity.

Political Bias of Site. Overall, we find that political ads appeared more frequently on sites with stronger partisan bias. Fig. 4 shows the fraction of ads that were political across websites' political biases for mainstream and misinformation sites.

The percentages we calculate are the number of ads normalized by the total number of ads collected from sites for each level of bias. The number of ads collected from sites in each bias level varies, but no group of sites had overwhelmingly more ads. From Left to Right, the number of ads collected per site in each group were: 1,888, 1,950, 2,618, 2,092, and 2,172, and 1,676 had unknown bias.

Two-sample Pearson Chi-squared tests indicate a significant association between the political bias of the site and the percentage of ads that were political, for both mainstream news sites ($\chi^2(5, N = 1150676) = 25393.62, p < .0001$) and misinformation sites ($\chi^2(5, N = 206559) = 8041.43, p < .0001$). Pairwise comparisons using Pearson Chi-squared tests, corrected with Holm's sequential Bonferroni procedure, indicate that all pairs of website biases were significantly different ($p < .0001$).

On mainstream news sites, conservative sites had more political ads than others; 9% and 10.3% of ads on right-leaning and right sites were political, but only 6.9% and 4.4% of ads on left and left-leaning sites. On misinformation sites, 26% of ads on left sites were political, substantially more than right leaning sites. In 4 of the 7 left misinformation sites (AlterNet, Daily Kos, Occupy Democrats, Raw Story) over 19% of ads were political.

We also find that political advertisers tend to target sites matching their political affiliation: Democratic and liberal groups ran the majority of their ads on left-of-center sites, and likewise for Republican and conservative groups on right-of-center sites (Fig. 5). In particular, ads for Democratic political candidates and progressive nonprofits and causes ran substantially more on 2 of 7 Left misinformation sites (Daily Kos and Occupy Democrats).

Two-sample Pearson Chi-squared tests indicate a significant association between the political bias of the site and the number of ads based on the advertiser's political affiliation, for both mainstream news sites ($\chi^2(25, N = 1,150,676) = 22575.49, p < .0001$) and misinformation sites ($\chi^2(20, N = 206,559) = 22168.50, p < .0001$). Pairwise comparisons using Pearson Chi-squared tests, corrected

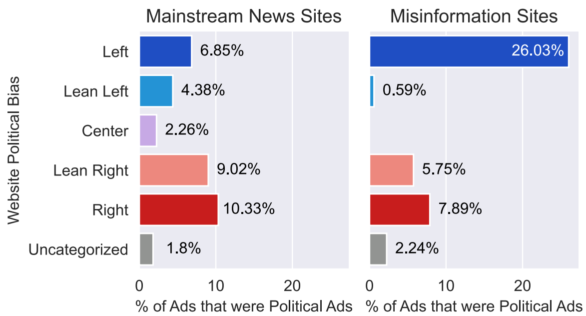


Figure 4: The percentage of ads, out of all ads on those sites, that were political, by sites' political bias and misinformation label. Higher percentages of ads on partisan sites were political, compared to centrist/uncategorized sites.

the Holm-Bonferroni method, indicate that all pairs of website biases were significantly different ($p < .0001$) except for the (Lean Left, Uncategorized) Misinformation Sites.

Site Popularity. We found little relationship between site popularity and the number of political ads on it (Fig. 6). While sites hosting many political ads tended to be popular politics sites (e.g., dailykos.com, mediaite.com), some popular sites (e.g., nytimes.com, cnn.com) ran <100 political ads. A linear mixed model analysis of variance indicates no statistically significant effect of site rank on the number of political ads ($F(1, 744) = 0.805, n.s.$).

At a high level, we find that political ads are seen more on websites that are political and partisan in nature. We hypothesize that this is either due to contextual targeting (political groups advertising to co-partisans), and/or because neutral news websites choose to block political advertising on their sites to appear of impartiality.

4.5 Advertisers of Campaign Ads

Next, we analyze the advertisers who ran campaign and advocacy ads: their organization type, their affiliations, and how many they ran. Fig. 7 shows these ads by organization type and affiliation.

Registered Committees. Most campaign ads (12,131, 55.1%) were purchased by registered committees (FEC or state PACs). These ads were roughly evenly split between Republican- and Democratic-affiliated committees, including official candidate committees, like Biden for President, as well as Hybrid PACs and party-affiliated Super PACs, such as the Progressive Turnout Project and the Trump Make America Great Again Committee. These also include candidate committees for other state, local, and federal offices.

Nonprofits. We observed campaign ads from nonpartisan nonprofits, e.g., AARP (259 ads, 1.2%), ACLU (256 ads, 1.2%), as well as explicitly conservative ones, e.g., Judicial Watch (504 ads, 2.3%), Pro-Life Alliance (471 ads, 2.1%). Few explicitly liberal nonprofits ran ads under our categorization system. However, some may consider self-described nonpartisan organizations as liberal, e.g., issue organizations like the ACLU, or voting rights groups like vote.org.

News Organizations. Some news organizations ran explicitly political ads to promote candidates or policies — these were mostly conservative-leaning organizations. The top advertisers in this

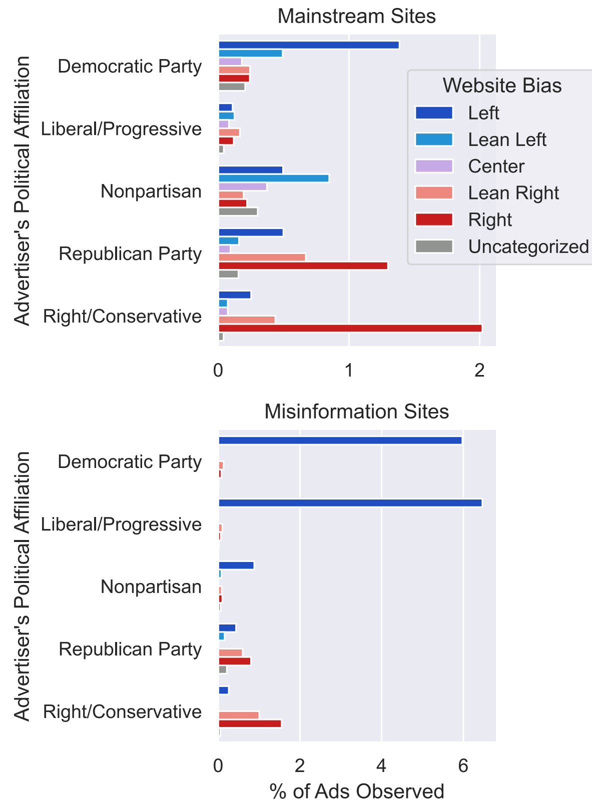


Figure 5: The percentage of ads observed on websites from advertisers of different political affiliations, by the political bias and misinformation label of the website. Advertisers tended to run ads on websites aligned with their politics.

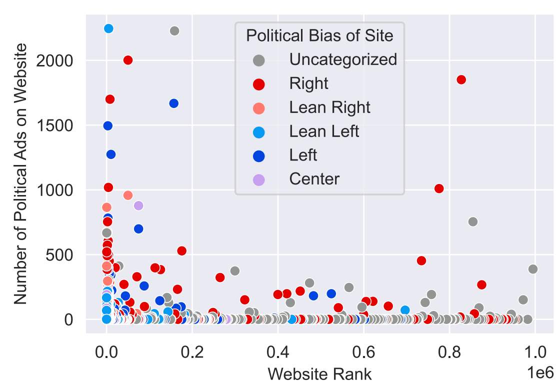


Figure 6: The total number of political ads observed on each site, by the site's Tranco rank. Though the largest outliers in terms of political ads tend to be popular sites, many popular sites show few if any political ads.

group are not well-known, e.g., ConservativeBuzz (1,199 ads, 5.4%), UnitedVoice.com (800 ads, 3.6%), and rightwing.org (393 ads, 1.8%). ConservativeBuzz does not have a website, despite claiming to be a

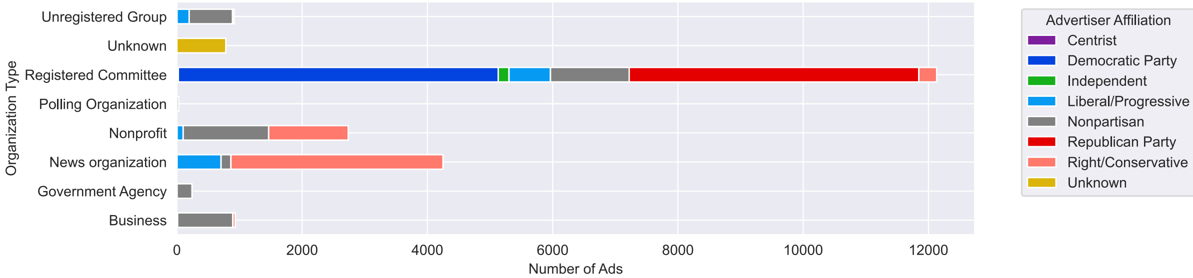


Figure 7: Campaign and advocacy ads by organization type of the advertiser, color-coded by the political affiliation of the advertiser. Ads from registered committees dominated, roughly evenly divided between Democratic and Republican ads, but ads from news organizations and nonprofits were more heavily conservative and nonpartisan respectively.

news source on their landing page; UnitedVoice and rightwing.org are ranked 248,997 and 539,506 on the Tranco Top 1m.

