The Inventory is Dark and Full of Misinformation: Understanding the Abuse of Ad Inventory Pooling in the Ad-Tech Supply Chain

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Abstract

Ad-tech enables publishers to programmatically sell their ad inventory to millions of demand partners through a complex supply chain. Bogus or low quality publishers can exploit the opaque nature of the ad-tech to deceptively monetize their ad inventory. In this paper, we investigate for the first time how misinformation sites subvert the ad-tech transparency standards and pool their ad inventory with unrelated sites to circumvent brand safety protections. We find that a few major ad exchanges are disproportionately responsible for the dark pools that are exploited by misinformation websites. We further find evidence that dark pooling allows misinformation sites to deceptively sell their ad inventory to reputable brands. We conclude with a discussion of potential countermeasures such as better vetting of ad exchange partners, adoption of new ad-tech transparency standards that enable end-to-end validation of the ad-tech supply chain, as well as widespread deployment of independent audits like ours.

1 Introduction

The complexity of online advertising lends itself to fraud. A key success driver of online advertising is the ability of advertisers and publishers to programmatically buy and sell ad inventory across hundreds of millions of websites in real-time [1]. Notably, Real-Time Bidding (RTB) allows publishers to list their supply of individual ad impressions for bidding at an auction hosted by an ad exchange [2]. The ad exchange then requests its advertising demand partners to bid on the listed ad inventory based on the associated contextual and behavioral information. The ad-tech supply chain is complex because it relies on hundreds of specialized entities to effectively buy and sell the ad inventory in real-time and at scale [3]. Another factor exacerbating this complexity is that each ad impression is sold and resold across multiple parallel or waterfall auctions [4]. Such scale and complexity, combined with the opaque nature of the ad tech supply chain, makes it a ripe target for fraud and abuse that has been extensively studied in both industry and academia [5–13]. One of the most common types of ad fraud involves creating bogus or low quality websites and monetizing the resulting ad inventory. The fraudsters attempt to drive large volumes of traffic to their website through various illicit means such as bots, underground marketplaces, traffic exchanges, or even driving legitimate traffic through click-bait and viral propaganda [14–16]. A notable example that motivated our work is that of the "Macedonian fake news complex" [17–19]. In this scheme, fraudsters created misinformation news sites with misleading and click-bait headlines intentionally designed to go viral on social media, garnered millions of page views, and resulted in tens of millions of monetized ad impressions.

Advertisers are invested in preventing fraud. Ad-tech has safeguards to protect against this type of ad fraud by blocking the ad inventory of bogus or low quality websites even though the ad impressions are from legitimate users. Specifically, brand safety features supported by ad exchanges allow advertisers to block ad inventory of web pages that contain hardcore violence, hate speech, pornography, or other types of clearly objectionable content [20]. All the effort of fraudsters would be wasted if they are unable to monetize their ad inventory through programmatic advertising due to these brand safety features. To circumvent brand safety protections, fraudsters are known to exploit the opaque nature of the complex ad tech supply chain by misrepresenting their ad inventory [21]. For example, in domain spoofing [22], bogus or low quality publishers spoof the URLs of their ad inventory with that of reputable publishers; thereby deceiving reputable brands into buying their ad inventory even though their own domain is blocked due to brand safety concerns [23–25]. To mitigate ad fraud due to misrepresented ad inventory, the Interactive Advertising Bureau (IAB) introduced two transparency standards. `ads.txt` [26] requires publishers to disclose a list of all sellers that are authorized to sell their ad inventory. `sellers.json` [27] requires ad exchanges to disclose a list of all publishers and intermediate sellers whose ad inventory is listed on their exchange. Together, these standards, if implemented correctly, would reduce the prevalence of ad fraud by allowing buyers of ad impressions to verify the sources of the inventory.

Transparency mechanisms to prevent fraud are falling short. There is increasing concern that the `ads.txt` and `sellers.json` standards are either not widely adopted, implemented in ways that do not facilitate effective supply-chain validation, or intentionally subverted by malicious actors in a variety of ways. In this paper, we empirically investigate these concerns. We find that the `ads.txt` and `sellers.json` disclosures are plagued by a large number of compliance issues and misrepresentations. From this investigation, we find extensive evidence of 'pooling' of ad inventory from unrelated websites — a practice that makes it impossible for a buyer to correctly identify ad inventory sources (i.e., where their ad will eventually be placed). This effectively allows malicious websites to 'launder' their inventory by making them indistinguishable from well-reputed websites. To better understand how malicious actors may subvert the transparency demanded by the `ads.txt` and `sellers.json` standards, we use a set of well-known misinformation websites as a case study. Focusing on these misinformation websites, we confirm: (1) their widespread failure to comply with the `ads.txt` and `sellers.json` standards; and (2) heavy engagement with the practice of pooling. As a consequence, we also find real world instances of reputable brands purchasing impressions on these websites, perhaps unintentionally. Taken together, we make three key contributions.

Measuring compliance with `ads.txt` and `sellers.json` transparency standards. We study a set of 'control' and well-known misinformation websites to measure their compliance with `ads.txt` and `sellers.json`. We find that although compliance issues are widespread even in our control websites, they are significantly more prominent in the misinformation websites and the ad exchanges that list their ad inventory.

Measuring the prevalence of (dark) pooling. We measure the high prevalence of ad inventory 'pooling' by our control and misinformation websites. By simply analyzing public `ads.txt` and `sellers.json` files associated with our control and misinformation websites, we identify over 79K instances of pooling, of which 8.7K (11%) are used by misinformation sites to effectively launder their ad inventory. By analyzing the RTB metadata, we are able to confirm 297 pools being used by misinformation websites.

Measuring the (in)effectiveness of brand safety tools. Brand safety protections aim to prevent brands from purchasing low quality or fraudulent ad inventory. In our investigation, we find that the practice of pooling allows misinformation domains to effectively circumvent these protections. In fact, we find that misinformation websites that participate heavily in pooling are *more likely* to attract ads from reputable brands such as Forbes, GoDaddy, and Amazon.

2 Background

In this section, we provide a high-level overview of the mechanisms behind the supply of programmatic ads (§2.1) and the vulnerabilities in the ad supply chain (§2.2).

2.1 Programmatic advertising

At it's core, programmatic advertising is the automated trading of ad slot inventory (made available by publishers) for impressions of ad creatives made available by brands or advertisers. Although there are a variety of mechanisms for programmatic advertising (e.g., real-time bidding, header bidding, exchange bidding, etc.) and the organizations participating in each might differ, the types of entities involved in the supply chain remain the same for each mechanism.

The supply chain of programmatic advertising. Internet-scale programmatic advertising is made possible by the following entities: *supply-side platforms* (SSPs) for publishers to list their ad slot inventory in real time, *ad exchanges* (AdX) which aggregate the inventory of multiple SSPs and facilitate bidding on individual slots, and *demand-side platforms* (DSPs) which allow advertisers and brands to identify targets for their ad creatives and make bids on inventory listed at ad exchanges. These platforms work together to create a supply chain for ads as follows: When a user visits a publisher, the ad slot inventory associated with that visit is put up for auction at an AdX by the SSP. DSPs, operating on behalf of advertisers and brands, then make bids on the ad slot inventory available at the AdX. These bids are informed by what is known (to the DSP) about the user and the publisher. The winner of the auction is then notified by the AdX and the associated ad creative is used to fill the ad slot on the publisher. In the event that the auction fails (either because of no bids or not meeting the floor value set by the publisher), the AdX may repeat the auction or sell the slot to other AdXs. Figure 1 provides an illustration of the supply chain mechanism.

Transparency in the supply chain. Crucial to the correct operation of the ad supply chain is that the participating organizations are able to trust that publishers and AdXs are not misrepresenting their inventories or their relationships with other entities. For example, it is important for DSPs to confirm that the ad slot inventory that they are bidding on is actually associated with a particular publisher. Similarly, it is important for DSPs to confirm that the AdXs that they are purchasing ad slot inventory from are actually authorized to (re)sell that inventory. The absence of trust in this supply chain can lead to situations where DSPs make premium bids for ad slots that are actually associated with non-premium publishers — ultimately leading to a brand's ad creatives being displayed on publishers that they may not want to have associations with. In an effort to introduce trust and the ability for DSPs to perform basic verification of the ad slot inventory, the Interactive Advertising Bureau (IAB) introduced two

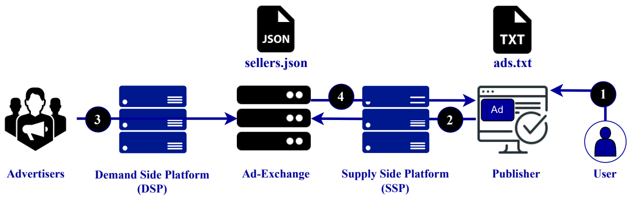

Figure 1: Programmatic Advertising Ecosystem: When a user visits a publisher website (Step 1), the publisher puts its ad-inventory for sale on ad-exchanges via SSPs in real-time (Step 2). Advertisers bid for these slots via DSPs (Step 3). Advertisement of the winning bid is displayed to the user on the publisher website (Step 4). To mitigate fraud, advertisers use `sellers.json` of ad exchanges and `ads.txt` of publishers to verify who is and who is not an authorized seller of a given inventory.

standards: `ads.txt` and `sellers.json`.

The `ads.txt` standard. The `ads.txt`[1] standard (introduced in 2017) aims to address ad slot inventory fraud by requiring each publisher domain to maintain an `ads.txt` file at the root level directory (e.g., `publisher.com/ads.txt`). The `ads.txt` file should contain entries for all AdXs that are authorized to sell or resell the ad slot inventory of the publisher. Each entry in the `ads.txt` file *must* contain the following fields:

- the authorized AdX,
- the publisher ID assigned to the publisher domain within the AdX network, and
- the authorized relationship between the publisher and authorized AdX — i.e., whether the AdX is authorized as a `DIRECT` seller or `RESELLER` of inventory for the domain.

Why `ads.txt` helps prevent fraud. When a bid request is sent by a publisher to an AdX (which forwards it to DSPs), the request contains the publisher ID and the domain associated with the inventory being listed. Importantly, because publisher IDs are typically associated with an organization and not a domain, it is possible for multiple domains to share the same publisher ID. This can make the prevention of domain spoofing challenging. The `ads.txt` file presents a mechanism for verifying that malicious websites are not spoofing domains in their bid requests. More specifically, `ads.txt` allows:

- AdXs to verify that the publisher ID in the bid request matches the publisher ID associated with the domain in the bid request and
- DSPs to verify that the AdX claiming to (re)sell the inventory of a domain is authorized by the domain to do so.

[1]"ads" stand for Authorized Digital Sellers and is fully specified at https://iabtechlab.com/wp-content/uploads/2021/03/ads.txt-1.0.3.pdf

Prior to the `ads.txt` standard, there were no mechanisms to facilitate such checks and the sale of fraudulent inventory was widespread [21].

The `sellers.json` standard. Similar to the `ads.txt` standard, `sellers.json` also aims to mitigate inventory fraud and misrepresentation. The `sellers.json` standard[2] requires each AdX and SSP to maintain a `sellers.json` file at the root level directory (e.g., `adx.com/sellers.json`)[3]. This `sellers.json` file *must* contain an entry for each entity that may be paid for inventory purchased through an AdX — i.e., one entry for each partner that is an inventory source for the AdX. Each of these entries contain the following fields:

- the seller type which indicates whether the entry is associated with a `PUBLISHER`, an `INTERMEDIARY` (i.e., inventory reseller AdX), or `BOTH` (i.e., this entity has their own inventory and also resells other inventory);
- the seller ID associated with the inventory source (same as the publisher ID in `ads.txt` if this entry is associated with a publisher); and
- the name and domain associated with the seller ID (these fields may be marked as "confidential" and hidden by AdXs to preserve the privacy of publishers).

Why `sellers.json` helps prevent fraud. When a bid request is received by a DSP from an AdX that is in compliance with the `sellers.json` standard, it must contain information about the provenance of the inventory in a Supply Chain Object (SCO) [4]. At a high level, the `sellers.json` file provides a mechanism for DSPs to identify and verify all the entities listed in this SCO. This is done as follows:

- When a bid request is received by the DSP, it should use the AdX's `sellers.json` file to verify that the final AdX has an authorized relationship with the prior holder (an SSP or another AdX) of the inventory.
- The previous step is applied recursively (on all intermediate neighbors in the SCO) to verify the end-to-end authenticity of the inventory.
- The DSP then uses the `sellers.json` files of all intermediaries and the `ads.txt` file of the publisher to verify that the publisher is legitimate and (re)sellers who handle the publisher's inventory are authorized to do so.

[2]Full specification of the `sellers.json` standard is available at: https://iabtechlab.com/wp-content/uploads/2019/07/Sellers.json_Final.pdf

[3]We observed several AdXs, including Google, use non-standard paths — e.g., Google's `sellers.json` is located at http://storage.googleapis.com/adx-rtb-dictionaries/sellers.json

[4]Supply Chain Object (SCO) contains an ordered list of all the entities involved in the ad transaction (e.g., publisher → SSP → reseller → AdX).

This ability to conduct end-to-end validation of the SCO helps DSPs identify cases where inventory is sourced from malicious publishers with fake `ads.txt` files or non-existent inventory is sold by malicious intermediaries.

2.2 Supply chain vulnerabilities

Despite the introduction of the `ads.txt` and `sellers.json` standards, there remain many vulnerabilities in the ad inventory supply chain. Our investigation focuses on the vulnerabilities that enable malicious publishers to gain ad revenue by misrepresenting or obscuring the sources of their ad slot inventory. Some of these vulnerabilities arise from misrepresentations in the `ads.txt` and `sellers.json` files, while others arise from pooling their (less marketable) inventory with the inventory of more desirable publishers. We refer to the former as *inventory misrepresentation* and the latter as *dark pooling*.

Inventory misrepresentation. Inventory misrepresentation is ad fraud that arises from misrepresentations of ad inventory by publishers. This misrepresentation is identified by discrepancies in the publisher's `ads.txt` file and is successful only when DSPs and AdXs do not follow the standards of the IAB's `ads.txt` and `sellers.json` specifications. Some examples of these misrepresentations are:

- a publisher's `ads.txt` file might falsely indicate that a popular AdX is an authorized (re)seller of it's inventory in order to boost it's reputation with other AdXs.
- a publisher's `ads.txt` file might falsely use publisher IDs of other popular publishers to suggest an authorized relationship with an AdX in order to boost the value of it's inventory.
- a publisher's `ads.txt` might have multiple conflicting entries for a single AdX making it possible to deceive certain implementations of `ads.txt` and `sellers.json` verification.
- a publisher's `ads.txt` file might list authorized relationships with (re)sellers that have no `sellers.json` files and make end-to-end verification of inventory impossible.

As we will show in this work, each of these occurs frequently in the case of misinformation publishers.

Dark pooling. *Pooling* is a common strategy to share resources in online advertising. Consider, for example, the case where two or more publishers are owned by the same parent organization. In such scenarios, the ability to share advertising infrastructure and AdX accounts allows for more efficient operation and management. One way to identify the occurrence of pooling is by noting a single AdX-issued 'publisher ID' shared by multiple publisher websites. *Dark pools* are pools in which publisher IDs are shared by organizationally-unrelated publishers (possibly of different reputations). It should be noted that simply using another domain's publisher ID in ad requests from a domain will result in any ad-related payments being made to the owner of the publisher ID. Therefore, for revenue sharing, the creation of these pools need to be facilitated either through intermediaries or by direct contract between the pooled organizations.