Other advertisers in this category are more well-known, e.g., Daily Kos, a liberal blog (690 ads, 3.1%, site rank 3,218); Human Events, a conservative newspaper (390 ads, 1.8%, rank 19,311); Newsmax, a conservative news network (117 ads, 0.5%, rank 2,441).

Unregistered Groups. Unregistered groups ran a small number of ads. The top advertiser was "Gone2Shit", a campaign from the marketing firm MullenLowe, which ran 228 ads for a humorous voter turnout campaign. The U.S. Concealed Carry Association ran 162 ads. Beyond these top two, a number of "astroturfing" groups or other industry interest groups ran ads, such as "A Healthy Future" (lobbying against price controls on Rx drugs), "Clean Fuel Washington", and "Texans for Affordable Rx" (a front for the Pharmaceutical Care Management Association, based on investigating their website). Other top ads came from unregistered, left-leaning groups, such as "Progress North" and "Opportunity Wisconsin", which describe themselves as grassroots movements. We also saw a small number of groups consisting of coalitions of registered nonprofits, who collectively fund an ad campaign, such as "No Surprises: People Against Unfair Medical Bills" and "votewith.us".

Businesses and Government Agencies. Some businesses, e.g., Levi's, Absolut Vodka, ran political ads: mostly nonpartisan ads for voter registration. State/local election boards also ran voter information ads, e.g. the NYC Board of Elections.

4.6 Misleading Political Polls

Focusing now on the content of ads in our campaign and advocacy category, rather than the advertisers, we highlight the use of polls, petitions, and surveys, many of which appear to contain misleading content, and manipulate users into providing their email addresses.

The purpose of many online political petitions and polls are to allow political actors to harvest personal details like email addresses, so that they can solicit donations, canvas, or advertise to those people in the future [66]. This phenomenon is present in our dataset. In a few cases (30 ads), ads we labeled as polls or petitions linked to nonpartisan public opinion polling firms such as YouGov and Civiqs, but most ads were from political groups, and had landing pages asking people to provide their email addresses.

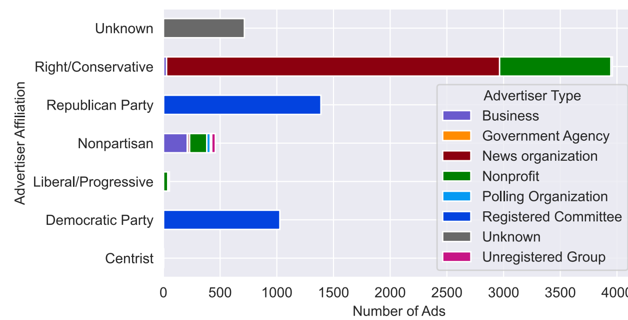


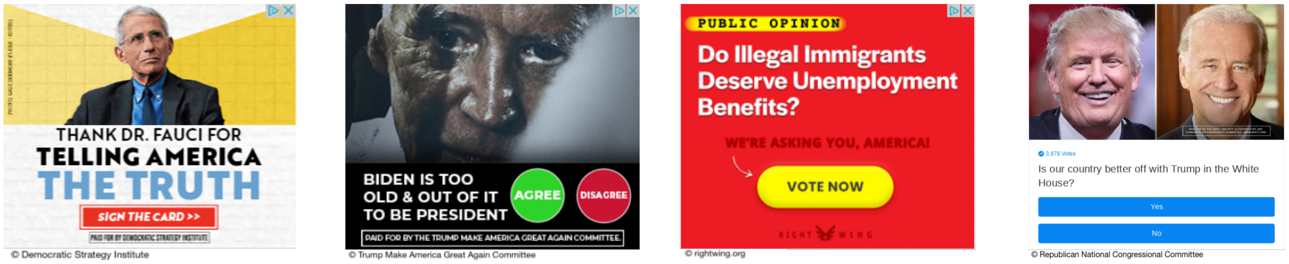
Figure 8: The political affiliation and organization types of poll/petition advertisers. These ads were primarily run by unaffiliated conservative advertisers, mostly news organizations and nonprofits.

We observe that poll and petition ads are more common from politically conservative advertisers. In Fig. 8, we visualize the number of poll ads by the political affiliation of their advertisers. Nonaffiliated conservative groups (mostly news organizations and nonprofits) ran the highest number of poll and petition ads (3,960 ads, 52% of total), followed by Republican party committees (1,389, 18.2%). Democratic committees ran fewer poll ads than their Republican counterparts (1,027 ads, 13.5%), while non-partisans and nonaffiliated liberals rarely use poll ads (458 ads, 6%; 53 ads, 0.6%).

Poll ads also made up a greater proportion of ads on right-leaning websites than other sites: 2.2% on Right and 1.1% on right-leaning websites were polls and petitions, compared to 1.1% on Left, 0.2% on left-leaning, and 0.2% on center sites.

Next, we describe several topics and manipulative tactics used by poll ads, which differ across political affiliations.

Democratic-Affiliated Groups. Most poll or petition ads from Democratic-affiliated groups were for highly partisan issue-based petitions, e.g., "Stand with Obama: Demand Congress Pass a Vote-by-Mail Option", "Official Petition: Demand Amy Coney Barrett Resign - Add Your Name". However, some petitions used even more contrived scenarios, such as posing as a "thank you card" for important politicians (Fig. 9a). These ads were run by affiliated PACs rather than party or candidate committees, such as the National Democratic Training Committee (290 ads), Progressive Turnout Project (282 ads), and Democratic Strategy Institute (215 ads).



(a) **(b)** **(c)** **(d)**

Figure 9: Examples of political ads purporting to be polls, including from: a Democratic-aligned PAC (a), the Trump campaign (b), a conservative news organization/email harvesting scheme (c), and a Republican-aligned PAC (d).

Republican-Affiliated Groups. The Trump campaign ran 906 ads with positive and neutral polls promoting President Trump and 479 ads with polls that attacked their opponent (e.g., Fig. 9b). Other Republican committees, such as the NRCC, used the LockerDome ad platform to run generic-looking polls not clearly labeled as political (e.g., Fig. 9d). Moreover, Lockerdome was also used by unaffiliated advertisers, e.g., "All Sears MD", rawconservativeopinions.com, to run nearly identical-looking ads that were used to sell political products; this homogenization makes it difficult for users to discern the nature of such ads. We also found 5 Lockerdome ads from the "Keep America Great Committee," whose operators turned out to be using it to commit fraud and pocket donations [50].

Conservative News Organizations. The largest subgroup of advertisers that used polls were right-leaning news organizations, such as such as ConservativeBuzz, UnitedVoice, and rightwing.org. Some polls use neutral language, e.g., "Who Won the First Presidential Debate?", while others used more provocative language, e.g., "Do Illegal Immigrants Deserve Unemployment Benefits?" (Fig. 9c).

Journalistic investigations have found that advertisers like ConservativeBuzz purport to be conservative news organizations but are actually run by Republican-linked digital marketing firms. Appearing as news, many of their stories are plagiarized and/or serve a political agenda. Their misleading poll ads are an entry point for harvesting email addresses for their mailing lists. They profit from these mailing lists by sending ads to their subscribers, including ads from political campaigns [6, 49].

Our data backs up these findings. We inspected poll ads from ConservativeBuzz, UnitedVoice, and rightwing.org, who comprise 55% of poll ads from Right/Conservative advertisers, and 29% of poll ads overall. The landing pages of their ads often asked for an email address to submit poll responses (Appendix E). We looked up these advertisers in the Archive of Political Emails to see the content of the emails that they send to subscribers [2]. We found that their emails often contained a mix of spam for various products (Subject: "This Toxic Vegetable Is The #1 Danger In Your Diet"), biased or inaccurate political news (Subject: "Fauci-Obama-Wuhan Connection Exposed in This Bombshell Report"), or a combination of the two (Subject: "URGENT – Think Trump Won? You need to see this...", selling a Trump mug).

[2]https://politicalemails.org/

4.7 Political Product Ads

We now consider ads in our dataset that used political content to sell products, divided into three categories.

4.7.1 Ads for Memorabilia. We observed 3,186 ads for political memorabilia, including clothing with slogans, collectibles, and novelty items. These ads were placed by commercial businesses – none were affiliated with political parties. Our GSDMM model produced 45 topics for political memorabilia ads; Tab. 4 shows the top seven.

We observe that the majority of memorabilia ads are targeted towards conservative consumers. 2,175 advertisements (68.3% of memorabilia ads) contained "Donald" and/or "Trump". Seven of the top ten topics are directly related to Trump, selling items such as special edition $2 bills (Fig. 10a), electric lighters, garden gnomes, and trading cards.

Some memorabilia ads targeting conservatives used potentially misleading practices. While some ads clearly advertised themselves as products, others disguised the memorabilia as "free" items, but requires payment to cover shipping and handling. Many ads did not clearly disclose the name of the advertiser. Some straddled the line between product ads and clickbait by making claims that the product "angered Democrats" or would "melt snowflakes." We also observed many collectible bills and coins, advertised as "Legal U.S. Tender", by sellers such as Patriot Depot, making dramatic claims like "Trump Supporters Get a Free $1000 Bill."