End-to-end validation of pooled supply chains. Pooling leads to a break down of any brand or DSP's ability to perform end-to-end verification of the ad inventory supply chain. Specifically, the final step of verification highlighted in §2.1 cannot be meaningfully completed unless *all* domains associated with a publisher account are publicly known (and unfortunately, this is not the case). This is because the end-to-end verification of the ad inventory supply chain, as specified by the IAB, implicitly relies on trust that publisher IDs are actually associated with specific organizations and that these associations are verified by AdXs. We illustrate this with an example.

- Consider a publisher domain `sportsnews.com` which has a legitimate subsidiary: `nbanews.com`. The owner of these domains registers for an account with a popular AdX (`adx`) and is issued the publisher ID `pubid` after being vetted by `adx`. It is expected that this domain can now share this publisher ID with it's subsidiary. Both sites will now list `adx` as a `DIRECT` seller through the `pubid` account in their `ads.txt` files.
- The publisher now enters into an agreement with the owners of `fakenews.com`, a site with dubious quality, to share `adx`'s issued publisher ID for a cut of the revenue generated from ads shown on `fakenews.com`. In it's `ads.txt` file, `fakenews.com` now adds `adx` as a `DIRECT` seller and also lists `pubid` as it's publisher ID.
- When a bid request is sent from `fakenews.com`, all basic supply chain validation checks are successful because the publisher ID `pubid` is in fact registered by `adx` in their `sellers.json` file. Any bidding DSP will therefore operate under the assumption that the site receiving their ads has been vetted by `adx` and is associated with `sportsnews.com` *unless* they maintain their own blocklist of low-quality or pooling domains.
- Complications only arise if any verification authority notices that `pubid` was only registered to the owner of `sportsnews.com` and the bid request actually originated at `fakenews.com`. However, invalidating the bid request because of this inconsistency will mean that even legitimate subsidiaries such as `nbanews.com` cannot pool their inventory. Instead, additional checks (perhaps by the AdX or bidding DSPs) are required to identify whether `fakenews.com` and `sportsnews.com` are

in fact owned by the same organization — a challenge that remains unaddressed by current validation mechanisms.

In essence, the trouble with the ability to pool multiple unrelated publisher websites behind a single publisher ID is that it provides a mechanism for publishers with undesirable ad slot inventory to effectively 'launder' their inventory by becoming indistinguishable from the inventory of more reputable publishers. Further, this can be achieved without the need to be explicitly verified by the AdX who issued the publisher ID. As we will show in this work, such pooling is common. In fact, we find some AdXs (e.g., Google) even providing services, via intermediaries, that facilitate pooling of unrelated entities.

3 Data Collection

In this section, we provide an overview of the publishers that are the subject of our research (§3.1) and our methodology for collection of `ads.txt`, `sellers.json`, and ad-related metadata associated with these websites (§3.2). [5]

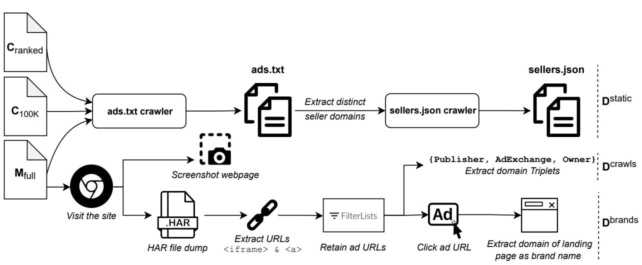

Figure 2: Overview of data gathering methodology.

3.1 Publisher domain selection

Our goal is to identify practices that prevent effective end-to-end validation of the ad inventory supply chain, among benign and malicious websites. We use domains from the Tranco top-100K websites as a stand-in for benign websites (referred to as a control) and well-known misinformation domains as a stand-in for malicious websites.

Selection of misinformation domains. Identifying misinformation websites is a hard problem and not the focus of this work. Therefore, rather than performing our own categorizations of domains, we leveraged existing datasets of misinformation domains curated by media scholars [28, 29] and computer scientists [30, 31].[6] To construct our misinformation domain set, we began by aggregating all domains from these lists and removing duplicates. This left us with 1276 domains. Next, we discarded 434 domains which were no longer active (e.g., http://donaldtrumpnews.co). Finally, we conducted manual verification to ensure that each remaining domain did contain content that was undeniably misinformation. This left us with a set of 669 *unique misinformation domains* ($\mathbf{M}_{\text{full}}$). Of these 669 domains, we created a subset of all the 251 domains that presented an `ads.txt` file and were also present in the Tranco top million website list [32] ($\mathbf{M}_{\text{ranked}}$). In parts of our analysis, $\mathbf{M}_{\text{ranked}}$ is used to perform a controlled comparison on the prevalence of `ads.txt` and `sellers.json` discrepancies between misinformation and non-misinformation sites.

Selection of benign (control) domains. In order to facilitate comparisons of the prevalence of specific behaviors between misinformation and benign domains, we created a control set of non-misinformation domains ($\mathbf{C}_{\text{ranked}}$). For each domain in $\mathbf{M}_{\text{ranked}}$, we included the most-similarly ranked non-misinformation domain that also had an `ads.txt` file. We performed matching based on ranks to avoid confounds related to popularity of domains. We also created a control set of the Tranco top 100K domains which contained an `ads.txt` file ($\mathbf{C}_{\text{100K}}$). This dataset was used to identify the broad prevalence of pooling. These four sets of domains ($\mathbf{M}_{\text{full}}$, $\mathbf{M}_{\text{ranked}}$, $\mathbf{C}_{\text{ranked}}$, and $\mathbf{C}_{\text{100K}}$) are the subject of our study.

3.2 Data gathering

We conducted our analysis using three sources of data: (1) `ads.txt` and `sellers.json` files related to publishers, AdXs, and other intermediaries; (2) real-time bid requests and responses made during visits to a publisher domain; and (3) brands placing advertisements on a publisher domain. An overview of our data gathering is illustrated in Figure 2.

`ads.txt` and `sellers.json` files. To build evidence for the occurrence of pooling and other misrepresentations, we need to analyze published `ads.txt` and `sellers.json` files associated with publishers and ad-tech entities.

Processing `ads.txt` files. We searched for an `ads.txt` file at the root of each domain in $\mathbf{M}_{\text{full}}$, $\mathbf{M}_{\text{ranked}}$, $\mathbf{C}_{\text{ranked}}$, and $\mathbf{C}_{\text{100K}}$. From these `ads.txt` files, we extracted the domains of all the entities that were listed as `DIRECT` sellers or `RESELLERS` of the publisher's inventory.

Processing `sellers.json` files. For each seller identified in our `ads.txt` files, we obtained the `sellers.json` file at their domain's root. When the `sellers.json` file was unavailable at this path, a best-effort attempt was made to manually identify any non-standard location of this file (e.g., Google used a non-standard location). We then parsed each `sellers.json` file to identify entities (and their domains) that were associated with `PUBLISHER`, `INTERMEDIARY`, or `BOTH` entries. Finally, until no new entities were discovered, we recursively fetched and parsed the `sellers.json` file as-

[5] The dataset used in our research is available at the following OSF project repository: https://osf.io/hxfkw/?view_only=bda006ebbd7d4ec2be869cbb198c6bd5.

[6] For domains obtained from [29], we discard those labeled as 'state', 'political', 'credible', and 'unknown'.

sociated with the entities labeled as either `INTERMEDIARY` or `BOTH`. This recursive fetching ensures that we have complete coverage of all the supply chain entities that may sell the inventory of all publishers in our datasets.