We observed far fewer ads for left-leaning consumers; the first topic containing left-leaning products was the 15th largest at 71 ads. Ads targeting liberals include a pin for "flaming feminists" or a deck of cards themed around the 2020 Senate Impeachment Trial of former President Trump (Fig. 10b).

4.7.2 Ads Using Political Context To Sell Something Else. We observed 1,258 ads that leveraged the political climate for their own marketing. Some of these ads were from legitimate companies, such as Capitol One advertising their alliance with the Black Economic Alliance to close opportunity gaps, or the Wall Street Journal promoting their market insight tools. However, many others were from relatively unknown advertisers peddling get-quick-rich schemes, like stocks that would "soar" from Biden winning the election (Fig. 10c) or election-proof security in buying gold.

Our GSDMM model found 29 topics for ads categorized as non-political products using political context. Tab. 5 details the largest 7 topics. The most prominent political contexts used for these topics were Congress (e.g., legislation related to the product) and the 2020

Topic	Weighted c-TF-IDF Terms	Ads
Trump wristbands and lighters	America, charger, USB, butane, require, vote, include	643
"free" Trump flags	dems, hate, give, foxworthynews, away, claim, flag	300
Trump electric lighters and garden deco	spark, instantly, generate, one, click, open, light, garden	253
$2 bills and "currency"	legal, tender, authentic, official, Donald, USA, make	186
Israel support pins	Israel, request, pin, Jew, fellowship, Christian	172
Trump camo hats, bracelets, and coolers	camo, gray, anywhere, discreet, go, sale, way, bracelet	156
Trump coins and bills	left, gold, coin, Democrat, upset, hat, supporter, value	133

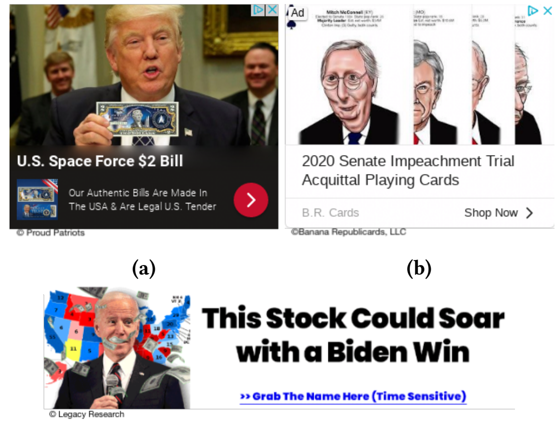
Table 4: Top Topics in Political Memorabilia Ads

Topic (Context)	Weighted c-TF-IDF Terms	Ads
Hearing devices (congress action)	hearing, aidion, slash, price, health, hear, act, sign, Trump	266
Retirement finance (congress action)	sucker, punch, law, pension, even, rob, retire, IRA	205
Investing (election-time)	former, presidential, Stansberry, congressional, veteran	123
Seniors' mortgage (congress action)	amount, reverse, senior, Steve, calculate, tap, age	97
Banking (racial justice)	JPMorgan, Chase, advance, co, racial, important, equality	66
Portfolio finance (election-time)	inauguration, money, Jan, wonder, oxford, communique	63
Dating sites (for Republicans)	Republican, single, date, woman, wait, profile, view	54

Table 5: Top Topics in Ads About Nonpolitical Products Using Political Context

election. Finance related topics in particular often cited market uncertainty around the election, e.g., referencing how a certain outcome might affect stocks and promoting their product as a hedge or chance to capitalize. Notably, three of the top four topics targeted older audiences: "hearing devices," "retirement finance," and "seniors' mortgage."

4.7.3 Where did political product ads appear? We find that political product ads appeared much more frequently on right-of-center websites (Fig. 11). This finding aligns with the qualitative content that we observed in these ads — a large amount of Trump memorabilia, and "scare" headlines about the election outcome. Two-sample Pearson Chi-Squared tests indicate a statistically significant association between the political bias of the site and the number of political product ads observed, both for mainstream news sites ($\chi^2(10, N = 1,150,676) = 4871.97, p < .0001$) and misinformation sites ($\chi^2(8, N = 206,559) = 414.75, p < .0001$). Pairwise comparisons using Pearson Chi-squared tests, corrected with the Holm-Bonferroni method, indicate that all pairs of website biases were significantly different ($p < .0001$), except for the following pairs on misinformation sites: (Lean Left, Lean Right), (Lean Left, Left), and (Lean Left, Uncategorized).



(a) (b)

(c)

Figure 10: Examples of political product ads, including those selling memorabilia (a-b) and those using the political context to sell something else (c).

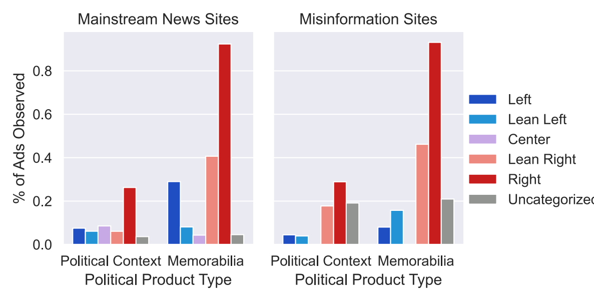


Figure 11: The percentage of ads observed that were for political products, by the political bias of the site. Right sites more frequently hosted ads for political products, both on misinformation and mainstream sites, and both for memorabilia or nonpolitical products using political contexts.

4.8 Political News and Media Ads

We observed 29,409 ads that were related to political news and media content. At 52.0% of all political ads, this was the most populous category and accounted for more than either of the other two categories. Unlike the product ads primarily selling goods or services, these ads advertised information or information-related services. We categorize these news and media ads into two groups: those that advertised specific political news articles, and those that advertised political outlets, events, or related media. Article ads contained a range of sensationalized, vacuous, or otherwise misleading content, especially with "clickbait-y" language that enticed people to click.

4.8.1 Sponsored Content / Direct Article Links. Overall, we find that most political news and media ads were sponsored content or links to articles (25,103 ads, 85.4%). Some of these ads reported substantive content, e.g., linking to a review of a documentary: "'All In: The Fight for Democracy' Tackles the Myth of Widespread Voter Fraud." Others were clickbait only using political themes for attention, e.g., "Tech Guru Makes Massive 2020 Election Prediction."

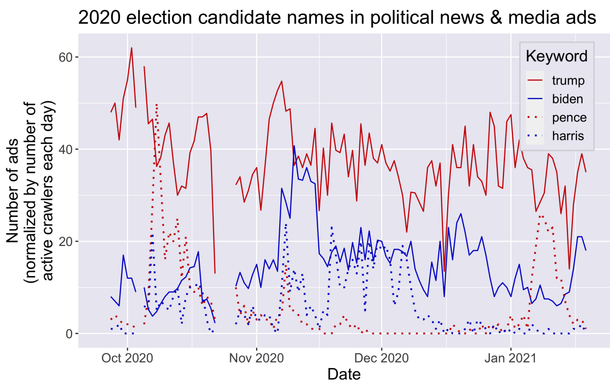


Figure 12: Number of ads including first and last names of the 2020 presidential and VP candidates.

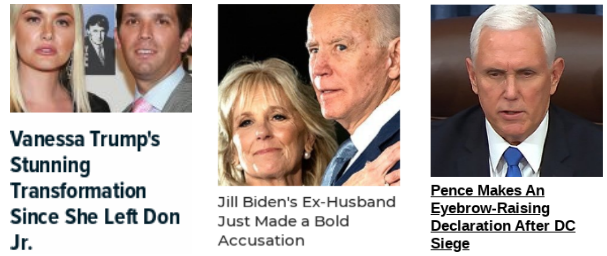
Misleading Ads and Headlines. Given that our ads were primarily scraped from news and media websites, many appeared as native ads that blend into the other content, albeit with an inconspicuous "Sponsored content" or similar label. Further, the headline shown in a political article ad did not always align with the actual content on the clickthrough page. For example, the ad shown in Fig. 13a links (via a Zergnet aggregation page) to an article[3] that recounts Vanessa Trump's life before marrying Donald Trump Jr., instead of after, as the title suggests. Many Zergnet ads with headlines implying controversy were unsubstantiated by the linked article.

Ads Mentioning Top Politicians. Overall, Trump and Biden were referenced in ads much more often than Pence and Harris (Fig. 12). Within political news and media ads, "Trump" is referenced in ads 2.5x more than "Biden" (11,956 ads vs. 4,691, or 40.7% vs. 16.0%), even even after the election. Eight of the top ten ads mentioning Trump actually involve his family: e.g., "Trump's Bizarre Comment About Son Barron is Turning Heads" (1,377 ads, 4.7%), or "Eric Trump Deletes Tweet After Savage Reminder About His Father" (415 ads, 1.4%). The top 10 ads mentioning Biden imply scandals with his wife, e.g., Fig. 13b (1,267 ads, 4.3%), and his health, e.g., "Ex-White House Physician Makes Bold Claim About Biden's Health" (423 ads, 1.4%).

Looking at the VP candidates, Pence is referenced in ads frequently during the run up to the election and immediately following the insurrection at the Capital, while a spike in the mentions of Harris occurs in late November and early December. Some of the top 10 ads mentioning Pence connect him to high-profile events, including the VP debate ("The Pence Quote from the VP Debate That Has People Talking," 143 ads, 0.5%) and the U.S. Capitol storming (Fig. 13c). Some of the top 10 ads mentioning Harris highlight her ex ("Why Kamala Harris' Ex Doesn't Think She Should Be Biden's VP," 246 ads, 0.8%) as well as her gender ("Women's Groups Are Already Reacting Strongly to Kamala," 51 ads, 0.2%).

Frequent Re-Appearances of Sponsored Content. Out of 25,103 political article ads, we counted only 2,313 unique ads, meaning that many political article ads were shown to our crawler multiple times. On average, a single (unique) political article ad appeared to our crawlers 9.9 times, compared to 9.3 times for campaign ads and 5.1 times for product ads. The frequent re-appearance of political article ads is likely an artifact of content farms' practice of producing high quantities of low-quality articles solely for revenue from clicks [12]. 79.4% of all political news articles were run by Zergnet, which accounted for 19,690 ads and only 1,388 unique ads. Other top ad platforms for political news articles were Taboola (10.0%), Revcontent (5.7%), and Content.ad (1.8%).

[3] https://www.thelist.com/161249/the-stunning-transformation-of-vanessa-trump/



(a) (b) (c)

Figure 13: Political news and media articles. © Zergnet

4.8.2 Political Outlets, Programs, Events, and Related Media. A small portion of political ads, just 4,306 (7%), advertised a political news outlet, event, or other media content. This includes ads run by well-known news organizations, e.g., Fox News, The Wall Street Journal, The Washington Post, that advertised their organizations at large, as well as highlighting specific events, such as CBS's coverage of the "Assault on the Capitol" (Appendix E), or special programs about the presidential election. Ads were also run by less-well known news organizations advertising themselves or their events, e.g., The Daily Caller, a right-wing news and opinion site, or advocacy groups and nonprofits, e.g., Faith and Freedom Coalition (Appendix E), a conservative 501(c)(4). We also observed ads about books, podcasts, movies, and more.

4.8.3 Where did political news and media ads appear? Political news and media ads appeared more often on right-of-center sites, compared to center and left-of-center sites (Fig. 14). Two-sample Pearson Chi-Squared tests indicate a statistically significant association between the political bias of the site and the number of political news and media ads, both for mainstream news sites ($\chi^2(10, N = 1,150,676) = 16729.34, p < .0001$) and misinformation sites ($\chi^2(8, N = 206,559) = 3985.43, p < .0001$). Pairwise comparisons using Pearson Chi-squared tests, corrected with the Holm-Bonferroni method, indicate that all pairs of website biases were significantly different ($p < .0001$). Nearly 5% of ads on both Right and Lean-Right sites are sponsored content, but only 3.9%, 2.2%, and 0.8% on Left, Lean Left, and Center sites.

5 DISCUSSION

5.1 Concerns About Problematic Political Ads

Our investigation adds to a growing body of work studying potentially problematic content in online ads, political and otherwise (see Sec. 2). Here, we discuss further the potential harms from the problematic political ads we found.

Manipulative Polls. The most common manipulative pattern we observed in our political ads was the poll-style ad. We view these ads

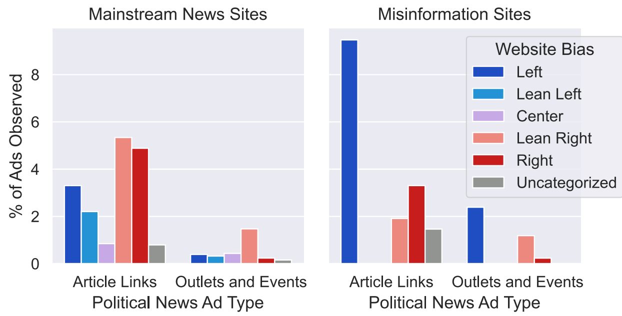


Figure 14: The number of political news ads observed per site, by the political bias of the site. Right sites more frequently host political news ads than others.

as problematic for two reasons. First, they manipulate people into clicking on ads by appealing to political motivations with (seemingly) clickable user interface elements. Second, once users click, they often ask users to provide personal information for further manipulation, e.g., to put them on manipulative email newsletters [52].

Political Clickbait. We observed attention-grabbing news and media ads that were not official political ads and thus do not appear in political ad transparency libraries. However, these ads are misleading: they are often designed to looks like real news articles, but the political controversies they imply (e.g., "Viral Video Exposes Something Fishy in Biden's Speeches," Figs. 13a-13c) are not usually substantiated by the underlying articles. Though we believe these ads' goal is to entice clicks for ad revenue, we worry that the provocative political "headlines" contribute to a climate of hyper-partisan political communication and muddy the information ecosystem to which voters are exposed. We argue that this type of political-adjacent advertising requires additional scrutiny from ad platforms and the public.

Exploitative Product Ads. Most ads aiming to make money through the sales of products and services are legitimate, identifiable as ads, and meet expectations of appropriateness [97]. However, we identified product ads that we would consider exploitative, e.g., that promise "free" products that turn out to not to be. Though such ads are not unique to political contexts, we observed many that leverage political controversy to attract potential buyers.

Misleading Political Organizations. Online ads (particularly native ads) have been criticized for being potentially hard to identify as ads, and thus regulated to require disclosure [11, 24]. We observe that these issues are compounded in a political context, where the advertiser's identity — e.g., political leaning, official (or not) political organization — is (or should be) key to a user's assessment of the ad. Being mistaken for a legitimate, official political organization can benefit problematic advertisers (e.g., exploitative product sellers or the fraudulent "Keep America Great Committee" [50]).

Partisan Ad Targeting. We observed more political ads, and more of the problematic ads that we discussed above, on more partisan websites, particularly right-leaning sites, as well as on low-quality and misinformation sites. Ad targeting in itself is not problematic, and naturally, political advertisers would wish to reach people with partisan alignments most likely to click on a given ad. However, we raise two concerns: first, the continued polarization of U.S. political discourse, reinforced by online ads; second, the risk that more vulnerable people are targeted with more manipulative and exploitative political ads.

5.2 Recommendations and Future Work

Recommendations for Ad Platforms and Policymakers. Political ads are already strongly regulated due to its sensitivity. We argue that ad platforms (which make and enforce ad policies) and policymakers (e.g., the FTC or FEC) should also consider the potential harms from ads not currently violating of existing policies. Many of the problematic ads that we saw were *not* official political ads but leveraged political themes and could have political ramifications (e.g., spreading misinformation via clickbait headlines). Ad platforms and regulators should consider these ads alongside official political ads in transparency and regulation efforts.

It is worth noting that there were types of problematic political ads that we did *not* observe. In a preliminary qualitative analysis, we did not find ads providing false voter information, e.g., incorrect election dates, polling places, or voting methods. While that does not mean they did not exist, it nevertheless suggests that ad platforms are regulating the most egregiously harmful ads.

The extreme decentralization of the online ad ecosystem poses additional challenges for ad moderation. Though Google periodically banned political ads during our data collection, we continued to see political ads, including problematic political ads, placed by other ad platforms. Thus, we call for more comprehensive ad moderation standards (and perhaps regulation) across advertising platforms — while recognizing the complex financial and political incentives that may hamper the clear-cut adoption of regulation [34].

Future Research. Future research should continue to audit ad content and targeting. While our study has focused on web ads appearing on news and media websites, the online ad ecosystem is large and requires analysis with different data collection and analysis methods. Future work should (continue to) consider political and other ads across various platforms — social media, mobile web and apps — and sites. Moreover, we focused on U.S. political ads, but future research should also critically study the role of online ads in non-U.S. political contexts or around other historical events.

Future work should also directly study people who view these ads, to better understand the actual impact of potentially problematic ads and for different user populations.

To enable other researchers to further analyze our collected ads, our dataset and codebook are available at: https://badads.cs.washington.edu/political.

6 CONCLUSION

We collected ads from 745 news and media sites around the time of the 2020 U.S. elections, including 55,943 political ads, which we analyzed using quantitative and qualitative methods. We identified the use of manipulative techniques and misleading content in both official and non-official political-themed ads, and we highlight the need for greater scrutiny by ad platforms and regulators, as well as further external study and auditing of the online ad ecosystem.

ACKNOWLEDGEMENTS

We thank our shepherd, Zakir Durumeric, as well as our anonymous reviewers, for helping improve this paper. We thank Kentrell Owens and Sudheesh Singanamalla for providing feedback on an earlier draft. This work was supported in part by the National Science Foundation under grant CNS-2041894, and by the UW Center for an Informed Public and the John S. and James L. Knight Foundation.

REFERENCES

[1] Albalawi, R., Yeap, T. H., and Benyoucef, M. Using Topic Modeling Methods for Short-Text Data: A Comparative Analysis. *Frontiers in Artificial Intelligence* (2020).

[2] Ali, M., Sapiezynski, P., Bogen, M., Korolova, A., Mislove, A., and Rieke, A. Discrimination through Optimization: How Facebook's Ad Delivery Can Lead to Biased Outcomes. *Proc. ACM Hum.-Comput. Interact. 3*, CSCW (Nov. 2019).

[3] AllSides. Balanced news via media bias ratings for an unbiased news perspective. https://www.allsides.com/unbiased-balanced-news.

[4] Amazon. Alexa Web Information Service API. https://awis.alexa.com/.

[5] Arthur, D., and Vassilvitskii, S. k-means++: The Advantages of Careful Seeding. In *Proceedings of the Eighteenth Annual ACM-SIAM Symposium on Discrete Algorithms* (USA, 2007), SODA '07, Society for Industrial and Applied Mathematics, p. 1027–1035.