The $\mathbf{D}^{static}$ *datasets.* The above process was repeated in 10/21 and 2/22. We refer to the corresponding datasets of `ads.txt` and `sellers.json` files as $\mathbf{D}^{\text{static}}_{10/21}$ and $\mathbf{D}^{\text{static}}_{2/22}$. In total, each dataset included over 98K relationships from `ads.txt` files and 2.4M relationships from `sellers.json` files. We primarily rely on $\mathbf{D}^{\text{static}}_{2/22}$ for the remainder of this study and only use $\mathbf{D}^{\text{static}}_{10/21}$ to understand temporal changes in publisher and seller behaviors (§7).

Limitations of this dataset. It should be noted that, by itself, this dataset *cannot present evidence that pooling is actually occurring.* There are two primary reasons for this. First, because each publisher is responsible only for the content of their own `ads.txt` file, misrepresentations in other publishers' `ads.txt` file does not necessarily signify collusion/pooling. This is because the `ads.txt` standard does not require a publisher to verify that their account IDs are not used by other unrelated entities. Second, there are non-pooling motives for publishers to engage in misrepresentations in their `ads.txt` files. For example, demonstrating a longer `ads.txt` file might suggest that the publisher has relationships with and has been vetted by many inventory sellers in the ad ecosystem — making it easier to achieve new relationships.

Obtaining real-time bidding metadata. To identify concrete evidence of pooling, we constructed a dataset of real-time bidding metadata. These include bid requests, responses, redirects, and payloads associated with ad requests and responses. Publisher IDs are communicated in requests and responses to entities in the advertising ecosystem. Therefore, during a crawl of a given publisher's website, observing an unrelated entity's publisher ID in these metadata constitutes concrete evidence of collusion (i.e., pooling) between them.

Crawling configuration. Following the best practices for crawling-based data collection and methodology specification [33, 34], we obtained this dataset by using a web crawler driven by Selenium (v4.1.0) and the Chrome browser (v91.0) with bot mitigation strategies (multiple randomly timed full page scrolls and randomized mouse movements), Xvfb from a non-cloud vantage point, and a 30-second waiting time after the completion of the page load. Prior work has shown that the bidders and content of ad slots are impacted by previous browsing history [35, 36]. Therefore, each page load was conducted with a new browser profile to avoid biases in our measurements of ad responses and content. With these settings, we loaded each website in $\mathbf{M}_{\text{full}}$ and saved the associated HAR files [7] and full-page screenshots. In order to improve the completeness of our dataset, each crawl was repeated two times in Feb'22.

Extracting ad-related requests and responses. From each HAR file, we obtained all requests to and responses from ad-related URLs by matching them against nine popular advertising and tracking filter lists used in prior work [37]. Matching was performed using the *adblockparser* Python library [8].

Extracting real-time bidding metadata from ad-related requests and responses. We extracted the URLs, content, and HTTP POST-encoded data from each ad-related request, response, and redirect. From this data, we identified all (key, value) pairs encoded as *key=value* (including minor variations such as *key="value"*). Finally, we performed a match of all identified values with the publisher/seller IDs extracted from the $\mathbf{D}^{\text{static}}_{2/22}$ dataset. To reduce the incidence rates of false-positives, we only matched IDs with a length greater than five characters. Requests, responses, and redirects containing a match are labeled as real-time bidding-related flows. For each of these real-time bidding-related flows, we assigned the publisher domain from which the request originated as the *publisher domain* (i.e., observed inventory source) and the AdX domain owning the detected publisher ID as the *AdX* (i.e., inventory seller). We then used the `sellers.json` of the AdX/inventory seller to identify the domain that owned the publisher ID found in the ad request. This domain is labeled as the *owner domain* (i.e., expected inventory source). All (*publisher domain*, *AdX*, *owner domain*) triples were saved for later analysis.

Methodology validation. To verify that our method for extraction of real-time bidding metadata was valid, we conducted a manual validation test which included all RTB-related flows recorded from one of our crawls. In this test, we manually examined the flows to verify that they did in fact include a *key* that suggested that the *value* was associated with a publisher/seller ID. Our manual verification yielded a false-positive rate of 1.5%.

The $\mathbf{D}^{crawls}$ *dataset.* We label this dataset of (*publisher domain*, *AdX*, *owner domain*) triples as $\mathbf{D}^{\text{crawls}}$. In total, the $\mathbf{D}^{\text{crawls}}$ dataset consisted of 3.1K distinct triples observed across 2 crawls of 669 $\mathbf{M}_{\text{full}}$ domains. In §4, we use these triples to identify evidence of (dark) pooling in the misinformation ecosystem.

Limitations of this dataset. The advertising ecosystem and real-time bidding is auction-driven and participation from entities is non-deterministic. Therefore, any observations of entities and IDs in requests and responses related to ads will vary from one visit to the next, even when all other client-related factors are identical. Further, the client browser provides a vantage point that only affords observations of the winners of real-time bidding auctions. Finally, it is possible that some communications of the seller/publisher ID are not visible to us due to hashing or other obfuscation. As a consequence,

[7]HTTP Archive (HAR) files contain logs of all requests from and responses to a browser.

[8]https://github.com/scrapinghub/adblockparser

the completeness of our data recorded by crawling is questionable (despite repetition of the crawl). Unfortunately, this limitation is unavoidable. It should be noted, however, that this limitation only impacts the completeness of our findings and *not the correctness*. In other words, the prevalence of pooling and other discrepancies, as measured by our crawls, are only a lower-bound for their actual prevalence.

Identifying brands placing advertisements on domains. We also analyzed the characteristics of the brands whose ads appear on misinformation sites. To curate brands advertising on different misinformation domains, we performed 10 separate crawls. This repetition was to account for the probabilistic nature of online advertising which allows a single user to receive multiple different ads on repeated visits to the same website. In each of the 10 crawls, after each page load was complete and the 30-second wait period ended, we identified and automated clicks on the DOM elements associated with each advertising-related URL found on the page. These clicks resulted in a number of redirects and eventually redirected the browser to the destination website for the brand associated with the advertisement in a new tab. We used this landing website's domain as the 'brand' associated with the ad.

Methodology validation. To test the effectiveness of the outlined methodology, we conducted a pilot test on one crawl where we compared the brand names identified through manual analysis and the automated approach. We found that in 30% of the displayed ads, the automated approach had completely failed to identify the brand associated with an ad. In these cases, failure was largely due to the fact that some ad-related URLs were associated with hidden 'unclickable' elements of the ad. As a result, our automated approach could not correctly trigger the redirects that reach the website associated with the brand. As a result, to ensure completeness, we supplemented our automated approach by manually annotating the ads that could not be associated with brands.

The $\mathbf{D}^{brands}$ *dataset.* Using the above methodology, we recorded all the (*publisher, brand*) pairs identified with this methodology in a dataset that we refer to as $\mathbf{D}^{\text{brands}}$. In total, the $\mathbf{D}^{\text{brands}}$ dataset consisted of 4.2K distinct (publisher, brand) pairs and 2.1K unique brands.

4 Measuring Problematic Representations

In this section, we answer the question: *what are the incidence rates of pooling and other problematic representations in the misinformation ecosystem?* Specifically, we focus on measuring the prevalence of situations which would result in the failure of any *reasonable* inventory supply chain validation efforts. In §4.1, we provide a broad overview of the types of errors and misrepresentations commonly seen in `sellers.json` and `ads.txt` files that hinder end-to-end supply chain validation. We compare the prevalence of these errors on our control and misinformation domains. Then, in §4.2, we present evidence for widespread pooling in the advertising ecosystem and highlight cases of pooling by misinformation domains.