[6] Baker, S. How GOP-linked PR firms use Google's ad platform to harvest email addresses. Engadget, November 2019. https://www.engadget.com/2019-11-11-google-political-ads-polls-email-collection.html.

[7] Ballard, A. O., Hillygus, D. S., and Konitzer, T. Campaigning Online: Web Display Ads in the 2012 Presidential Campaign. *PS: Political Science & Politics 49*, 3 (2016), 414–419.

[8] Ballotpedia. Presidential election, 2020. https://ballotpedia.org/Presidential_election,_2020.

[9] Bashir, M. A., Arshad, S., Robertson, W., and Wilson, C. Tracing Information Flows between Ad Exchanges Using Retargeted Ads. In *Proceedings of the 25th USENIX Conference on Security Symposium* (USA, 2016), SEC'16, USENIX Association, p. 481–496.

[10] Blei, D. M., Ng, A. Y., and Jordan, M. I. Latent Dirichlet Allocation. *Journal of Machine Learning Research 3* (2003), 993–1022.

[11] Campbell, C., and Grimm, P. E. The Challenges Native Advertising Poses: Exploring Potential Federal Trade Commission Responses and Identifying Research Needs. *Journal of Public Policy & Marketing 38*, 1 (2019), 110–123.

[12] Carr, A. Low quality websites: Content farms: What is a content farm?, 2021. https://researchguides.austincc.edu/contentfarms.

[13] Cillizza, C. Why the delayed election results prove the system is actually working, Nov. 2020. https://www.cnn.com/2020/11/04/politics/donald-trump-joe-biden-2020-election-results/index.html.

[14] Crain, M., and Nadler, A. Political Manipulation and Internet Advertising Infrastructure. *Journal of Information Policy 9* (2019), 370–410.

[15] Crovitz, L. G. How Amazon, Geico and Walmart fund propaganda. The New York Times, Jan. 2020. https://www.nytimes.com/2020/01/21/opinion/fake-news-russia-ads.html.

[16] Curiskis, S. A., Drake, B., Osborn, T. R., and Kennedy, P. J. An evaluation of document clustering and topic modelling in two online social networks: Twitter and Reddit. *Information Processing & Management 57*, 2 (2020), 102034.

[17] Dorsey, J. We've made the decision to stop all political advertising on Twitter globally, 2019.

[18] Dykhne, I. Persuasive or Deceptive - Native Advertising in Political Campaigns. *Southern California Law Review 91* (2018), 339.

[19] Easylist Filter List Project. Easylist. https://easylist.to.

[20] Edelson, L., Lauinger, T., and McCoy, D. A Security Analysis of the Facebook Ad Library. In *IEEE Symposium on Security and Privacy (Oakland)* (2020).

[21] Edelson, L., Sakhuja, S., Dey, R., and McCoy, D. An Analysis of United States Online Political Advertising Transparency. arXiv:1902.04385, Feb. 2019.

[22] Evelyn, K. Capitol attack: the five people who died, 2021. https://www.theguardian.com/us-news/2021/jan/08/capitol-attack-police-officer-five-deaths.

[23] FactCheck.org. Misinformation directory. https://www.factcheck.org/2017/07/websites-post-fake-satirical-stories/.

[24] Federal Trade Commission. .com Disclosures: How to Make Effective Disclosures in Digital Advertising, Mar. 2013. https://www.ftc.gov/system/files/documents/plain-language/bus41-dot-com-disclosures-information-about-online-advertising.pdf.

[25] Fischer, S. Scoop: Google to block election ads after election day, 2021. https://www.axios.com/google-to-block-election-ads-after-election-day-4b60650d-b5c2-4fb4-a856-70e30e19af17.html.

[26] Fischer, S. Scoop: Google to lift political ad ban put in place following capitol siege, 2021. https://www.axios.com/capitol-siege-google-political-ad-ban-5000245d-35d6-4448-b7b2-daa7ccfe816a.html.

[27] Global Disinformation Index. The Quarter Billion Dollar Question: How is Disinformation Gaming Ad Tech?, Sept. 2019. https://disinformationindex.org/wp-content/uploads/2019/09/GDI_Ad-tech_Report_Screen_AW16.pdf.

[28] Google. Puppeteer. https://developers.google.com/web/tools/puppeteer/.

[29] Google. Adwords API - Verticals. Google Developers, 2021. https://developers.google.com/adwords/api/docs/appendix/verticals.

[30] Google. Political advertising in the United States. https://transparencyreport.google.com/political-ads/region/US, 2021. Google Transparency Report.

[31] Graham, M. Pinterest says it will no longer allow ads on elections-related content, employees get time off to vote, 2020.

[32] Grootendorst, M. BERTopic: Leveraging BERT and c-TF-IDF to create easily interpretable topics, 2020.

[33] Grootendorst, M. Creating a class-based TF-IDF with Scikit-Learn. https://towardsdatascience.com/creating-a-class-based-tf-idf-with-scikit-learn-caea7b15b858, October 2020. Towards Data Science.

[34] Haenschen, K., and Wolf, J. Disclaiming responsibility: How platforms deadlocked the Federal Election Commission's efforts to regulate digital political advertising. *Telecommunications Policy 43*, 8 (2019), 101824.

[35] Hao, S., Chen, L., Zhou, S., Liu, W., and Zheng, Y. Multi-layer multi-view topic model for classifying advertising video. *Pattern Recognition 68* (2017), 66–81.

[36] Herbert, C. The Fake News Codex. http://www.fakenewscodex.com, December 2018.

[37] Hoffman, M., Bach, F., and Blei, D. Online Learning for Latent Dirichlet Allocation. In *Advances in Neural Information Processing Systems* (2010), J. Lafferty, C. Williams, J. Shawe-Taylor, R. Zemel, and A. Culotta, Eds., vol. 23, Curran Associates, Inc.

[38] Hubert, L., and Arabie, P. Comparing partitions. *Journal of Classification 2* (dec 1985), 193–218.

[39] Irvine, M. Google ads benchmarks for your industry. https://www.wordstream.com/blog/ws/2016/02/29/google-adwords-industry-benchmarks, 2021. Wordstream: Online Advertising Made Easy.

[40] Joshua Gillin. The more outrageous, the better: How clickbait ads make money for fake news sites. https://www.politifact.com/punditfact/article/2017/oct/04/more-outrageous-better-how-clickbait-ads-make-mone/, October 2017.

[41] Kim, Y. M., Hsu, J., Neiman, D., Kou, C., Bankston, L., Kim, S. Y., Heinrich, R., Baragwanath, R., and Raskutti, G. The Stealth Media? Groups and Targets behind Divisive Issue Campaigns on Facebook. *Political Communication 35*, 4 (2018), 515–541.

[42] Kim LaCapria. Snopes' field guide to fake news sites and hoax purveyors. Snopes, January 2016. https://www.snopes.com/news/2016/01/14/fake-news-sites/.

[43] Kingsley, S., Wang, C., Mikhalenko, A., Sinha, P., and Kulkarni, C. Auditing Digital Platforms for Discrimination in Economic Opportunity Advertising. *ArXiv 2008.09656* (2020).

[44] Le Pochat, V., Van Goethem, T., Tajalizadehkhoob, S., Korczyński, M., and Joosen, W. Tranco: A Research-Oriented Top Sites Ranking Hardened Against Manipulation. In *26th Network and Distributed System Security Symposium (NDSS)* (2019).

[45] Lécuyer, M., Spahn, R., Spiliopolous, Y., Chaintreau, A., Geambasu, R., and Hsu, D. Sunlight: Fine-grained Targeting Detection at Scale with Statistical Confidence. In *ACM Conference on Computer and Communications Security (CCS)* (2015).

[46] Lemire, J., Miller, Z., and Weissert, W. Biden defeats Trump for White House, says 'time to heal', 2021. https://apnews.com/article/joe-biden-wins-white-house-ap-fd58df73aa677acb74fce2a69adb71f9.

[47] Li, Z., Zhang, K., Xie, Y., Yu, F., and Wang, X. Knowing Your Enemy: Understanding and Detecting Malicious Web Advertising. In *ACM Conference on Computer and Communications Security (CCS)* (2012).

[48] Looper, E., and Bird, S. NLTK: The Natural Language Toolkit. *ArXiv https://arxiv.org/abs/cs/0205028* (2002).

[49] Markay, L. Pro-trump 'news sites' are harvesting your emails to sell to the campaign. https://www.thedailybeast.com/pro-trump-news-sites-are-harvesting-your-emails-to-sell-to-the-campaign, August 2020. The Daily Beast.

[50] Markay, L. Pro-Trump scam PAC operator hit with wire fraud charge. Axios, April 2021. https://www.axios.com/pro-trump-scam-pac-operator-wire-fraud-charge-d888876f-680c-4b47-83d8-d72da709ce8b.html.

[51] Mathur, A., Narayanan, A., and Chetty, M. Endorsements on Social Media: An Empirical Study of Affiliate Marketing Disclosures on YouTube and Pinterest. *Proceedings of the ACM on Human-Computer Interaction (CSCW) 2* (Nov. 2018).