4.1 Prevalence of misrepresentations

Certain types of errors or misrepresentations in a publisher's `ads.txt` file or an AdX's `sellers.json` file may prohibit automated end-to-end verification of the ad inventory supply chain. In our dataset, we identified eight such problematic representations: (1) *Misrepresented direct relationships:* These are cases when a publisher claims that an AdX is a `DIRECT` seller of its inventory, but the AdX `sellers.json` lists it as an `INTERMEDIARY` (reseller) relationship; (2) *Fabricated publisher/seller IDs:* A publisher's `ads.txt` claims that an AdX is authorized to sell its inventory, but the AdX `sellers.json` does not claim *any* relationship with the publisher; (3) *Conflicting relationships:* A publisher claims multiple relationships with an AdX in their `ads.txt`, but the AdX only lists one of these in their `sellers.json`; (4) *Invalid seller type:* The `sellers.json` does not use any of the three acceptable types (`PUBLISHER`, `INTERMEDIARY`, or `BOTH`) to describe the source of the inventory associated with a specific publisher/sellerID; (5) *Invalid domain names:* The `sellers.json` does not present a valid domain name in the 'domain' field; (6) *Confidential sellers:* The `sellers.json` lists the domain associated with the publisher/sellerID as 'confidential'. It should be noted that this is not a violation of the `sellers.json` standard, but does prevent end-to-end supply chain verification; (7) *Listing intermediaries without* `sellers.json`*:* An AdX's `sellers.json` lists intermediaries that do not have a `sellers.json`; and (8) *Non-unique publisher/seller IDs:* The `sellers.json` lists multiple publishers and domains with the same seller/publisherID.

In Table 1, we present the prevalence of these misrepresentations in `ads.txt` files from $\mathbf{C}_{\text{ranked}}$ and $\mathbf{M}_{\text{ranked}}$ domains. We find a statistically significant difference in the number of errors present in `ads.txt` files from $\mathbf{C}_{\text{ranked}}$ and $\mathbf{M}_{\text{ranked}}$ domains (χ^2-test; $p < .05$). We find that, even when controlling for the rank of a website, misinformation domains are more likely to contain higher rates of `ads.txt` errors that result in failed supply chain validation. Table 2 compares the fraction of misrepresented/erroneous entries from `sellers.json` of AdXs that serve $\mathbf{M}_{\text{full}}$ (344 AdXs) domains with the `sellers.json` from AdXs that do not serve any of our $\mathbf{M}_{\text{full}}$ domains (483 AdXs). Once again, we see that the AdXs that engage with misinformation domains are significantly more likely to have errors in their `sellers.json` that result in the inability to perform supply chain validation. Taken all together, these results highlight the broad unreliability of the `ads.txt` and `sellers.json` standards and their current inability to allow end-to-end validation of the supply chain. This problem is especially pronounced for the ad inventory associated with misinformation domains.

Type	$\mathbf{C}_{\text{ranked}}$	$\mathbf{M}_{\text{ranked}}$
Misrepresented direct relationships	51%	64%
Fabricated publisher/seller IDs	65%	83%
Conflicting relationships	33%	49%

Table 1: Prevalence of problematic representations in `ads.txt` from domains in $\mathbf{C}_{\text{ranked}}$ and $\mathbf{M}_{\text{ranked}}$.

Type	No $\mathbf{M}_{\text{full}}$	≥ 1 $\mathbf{M}_{\text{full}}$
Invalid seller type	0.7%	0%
Invalid domain names	0.8%	54.8%
Confidential sellers	0.1%	46.1%
Intermed. w/o `sellers.json`	13.3%	49.8%
Non-unique IDs	62.6%	95.3%

Table 2: Fraction of `sellers.json` entries that contain different problematic representations from AdXs serving no $\mathbf{M}_{\text{full}}$ domains and at least one $\mathbf{M}_{\text{full}}$ domain.

4.2 Prevalence of pooling

As described in §2.2, pooling is the practice of using a single AdX account to manage the inventory of multiple domains. This results in a single AdX-issued publisher ID being associated with multiple domains. Although this practice enables more efficient management of advertising resources for publishers, it comes at the cost of increased opacity in the advertising ecosystem and reduces the usefulness of the end-to-end supply chain validation mechanisms introduced by the IAB.

Gathering evidence of pooling with the $\mathbf{D}^{\text{static}}_{2/22}$ dataset. We begin by identifying evidence of pooling in the $\mathbf{C}_{100\text{K}}$ and $\mathbf{M}_{\text{full}}$ websites from our $\mathbf{D}^{\text{static}}_{2/22}$ dataset. We use this dataset of `ads.txt` files associated with the Tranco top-100K domains to identify all cases where multiple domains listed the same publisher ID and AdX as a seller of their inventory. In total, we observed 79K unique pools — i.e., 79K unique (publisher ID, AdX) pairs were observed to have been shared by multiple publisher domains. Of these 79K pools, 8.7K (11%) of the pools also included at least one of the misinformation domains in $\mathbf{M}_{\text{full}}$. We refer to these 79K pools identified through the $\mathbf{D}^{\text{static}}_{2/22}$ dataset as *static pools*. The size of these pools ranged from 2 to nearly 9K domains, with an average of 70 domains per pool.

Characteristics of pools identified in the $\mathbf{D}^{\text{static}}_{2/22}$ dataset. These above reported pool sizes were certainly larger than what we anticipated and necessitated additional inspection for a better understanding of our findings. Specifically, we paid attention to the organizational relationships between pooled entities and whether pooling was occurring due to some ad-tech related mechanism.

Organization homogeneity of pools. From a cursory manual inspection of our pools, we observed (rather unsurprisingly) that larger pools appeared to contain many organizationally unrelated domains — i.e., they were *heterogeneous*. To measure the prevalence of such types of pools at scale, we mapped each domain in a pool to their parent organizations using the DuckDuckGo entity-organization list [38] and labeled each pool as follows: (1) *Homogeneous:* Pools whose member domains could all be mapped to a single parent organization; (2) *Potentially homogeneous:* Pools for which the parent organizations of all domains could not be identified. However, all domains that could be mapped were found to have the same parent organization; (3) *Heterogeneous:* Pools whose member domains were owned by more than one parent organization; and (4) *Unknown:* Pools for which no domain could be mapped to a single parent organization.

A breakdown of the prevalence of each of these types of pools is provided in Table 3. We make three key observations. First, we notice that *heterogeneous pools comprise a large fraction of all pools* — a deviation from the expectation that pools are allowed in order to facilitate resource sharing between sibling domains. The high incidence rates of heterogeneous pools in non-misinformation domains also *suggests* that there may be legitimate (i.e., not ill-intentioned) mechanisms that facilitate publisher ID sharing between organizations. Second, *pools containing misinformation domains are statistically significantly more likely to be heterogeneous* (85%) than pools without misinformation domains (41%) [χ^2-test $p < .05$]. Finally, we see that *pools containing misinformation domains are statistically significantly larger* (412.1 domains/pool) than pools without misinformation domains (20.3 domains/pool) [2-sample t-test $p < .05$]. Taken together, the latter two findings lend credence to the theory that misinformation domains are effectively 'laundering' their ad inventory by participating in mechanisms that facilitate large pools.

Pool Type	Pools w/ $\mathbf{M}_{\text{full}}$		Pools w/o $\mathbf{M}_{\text{full}}$	
	# Pools	μ_{size}	# Pools	μ_{size}
Homogeneous	40 (0.4%)	2.6	6.7K (9.6%)	2.6
Pot. Homog.	913 (9.1%)	18.8	18.4K (26.6%)	7.0
Heterogeneous	8.6K (85.0%)	482.5	28.4K (41.0%)	42.2
Unknown	563 (5.6%)	4.3	15.7K (22.7%)	3.9
All pools	8.7K	412.1	70.5K	20.3

Table 3: **(From $\mathbf{D}^{\text{static}}_{2/22}$) Prevalence of pools in $\mathbf{C}_{100\text{K}}$.** Pools are broken down by organization homogeneity and whether they contained a misinformation domain from the $\mathbf{M}_{\text{full}}$ dataset. μ_{size} denotes the average (mean) number of domains in a pool.

Pools facilitated by authorized ad-tech mechanisms. Our previous findings about the high rate of heterogeneous pools of large sizes, even among non-misinformation domains, suggests that there are ad-tech mechanisms that organically facilitate pooling. After further investigation we found that many of the heavily pooled (publisher ID, AdX) pairs appeared to be issued by a small number of AdX's whose `sellers.json` file indicated that the issued publisher IDs were not associated with specific publishers but instead with specific RTB platforms (notably Google). Put in other words, the publisher ID issuing AdX's `sellers.json` file indicated that the 'owner domain' of the pooled publisher ID was another AdX platform — suggesting that these pooling mechanisms might be authorized by the platforms themselves.

In Table 4 we see that three of the most commonly pooled owner domains are in fact associated with large AdXs (`google.com`, `justpremium.com` owned by GumGum, and `townnews.com`). Notably, nearly 25% and 12% of the pools that used GumGum- and Google-owned publisher IDs also contained known misinformation domains. For example, `100percentfedup.com`, a site that promoted anti-vax and stolen-election theories, received ads through pools using Google-owned publisher IDs issued by the AdX 'Index Exchange'. In contrast, TownNews, an advertising firm focused on serving local media organizations did not have a single pool containing known misinformation domains.

To uncover whether the actions of the publisher ID-issuing AdXs (bottom of Table 4) might be authorized by the AdX platforms that were listed as domain owners of the publisher ID (top of table 4), we conducted a search for any programs run by AdX platforms that might require pooling — i.e., is there public documentation of *authorized* programs to allow unrelated publishers to pool their inventory through intermediaries. Of the AdXs in Table 4, we only found public documentation of a Google program that authorized sharing of publisher IDs. Google's Multiple Customer Management (MCM) ad manager platform allows 'Google MCM-partner' ad organizations to manage the inventory of multiple client domains through a single AdMob account [39]. This results in all associated domains sharing the publisher ID of the intermediary organization. *Our results highlight a violation of Google's own policies regarding advertising on websites 'making unreliable claims' or 'distributing manipulated media'* [40]. However, public documentation does not state whether Google delegates all domain and content verification responsibilities to their MCM partners and therefore it remains unclear if the violation is a failure of Google's own verification practices or those of their MCM partners'. Similarly, the pooled misinformation domains using GumGum-owned publisher IDs were also in violation of GumGum's content policy [41].

Pools using publisher IDs with hidden or unknown owner domains. During our investigation, we also discovered that many AdX `sellers.json` files did not allow identification of the owner domain of the publisher ID that was used. This comprised nearly half of all identified pools. The breakdown of reasons for this is provided in Table 5. Here, we see that the most common reasons for failed identification of the owners of publisher IDs being used in pooling are: (1) the publisherID is itself unlisted in the issuing AdX's `sellers.json` file and (2) the unavailability of a public `sellers.json` from the AdX that issued the publisherID. It is important to note

Type	Domain	Pools	Pools w/ M_{full}
Owner of pub.ID	`google.com`	5.1K	598
	`gannett.com`	370	5
	`justpremium.com`	337	84
	`townnews.com`	313	0
	`hearst.com`	219	1
AdX issuer of pub.ID	`google.com`	10.3K	461
	`taboola.com`	6.6K	132
	`freewheel.com`	3.9K	625
	`pubmine.com`	3.6K	2
	`openx.com`	2.4K	524

Table 4: **(From $D^{static}_{2/22}$) Most pooled domains and AdXs.** The top five rows represent the most frequently observed domains whose publisher IDs were used in pools. The bottom five rows represent the most frequently observed AdXs who issued the publisher IDs that were used for pooling.

Reason	All pools	Pools w/ M_{full}
Total pools	79K	8.7K
PubID unlisted	20.9K	2.5K
`sellers.json` not public	16.5K	2.0K
Owner not listed	2.6K	135
Owner is 'confidential'	3.4K	86

Table 5: **(From $D^{static}_{2/22}$) Pools using IDs of unknown owners.** Reasons for failed identification of the owners of publisher IDs used in pools.

that any of the reasons shown in Table 5 would result in the impossibility of any end-to-end supply chain verification. Interestingly, we find no statistical differences (χ^2-test $p < .05$) between the reasons for failed identification of owners of non-misinformation and misinformation pools. This suggests that the issues of poor compliance with end-to-end supply chain verification procedures are industry-wide and no specific cause for these failures are exploited by misinformation domains.

Finding actual occurrences of pooling with the D^{crawls} dataset. Because of the high rates of errors, misrepresentation, and unreliability of publisher-sourced `ads.txt` files and the incompleteness of AdX-sourced `sellers.json` files, it is important to note that our analysis of the $D^{static}_{2/22}$ can only be used as evidence that suggests the widespread practice of pooling. In order to confirm a pool's existence with certainty we need to observe it 'in the wild'. To achieve this, we leverage the set of all (publisher domain, AdX, owner domain) triples recorded in our D^{crawls} dataset (cf. §3.2). Since these were obtained from actual real-time bidding from multiple crawls of the M_{full} dataset, they provide concrete evidence of pooling being leveraged by known misinformation sites (i.e., dark pooling). In total, we gathered 2.8K (publisher domain, AdX, owner domain) triplets from which we identified 297 unique pools, which are depicted in Figure 11 (§C). Of these, 218 pools (73.4%) overlapped with those identified in our analysis of the $\mathbf{D}_{2/22}^{\text{static}}$ dataset and 79 were new. The existence of 79 pools that were absent in the $\mathbf{D}_{2/22}^{\text{static}}$ dataset once again highlights the ad-industry's poor compliance with `ads.txt` and `sellers.json` standards. Google and Pubmatic were found to be the issuers of the publisherIDs associated with 120 and 48 pools, respectively. These pools enabled advertising supply chains for 127 (Google) and 67 (Pubmatic) unique misinformation domains. 33across and Gourmet Ads were found to be the owners of publisherIDs that were shared by the most number of misinformation domains (30 and 23 domains, respectively). Both publisherIDs were issued by Pubmatic.

Homogeneity of $\mathbf{D}^{crawls}$ *pools.* We were able to identify the presence of 14 homogeneous and 200 heterogeneous pools. The homogeneity of the remaining pools could not be determined. The largest homogeneous pool shared a publisherID issued to `funkedigital.de` by Pubmatic. This pool included nine domains such as `principia-scientific.org`, `allnewspipeline.com`, and `russia-insider.com` — Media Bias/Fact Check identified all the nine domains as 'Conspiracy Theory' or 'Propaganda' domains with 'Low' factual reporting and having 'Right' to 'Extreme-Right' bias. We identified stories related to climate change denial, anti-vaccination misinformation, and pro-insurrection views — all in violation of PubMatic's own content guidelines for publishers [42]. Incidentally, Pubmatic also supplied the publisherID associated with the largest heterogeneous pool with 47 unique misinformation domains, including `drudgereport.com` and `worldtruth.tv`. Unfortunately, the Pubmatic `sellers.json` file did not list the actual owner of the publisherID associated with this heterogeneous pool.

$\mathbf{D}^{crawls}$ *pools and the Google MCM program.* In order to identify occurrences of pooling due to Google's MCM program, we identified pools associated with publisherIDs issued by Google to their MCM partners. Of the 316 heterogeneous pools identified, 32 were associated Google's MCM program. In total, these 30 MCM pools were associated with 29 misinformation domains. Indeed, the same domains utilized multiple MCM partners to gain access to Google's AdMob platform. Misinformation domains supported by Google's MCM program included `369news.net` (pseudoscience/anti-vaxx theories) and `truthandaction.org` (extreme-right propaganda/misinformation), amongst other similar domains. The MCM partners most frequently found to be using their Google-issued publisherID for pools containing misinformation were Monumetric (5 pools) and Freestar (4 pools).