[52] Mathur, A., Wang, A., Schwemmer, C., Hamin, M., Stewart, B. M., and Narayanan, A. Manipulative tactics are the norm in political emails: Evidence from 100K emails from the 2020 U.S. election cycle. https://electionemails2020.org, 2020.

[53] McHugh, M. L. Interrater reliability: the kappa statistic. *Biochem Med (Zagreb) 22*, 3 (October 2012), 276–82.

[54] Media Bias/Fact Check Team. Media Bias/Fact Check: The Most Comprehensive Media Bias Resource. https://mediabiasfactcheck.com/fake-news/.
[55] Misra, S. Deceptive political advertising: Some new dimensions. *Journal of Legal, Ethical and Regulatory Issues 18* (2015), 71–80.
[56] Muller, M. *Ways of Knowing*. Springer, 2014, ch. Curiosity, Creativity, and Surprise as Analytic Tools: Grounded Theory Method.
[57] Narayanan, A., Mathur, A., Chetty, M., and Kshirsagar, M. Dark patterns: Past, present, and future. *Communications of the ACM 63*, 9 (Aug. 2020), 42–47.
[58] Nelms, T., Perdisci, R., Antonakakis, M., and Ahamad, M. Towards Measuring and Mitigating Social Engineering Software Download Attacks. In *Proceedings of the 25th USENIX Conference on Security Symposium* (USA, 2016), SEC'16, USENIX Association, p. 773–789.
[59] Nikiforakis, N., Kapravelos, A., Joosen, W., Krügel, C., Piessens, F., and Vigna, G. Cookieless Monster: Exploring the Ecosystem of Web-Based Device Fingerprinting. *IEEE Symposium on Security and Privacy* (2013), 541–555.
[60] Ohlheiser, A. This is how Facebook's fake-news writers make money. Washington Post, Nov. 2016. https://www.washingtonpost.com/news/the-intersect/wp/2016/11/18/this-is-how-the-internets-fake-news-writers-make-money/.
[61] OpenSources Contributors. Opensources. https://github.com/OpenSourcesGroup/opensources, April 2017.
[62] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., and Duchesnay, E. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research 12* (2011), 2825–2830.
[63] Provos, N., Mavrommatis, P., Rajab, M. A., and Monrose, F. All your iframes point to us. In *Proceedings of the 17th Conference on Security Symposium* (USA, 2008), SS'08, USENIX Association, p. 1–15.
[64] Qi, P., Zhang, Y., Zhang, Y., Bolton, J., and Manning, C. D. Stanza: A Python Natural Language Processing Toolkit for Many Human Languages. *Association for Computational Linguistics System Demonstrations* (2020).
[65] Qiang, J., Qian, Z., Li, Y., Yuan, Y., and Wu, X. Short Text Topic Modeling Techniques, Applications and Performance: A Survey. *ArXiv https://arxiv.org/abs/1904.07695* (2019).
[66] Rakoczy, C. The sneaky reason you should never sign petitions or answer surveys online. Mic.com, May 2017. https://www.mic.com/articles/175333/want-to-save-money-heres-the-surprising-reason-why-you-should-never-sign-an-online-petition.
[67] Rastogi, V., Shao, R., Chen, Y., Pan, X., Zou, S., and Riley, R. Are these Ads Safe: Detecting Hidden Attacks through the Mobile App-Web Interfaces. In *Network and Distributed System Security Symposium (NDSS)* (2016).
[68] Řehůřek, R., and Sojka, P. Software Framework for Topic Modelling with Large Corpora. In *Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks* (Valletta, Malta, May 2010), ELRA, pp. 45–50. http://is.muni.cz/publication/884893/en.
[69] Ridout, T. N., Fowler, E. F., and Franz, M. M. Spending Fast and Furious: Political Advertising in 2020. *The Forum 18*, 4 (2021). https://www.degruyter.com/document/doi/10.1515/for-2020-2109/html.
[70] Röder, M., Both, A., and Hinneburg, A. Exploring the Space of Topic Coherence Measures. In *Proceedings of the Eighth ACM International Conference on Web Search and Data Mining* (New York, NY, USA, 2015), WSDM '15, Association for Computing Machinery, p. 399–408.
[71] Roesner, F., Kohno, T., and Wetherall, D. Detecting and Defending Against Third-Party Tracking on the Web. In *USENIX Symposium on Networked Systems Design and Implementation (NSDI)* (2012).
[72] Romano, S., Vinh, N. X., Bailey, J., and Verspoor, K. Adjusting for Chance Clustering Comparison Measures, 2015.
[73] Rosenberg, A., and Hirschberg, J. V-measure: A conditional entropy-based external cluster evaluation measure. In *Proceedings of the 2007 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP-CoNLL)* (Prague, Czech Republic, June 2007), Association for Computational Linguistics, pp. 410–420.
[74] Saldana, J. *The Coding Manual for Qualitative Researchers*. SAGE Publications, 2012.
[75] Sanchez-Rola, I., Dell'Amico, M., Balzarotti, D., Vervier, P.-A., and Bilge, L. Journey to the Center of the Cookie Ecosystem: Unraveling Actors' Roles and Relationships. In *IEEE Symposium on Security and Privacy* (2021).
[76] Sanh, V., Debut, L., Chaumond, J., and Wolf, T. Distilbert, a distilled version of bert: smaller, faster, cheaper and lighter. *ArXiv https://arxiv.org/abs/1910.01108v4* (2020).
[77] Schmidt, M. S., and Broadwater, L. Officers' Injuries, Including Concussions, Show Scope of Violence at Capitol Riot, 2021. https://www.nytimes.com/2021/02/11/us/politics/capitol-riot-police-officer-injuries.html.
[78] Schneider, E. Google will end political ad ban this week, 2021. https://www.politico.com/news/2020/12/09/google-end-political-ad-ban-443882.
[79] Silverman, C., and Alexander, L. How Teens In The Balkans Are Duping Trump Supporters With Fake News, Nov. 2016. https://www.buzzfeednews.com/article/craigsilverman/how-macedonia-became-a-global-hub-for-pro-trump-misinfo#.tcR3aZa5r.
[80] Smith, A., and Banic, V. Fake News: How a Partying Macedonian Teen Earns Thousands Publishing Lies. NBC News, December 2016. https://www.nbcnews.com/news/world/fake-news-how-partying-macedonian-teen-earns-thousands-publishing-lies-n692451.
[81] Sosnovik, V., and Goga, O. Understanding the Complexity of Detecting Political Ads. In *The Web Conference (WWW)* (2021).
[82] Spring, M. 'Stop the steal': The deep roots of Trump's 'voter fraud' strategy, 2021. https://www.bbc.com/news/blogs-trending-55009950.
[83] staff, P. Politifact's guide to fake news websites and what they peddle. Politifact, April 2017. https://www.politifact.com/article/2017/apr/20/politifacts-guide-fake-news-websites-and-what-they/.
[84] Steenburg, E. V. Areas of research in political advertising: a review and research agenda. *International Journal of Advertising 34*, 2 (2015), 195–231.
[85] Stromer-Galley, J., Hemsley, J., Rossini, P., McKernan, B., McCracken, N., Bolden, S., Korsunska, A., Gupta, S., Kachhadia, J., Zhang, W., and Zhang, F. The Illuminating Project: Helping Journalists Cover Social Media in the Presidential Campaign, 2020. https://illuminating.ischool.syr.edu/.
[86] Surian, D., Nguyen, D. Q., Kennedy, G., Johnson, M., Coiera, E., and Dunn, A. G. Characterizing Twitter Discussions About HPV Vaccines Using Topic Modeling and Community Detection". *J Med Internet Res 18*, 8 (Aug 2016), e232.
[87] Team, A. Google Display Ads CPM, CPC, & CTR Benchmarks in Q1 2018. https://blog.adstage.io/google-display-ads-cpm-cpc-ctr-benchmarks-in-q1-2018, 2018. AdStage.
[88] Team, B. V. J. Capitol riots: A visual guide to the storming of Congress, 2021. https://www.bbc.com/news/world-us-canada-55575260.
[89] Trish, B. From recording videos in a closet to Zoom meditating, 2020's political campaigns adjust to the pandemic. https://theconversation.com/from-recording-videos-in-a-closet-to-zoom-meditating-2020s-political-campaigns-adjust-to-the-pandemic-145788, 2020. The Conversation.
[90] Venkatadri, G., Andreou, A., Liu, Y., Mislove, A., Gummadi, K. P., Loiseau, P., and Goga, O. Privacy Risks with Facebook's PII-Based Targeting: Auditing a Data Broker's Advertising Interface. In *IEEE Symposium on Security and Privacy* (2018).
[91] Vinh, N. X., Epps, J., and Bailey, J. Information Theoretic Measures for Clusterings Comparison: Variants, Properties, Normalization and Correction for Chance. *Journal of Machine Learning Research 11*, 95 (2010), 2837–2854.
[92] Wolf, T., Debut, L., Sanh, V., Chaumond, J., Delangue, C., Moi, A., Cistac, P., Rault, T., Louf, R., Funtowicz, M., Davison, J., Shleifer, S., von Platen, P., Ma, C., Jernite, Y., Plu, J., Xu, C., Scao, T. L., Gugger, S., Drame, M., Lhoest, Q., and Rush, A. M. HuggingFace's Transformers: State-of-the-art Natural Language Processing, 2020.
[93] Xing, X., Meng, W., Lee, B., Weinsberg, U., Sheth, A., Perdisci, R., and Lee, W. Understanding Malvertising Through Ad-Injecting Browser Extensions. In *24th International Conference on World Wide Web (WWW)* (2015).
[94] Yin, J., and Wang, J. A Dirichlet Multinomial Mixture Model-Based Approach for Short Text Clustering. In *Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (New York, NY, USA, 2014), KDD '14, Association for Computing Machinery, p. 233–242.
[95] Zarras, A., Kapravelos, A., Stringhini, G., Holz, T., Kruegel, C., and Vigna, G. The dark alleys of Madison Avenue: Understanding malicious advertisements. In *ACM Internet Measurement Conference* (2014).
[96] Zeng, E., Kohno, T., and Roesner, F. Bad News: Clickbait and Deceptive Ads on News and Misinformation Websites. In *Workshop on Technology and Consumer Protection* (2020).
[97] Zeng, E., Kohno, T., and Roesner, F. What Makes a "Bad" Ad? User Perceptions of Problematic Online Advertising. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (New York, NY, USA, 2021), CHI '21, Association for Computing Machinery.