Takeaways. Our analysis shows a widespread failure to adhere to the `ads.txt` and `sellers.json` standards and compliance is even weaker amongst misinformation domains (§4.1). This poor adherence has one major consequence: end-to-end validation of the ad-inventory supply chain is not always possible, particularly in the case of misinformation domains. Further compounding supply chain validation challenges, we find that the pooling of publisher/seller IDs by unrelated publishers is also widespread (§4.2). Misinformation domains, which violate the publisher content policies of many AdXs, are able to monetize their ad inventory through these pools. In fact, we find that in many cases they are able to leverage the authorized programs of the same AdXs whose policies they violate.

5 Display Ad Analysis

In this section, we analyze the display ads loaded on misinformation websites to identify the brands that buy their ad inventory.

Overview of brand safety. DSPs and AdXs provide brand safety [43] features to avoid buying ad impressions next to unwanted content. Brand safety features allow brands to block such unwanted ad inventory through a block list of keywords or domains/URLs. In keyword-based brand safety, the ad inventory of webpages containing sensitive content (e.g., relating to violence or pornography) is avoided. In domain/URL-based brand safety, the ad inventory of certain publisher domains/URLs that are deemed to host unwanted content (e.g., misinformative or clickbait content) is avoided. One would expect that reputable brands would avoid buying the ad inventory of misinformation websites through these standard brand safety features. However, as we describe in Section 4.2, we suspect that some unsuspecting reputable brands may end up buying the ad inventory of misinformation websites despite these brand safety safeguards due to the prevalence of dark pooling.

Dataset summary. To investigate whether misinformation websites that employ dark pooling are able to evade brand safety safeguards and trick reputable brands into buying their ad inventory, we curate $\mathbf{D}^{\text{brands}}$ by crawling each of the 669 misinformation website ten times as discussed in §3.2. We are able to collect a total of 4,246 ads belonging to 2,068 distinct brands. Figure 3 plots the distribution of the number of distinct brands across misinformation websites. We find that a non-trivial fraction of misinformation sites are able to get ads from tens of distinct brands. Specifically, 23 misinformation sites have ads from at least 41 distinct brands each while 142 misinformation sites have ads from at most 10 distinct brands each.

Reputable brand classification and prevalence. To assess whether these ads are from reputable brands, we use their Tranco ranks as a rough proxy for their reputation. Specifically, we classify brands with top-1K Tranco ranking as "reputable". Figure 4 shows the number of distinct reputable and non-reputable brands across top-20 misinformation websites that contain ads from the highest distinct brands. Perhaps surprisingly, we find that Breitbart – a well-known misinformation site – is able to attract ads from the highest number of distinct brands. The two reputable brands with ads on Breitbart include Forbes and GoDaddy. We note that these top-20

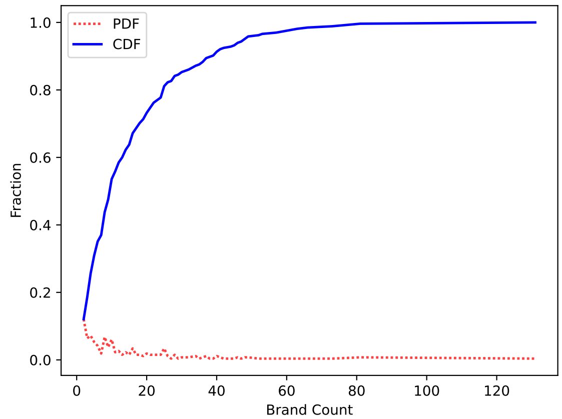

Figure 3: Distribution of the number of distinct brands across different misinformation websites.

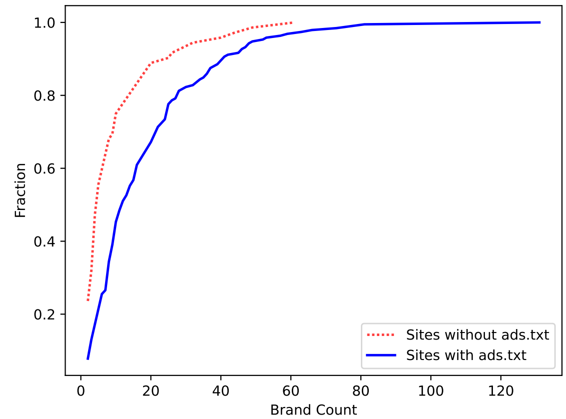

Figure 5: Distribution of number of distinct brands on misinformation websites with/without `ads.txt`.

misinformation sites tend to have more ads from reputable brands on average as compared to the remaining misinformation sites. Specifically, the average number of reputable brands is 2.05 for the top-20 misinformation sites in Figure 4 and 0.78 for the remaining misinformation sites.

Impact of ad inventory misrepresentation on brand safety. Next, we investigate whether the misrepresentation of ad inventory by misinformation websites impacts their ability to sell their ad inventory.

First, Figure 5 plots the distribution of number of distinct brands for misinformation sites with/without `ads.txt`. Note that we are looking for existence of `ads.txt` – the mere existence of `ads.txt` of course does not guarantee that the veracity of its content. We find that misinformation sites with `ads.txt` are able to attract ads from twice as many distinct brands on an average as compared to the sites without

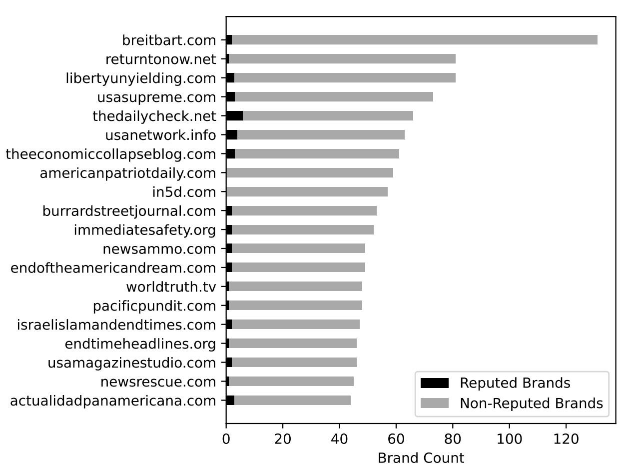

Figure 4: Distribution of reputable and non-reputable brands among the Top 20 misinformation sites with the highest number of distinct brands advertising on their website.

`ads.txt`. We conclude that some brands do at least seem to avoid the misinformation websites without `ads.txt`.

Second, Figure 6 shows the scatter plot of median Tranco ranks of brands and the number of pools[9] for each misinformation website. We find that misinformation websites that are part of more pools tend to attract higher ranked, and likely more reputable, brands. To quantitatively understand this correlation, we use simple linear regression and measure the slope. We find that the slope is -36.53, reaffirming our conclusion that pooling indeed enables misinformation websites to evade brand safety protections. A refinement of the regression analysis where we only take into account heterogeneous pool (signaling dark pooling) results in the slope of -55.09, indicting an even stronger correlation.

In summary, our results clearly show that the misrepresentation of ad inventory and the abuse of dark pooling by misinformation sites indeed plays a role in their ability to evade brand safety protections and better monetize their ad inventory through reputable brands.

Brands in display ads on misinformation websites. Next, we examine the brands that end up buying the ad inventory of misinformation websites. Figure 7 plots the prevalence of brands across the misinformation websites in our dataset. We find that only a small fraction of brands appear across a large fraction of misinformation sites. Specifically, 12 brands appear across at least 20 misinformation websites in our dataset. These most prevalent brands tend to be well-known such as Yahoo!, Amazon, and Alibaba. The brands that appear on only a few misinformation sites tend to be less known. In fact, many of these less known brands themselves appear to be misinformative (e.g., Battlefield America, Health Sciences Institute, Healthy Gem, Liberty Powered News, National Justice Party, IN5D).