A HISTORICAL BACKGROUND

Election day was November 3, 2020, but the results of the election were significantly delayed due to the COVID-19 pandemic as states continued to receive mail-in votes and count ballots in subsequent days [13]. During this time, Trump and his campaign maintained that there was widespread voter fraud [82]. Most major news outlets declared the results — that Biden had obtained enough electoral votes to defeat Trump — on November 7 [46]. Sparked by a speech from Donald Trump on January 6, 2021 in which he continued to falsely claim that he had won the election, thousands of his supporters marched to the U.S. Capitol complex, where Congress had assembled to certify the electoral result [88]. The storming of the Capitol resulted in over 140 injuries [77] and 5 deaths [22]. The certification was completed the next day and President Biden's inauguration was held on January 20, 2021.

On November 3, elections were also held for seats in the Senate and House of Representatives. In state and local politics, elections were held for 13 governorships in 11 states and 2 territories, as well as for state legislative chambers, attorneys generals, state supreme court seats, and various referendums and ballot measures. In the state of Georgia, no Senate candidates received a majority of the vote during the first round, leading to a run-off election on January 5, 2021.

B TEXT CLUSTERING EXPERIMENTS

To qualitatively categorize the overall dataset, we used topic modeling and text clustering algorithms to group ads with similar content, and then created qualitative descriptions for each grouping via term frequency evaluation and manual labeling. The short-content, low-context nature of many of ads in the dataset most closely aligns with short-text topic modeling problems [1, 16, 65], however prior work on topic modeling advertisement text specifically is minimal [35]. As such, we pursued several diverse approaches to the NLP pipeline. For tokenization and lemmatization, we experimented with three pre-processing models: NLTK [48], Stanford NLP Group's Stanza [64], and DistilBERT [76]. Our pre-processing filtered on NLTK's english stopword corpus [4] along with several OCR artifacts such as "sponsoredsponsored." For topic generation, we experimented with several models and techniques: Latent Dirichlet Allocation (LDA) [10, 37], Gibbs-Sampling Dirichlet Mixture Model (GSDMM) [5] [94], DistilBERT + K-means Clustering [5, 76], and BERTopic [32]. We tested two implementations of LDA: Scikit-learn [62] and Gensim [68] with both Stanza and NLTK pre-processing. The selection of LDA parameter values to evaluate was based on results from Hoffman et al. [37]. The GSDMM model was tested on parameter values following suggestions from Yin and Wang [94] for both Stanza and GSDMM pre-processing as well. The DistilBERT model and DistilBERT pre-processing, implemented via Huggingface [92], were used to generate feature vectors for use by K-means clustering via Sklearn [62], which was tested on topic count. Lastly, BERTopic was tested on topic count as well.

To establish an approximate baseline for topic cardinality tuning and evaluation on the full deduplicated dataset, we manually labeled 2,583 unique randomly-sampled advertisements from the dataset (1.52% of the deduplicated ads), using a list of verticals that Google Adwords provides to publishers for targeting purposes [29] (e.g. "/Shopping", "/Shopping/Apparel", "/Shopping/Apparel/Men's Clothing"). For each ad we used the most descriptive label, but later collapsed the hierarchies to the second level to form larger groups. This process produced 171 unique label groups in the sample, which served as reference for topic count selection and as test data for evaluation. After generating topics for the full deduplicated dataset, the subset of ads corresponding to those labeled manually were isolated for similarity evaluation, assuming that a good model would roughly place ads in the same product sector in the same group.

[4] https://www.nltk.org/book/ch02.html
[5] https://github.com/rwalk/gsdmm

Model	ARI	AMI	H	C	C_v
BERT+K-means	0.0119	0.0337	0.3243	0.3119	0.5333
BERTopic	0.0109	0.1411	0.3424	0.4524	**0.5590**
LDA	0.2616	0.2306	**0.5343**	0.4696	0.4198
GSDMM	**0.4743**	**0.4438**	0.5297	**0.6328**	0.5457

Table 6: Best Performance by Model on Full Deduplicated Dataset

Model	Preprocessor	α	β	K	n_iters
Full Deduplicated Dataset	Stanza	0.1	0.05	180	40
Political Memorabilia	NLTK	0.1	0.1	75	40
Nonpolitical Products Using Political Topics	NLTK	0.1	0.1	30	40

Table 7: Selected GSDMM Model Parameters by Data Subset

Model	Topics
Full Deduplicated Dataset	180
Political Memorabilia	45
Nonpolitical Products Using Political Topics	29

Table 8: Selected GSDMM Model Topic Count by Data Subset

To evaluate similarity to our training clusters we used Adjusted Rand Index (*ARI*) [38] and Adjusted Mutual Index (*AMI*) [91] metrics implemented via Scikit-learn, accounting for possible imbalanced or balanced cluster sizes [72]. For evaluating intra-topic similarity, we measured Homogeneity (*H*) and for inter-topic similarity, we measured Completeness (*C*) [73], both via Scikit-learn. As a general measure of topic quality, we recorded C_v coherence via Gensim, based on Röder et al [70].

Table 6 details the best performances by model during tuning and testing. GSDMM performed the best (likely because it is designed specifically for short text documents), with an $ARI = 0.4743$, $AMI = 0.4438$, $H = 0.5297$, $C = 0.6328$, and C_v Coherence= 0.5457, and thus was selected. These values are comparable to other GSDMM results on Twitter data [16, 65, 86]. We ran the model on the top parameters 8 more times and selected the best iteration for use in our final results. The final GSDMM model produced 180 clusters on the full deduplicated dataset.

Labels for topics were designated after reviewing random samples of ads from within the topic and incorporating term results from c-TF-IDF, which utilizes a modified term frequency - inverse document frequency (TF-IDF) algorithm to select important terms from a given topic cluster [33].

Based on the performance of GSDMM on the overall dataset, we further used GSDMM for topic modeling on the political ad subsets of "political memorabilia" and "nonpolitical products using political topics." To evaluate performance in the absence of a ground truth, we measured C_v coherence. For both subsets, we tuned parameters of topic count, alpha, and beta. After identifying the best performing parameters, we ran the models 10 additional times each before selecting the best iteration. The top "political memorabilia" model achieved a C_v coherence of 0.7109 with 45 topics, and the top "nonpolitical products using political topics" model achieved a C_v coherence of 0.6777 with 29 topics. As before, we manually labeled the largest topics after reviewing random samples of ads from within the topic. However, due to the smaller topic sizes in the political subsets as compared to the full dataset, we weighted ads by their duplicate counts when generating c-TF-IDF results (e.g. an ad with 10 duplicates would have its text weighted 10x).

Table 7 contains the GSDMM parameters used in our selected GSDMM models by dataset subset, and table 8 details the topic count by the end of each model's runtime. For all three models, topic labels were scaled up from the deduplicated subsets to the full dataset.

C QUALITATIVE CODEBOOK

C.1 Methodology

We generated a qualitative codebook using grounded theory [56], an approach for generating themes categories via observation of the ground-level data. First, three researchers conducted a preliminary analysis of around 100 political ads each, creating open codes describing the characteristics of ads. We met to discuss and organized them into axial codes (i.e., multiple choice categories for different concepts) that best addressed our research questions.

Using these codes, three researchers coded the 8,836 ads, meeting multiple times during the process to iteratively refine the codebook based on new data. To assess the consistency of the coding, all coders coded a random subset of 200 ads, and we calculated Fleiss' κ (a statistical measure of intercoder agreement, $\kappa = 0$ indicates zero, $\kappa = 1.0$ indicates perfect) on this subset. We achieved an average $\kappa = 0.771$ across our 10 categories ($\sigma = 0.09$), indicating moderate-strong agreement [53].

Supplementing our qualitative codes, one researcher also labeled each campaign-related ad with the advertisers' name and legal classification (e.g., 501(c)(4) nonprofit), using information such as the "paid for" box in the ad, or the organization's website.

C.2 Codebook Contents

Our codebeook included three mutually exclusive high-level themes: **(1) campaigns and advocacy ads**, **(2) political product ads**, and **(3) political news and media ads**. To account for technical errors in crawling and classification, ads were classified as **Malformed/not political** if the extracted text and/or image content was incomplete or non-political, e.g., if screenshots failed to capture the whole ad, pop-ups or other material covered the ad, multiple ads were captured, incorrect model classification.

C.3 Campaigns and Advocacy Ads

We define campaign and advocacy ads as those that explicitly addressed or promoted a political candidate, election, policy, or call to action. Within this category, we further define the level of election, the purpose of the ad, and advertiser-related information.

C.3.1 Level of Election. Election level refers to candidate's jurisdiction, e.g., Senate elections were classified as federal. Specific codes of election level are: presidential, federal, state / local, no specific election, none. These codes are mutually exclusive. Note that "state / local" encompasses ballot initiatives and referenda as well as candidates.

C.3.2 Purpose of Ad. Ad purpose is mutually inclusive, meaning one campaign and advocacy ad can be assigned multiple purposes, e.g. voter information coupled with promoting a candidate. We coded for five purposes: promote candidate or policy; poll, petition, or survey; voter information; attack opposition; fundraise.

C.3.3 Advertiser Affiliation and Organization Type. To facilitate insights into the advertisers, we identified their political affiliation and type of organization (both mutually exclusive). First, we labeled each advertiser by name, using information from the ad content and/or the landing page (e.g., disclosures that say "Paid for By...").

Then, for each advertiser, we investigated their legal organization status, based on criteria developed by Kim et al. [41]. Organizations listed on the Federal Election Commission website, or state elections boards were labeled as Registered Committees. 501(c)(3), 501(c)(4), and 501(c)(6) tax-exempt nonprofits, and legitimate foreign nonprofits that were visible in the Propublica Nonprofit Explorer or Guidestar were labeled as Nonprofit organizations. Advertisers whose websites' home pages were news front pages were labeled as news organizations (regardless of their legitimacy). Elections boards, state Secretaries of State, or any other state or local government institutions were labeled as Government Agencies. Advertisers who ran poll ads, and were listed FiveThirtyEight's Pollster Ratings were labeled as poll organizations. Ads from corporations and other commercial ventures were listed as businesses. Any ads where the advertiser was not identifiable was listed as unknown.

We also attempted to determine the political affiliation of the advertiser. We coded affiliations as Democratic party, Republican party, or independent if the advertiser was officially associated with those political parties (local or national branches), or a candidate running under that party's ticket. Codes of right/conservative, liberal/progressive, and centrist apply to advertisers not officially associated with a party, but that explicitly indicate their political alignment with words like "conservative" or "progressive", either in the ad itself or on their websites. Nonpartisan affiliation refers to explicitly nonpartisan advertisers or nonpartisan election positions, e.g. some local sheriff offices.

C.4 Political Product Ads

We define political products ads as those centered on selling a product or service, using political imagery or content. This is further delineated into three mutually exclusive subcategories: political memorabilia, nonpolitical products using political topics, and political services.

C.4.1 Political Memorabilia. Political memorabilia includes all ads marketing products with some form of political design, e.g. 2nd-amendment-themed apparel, keepsakes such as election trading cards, and merchandise such as Trump flags. This encompasses products sold for profit and those marketed as free or giveaways.

C.4.2 Nonpolitical Products Using Political Topics. We coded ads as nonpolitical products using political topics if they used political messaging or context to advertise products ordinarily unrelated to politics. For instance, this covers investment firms marketing their stock reports in the context of election uncertainty.

C.4.3 Political Services. Political services includes ads promoting services directly involved in political industry such as lobbying or election prediction sites.

C.5 Political News and Media Ads

We define political news and media ads as those advertising a specific political news article, video, program, or event, regardless of the content style or quality. This categorization encompasses political clickbait and tabloid-style coverage of political figures as well as traditional news and media. We further define two mutually exclusive subcategories: sponsored articles / direct links to stores, and news outlets, programs, and events.

C.5.1 Sponsored Articles / Direct Links to Stories. We coded ads as sponsored articles / direct links to stories if they advertised a specific news article or media piece, e.g. an authored story or video regarding a current event. We automatically assigned 1,038 ads to this category from Zergnet, a well-known content recommendation company, as we determined via their advertisement methods that all ads from their domain fit this category.

C.5.2 News Outlets, Programs, Events, And Related Media. News outlets, programs, and events ads are distinguished from sponsored articles / direct links to stories in specificity, longevity, or reference. This category includes ads for political news outlets (as opposed to individual news pieces), lasting programs such as NBC election shows (in contrast to a single media clip), or future events such as panels or livestreams (rather than already existing news). We also included ads that were related media, such as podcasts, books, and interviews.

D WORD FREQUENCY ANALYSIS OF POLITICAL NEWS ADS

Unique Word Frequency Analysis. We looked at the most common words in political article ads by first deduplicating ads (Sec. 3.2.2), then tokenizing and lemmatizing the ad text. The top 10 words and their frequencies, as well as a word cloud of the top 50 words, is shown in Fig. 15. Among the top 50, we find frequent mentions of "trump" (1,050 times, more than double the next most common word, "biden"), as well as other politically relevant terms and names. Many of top 50 words reveal the general tone of these article ads, which often emphasize urgency, e.g., "new," "top," or scandal, e.g., "just," "claim," "reveal," "watch." The colloquialism "turn heads" was particularly common, e.g., "What Michigan's Governor Just Revealed May Turn Some Heads."

Word	Freq.
trump	1,050
biden	415
elect	314
read	235
new	219
top	215
articl	196
presid	176
thi	170
video	162

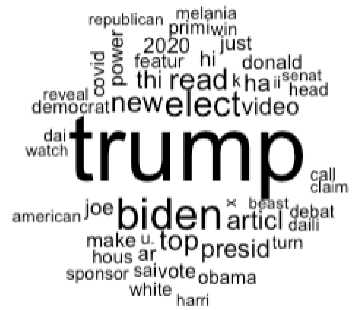


Figure 15: Frequencies of the top 10 words in political news article ads, and a word cloud showing the top 50. Ad text was deduplicated by ad, and then tokenized and lemmatized.

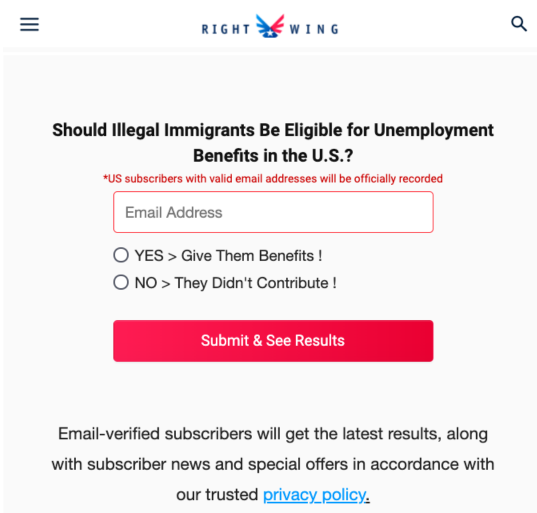


Figure 17: The landing page of the poll from Figure 9c. Viewers are asked to submit an email address to vote in the poll, and are signed up a newsletter. Prior reporting has shown this is typically a scheme to generate mailing lists and audiences for political campaigns to advertise to. © rightwing.org

Figure 18: Examples of political news and media ads about political outlets and events. Images © CBS and © Faith and Freedom Coalition

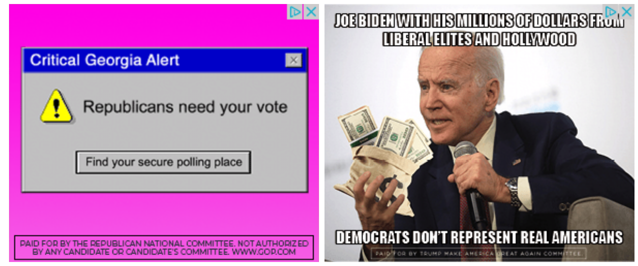


Figure 16: Other misleading campaign ads: an RNC ad imitates a system popup (a), and a Trump campaign meme-style ad attacking Biden (b). Images © Republican National Committee and © Trump Make America Great Again Committee.

E ADDITIONAL AD SCREENSHOTS

E.0.1 Other Misleading Campaign Ads: Phishing Ads and Memes. Though many campaign and advocacy ads in the dataset were potentially misleading or factually incorrect, we highlight two types that appeared particularly egregious.

In December, the Republican National Committee ran ads that imitate a system alert popup, like an impersonation attack (Figure 16a). We found 162 ads of this style in our dataset. Though the popup's style is outdated, it is generally misleading for ads and websites to imitate operating system dialogues or other programs.

Before the general election, the Trump Make America Great Again Campaign launched several attack ads in the style of an "image macro" meme. They featured (obviously) doctored photos of Joe Biden, holding Chinese flags, handfuls of cash, or depicting him approving of rioting (Fig. 16b). We found 119 meme-style ads in our dataset. Though attack ads and smears are fairly normalized, we did not observe the use of memes for attacks by any other campaigns. These ads contrast with more polished ads placed by other campaigns, and could be misleading if users assume meme-style ads are placed by other users, not an official political campaign.

E.0.2 Misleading Political Polls. Figure 17 shows the landing page of the misleading political poll depicted in Figure 9c.

E.0.3 Political News and Media. .

Figures 18a and 18b show examples of political news ads in the outlets, events, and programs subcategory. These ads, rather than advertising a sponsored link to a news article, instead advertise the outlet as a whole, or a larger event or program hosted by the outlet.