[9] We use the list of 79K static pools from $\mathbf{D}_{2/22}^{\text{static}}$ dataset and quantify the number of pools that each misinformation domain is a part of.

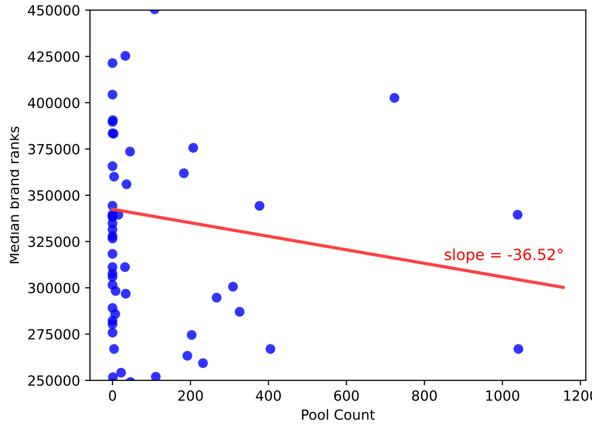

Figure 6: Scatter plot showing the relationship between median brand rank vs. pool count for each misinformation site

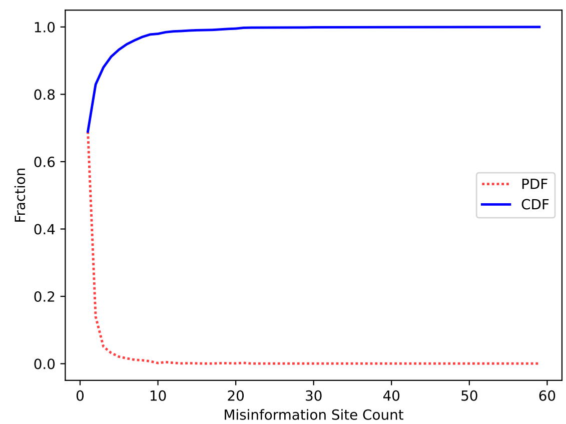

Figure 7: Distribution of the prevalence of brands across misinformation websites in our dataset.

Finally, we classify the brands across 58 content categories using a URL classification engine [44]. We are able successfully classify more than 95% of the brands into one ore more categories. Table 7 lists top-3 most prevalent brands across the top-6 categories of business, shopping, computers & technology, health & medicine, finance, and education. While most of these brands are self-evident, some of them are not. For example, while most Amazon ads were related to Amazon Smile, some of these Amazon ads were in fact static links to certain Amazon products that included books about conspiracy theories (e.g., "The Dark Path: Conspiracy Theories of Illuminati and Occult Symbolism in Pop Culture, the New Age Alien Agenda & Satanic Transhumanism". Beyond the brands listed in this table, we also found multiple other instances of outright misinformative ads such as FDA unverified health supplements such as Bioage and Boston Brain Science. Finally, there are also some instances of political ads such as Let's Go Brandon and Battlefield America. Such unscrupulous ads on misinformation websites are because either the ad inventory is directly sold or bought at the bottom of the programmatic funnel.

Takeaways. Overall, we find that misinformation websites are able to evade brand safety safeguards and monetize their ad inventory through unsuspecting reputable brands. Crucially, we showed that it is in part because misinformation sites misrepresent their ad inventory. We found that the ad inventory of misinformation websites that use tactics such as dark pooling is more likely to be bought by reputable brands.

6 Related Work

Examining the online advertising ecosystem. In recent years, there have been many research efforts to bring transparency to the mechanisms of online advertising. A large number of these have focused on identifying the gathering and distribution of user data to deliver personalized ads [45–50]. Our work instead focuses on the prevalence of inventory fraud, pooling, and its impact on brands.

Inventory fraud. There have been a few measurements related to `ads.txt` standard and related inventory fraud since its introduction. However, no work has focused on `sellers.json` or the ad-fraud that emerges by combined failure of `ads.txt` and `sellers.json`. In 2019, Bashir et al. [21] gathered and conducted a longitudinal analysis of `ads.txt` files associated with popular websites. In their analysis they found that although deployment was widespread, there were many syntactic errors and inconsistencies in these files that made them difficult to process in an automated fashion. Tingleff [51] and Pastor et al. [52] highlighted flaws of the `ads.txt` standard that reduce it's effectiveness in preventing ad fraud, albeit without measurements to supplement their hypotheses. Some of these identified flaws are, however, corroborated by measurements from Papadogiannakis et al. [53]. These findings, which suggest that the `ads.txt` standard is not effectively enforced even after years since its deployment is corroborated by our study. Our work complements these efforts by undertaking a measurement study of both the standards of `ads.txt` and `sellers.json` for the first time to measure inventory fraud as well as prevalence of pooling, which allows domains to circumvent the protections brought by the `ads.txt` and `sellers.json` standards.

Brand safety. There have been many studies that have highlighted the impact of ads (and the websites on which they appear) on the reputation of a brand [43, 54–56]. In fact, the impacts are so strong that there have been several activist efforts that have successfully weaponized brand safety to prevent the spread of misinformation. Notable among these are the efforts of Check My Ads and Sleeping Giants [57] which successfully launched public campaigns to pressurize 820 brands to add Breitbart News' domains to their advertising block lists. Our cataloging of brands found on known misinformation sites aim to supplement these efforts and increase pressure on ad-tech to enforce it's own `ads.txt` and `sellers.json` standards more effectively. Other work has focused on measuring or improving the effectiveness of mechanisms for identifying 'brand safe' web content. Hemmings [58] and Braun et al. [59] provide an overview of these approaches and the trade-offs they present. Most recently, Vo et al. [60] built an image-based brand-safety classifier to prevent ad placement on inappropriate pages. Numerous products from popular ad-tech firms such as DoubleVerify [61], Integral Ad Science [62], and Oracle [63] have also recently started promoting their 'brand safety' features.

Funding infrastructure of misinformation. Ours is not the first work to consider the role of the online advertising ecosystem in funding misinformation. In fact, it has been known for several years that online advertising provides the primary revenue stream for misinformation websites [64–68]. Han et al. [69], in their study focused on network infrastructure, also explored the revenue streams on misinformation websites and identified disproportionately high reliance on advertising and consumer donations. Bozarth et al. [70] showed that although there is a unique ecosystem of 'risky' AdXs that partner with publishers of misinformation, there is also a heavy presence of mainstream AdXs (e.g., Google) in the misinformation ecosystem. Braun & Eklund [59] take a qualitative approach to understand the role of the advertising ecosystem in increasing revenues of misinformation and the dismantling of traditional journalism. Their work, along with numerous others [71–73], have highlighted the need for additional transparency to realize the promise of market-based strategies to curb funding of misinformation. Considering another angle, several studies have also examined how deceptive ads are used to promote and fund harmful products [74–76] and ideologies [31, 77, 78].

At a high-level, our work complements all these efforts to better understand how the misinformation ecosystem is funded by online advertising by uncovering and analyzing the exploitation of specific advertising-related vulnerabilities such as pooling and relationship misrepresentations by the misinformation ecosystem.

7 Concluding Remarks

In this paper, we investigated for the first time unexplored issues in the ad-tech supply chain. We showed how misinformation sites exploit the opaque nature of the complex ad supply chain to deceptively monetize their ad inventory. Through our measurements, we documented widespread lack of compliance with the IAB's `ads.txt` and `sellers.json` standards as well as the abuse of ad inventory pooling by misinformative outlets. We also uncovered that reputable brands often fall prey to such evasive tactics and end up buying misrepresented ad inventory. Our results raise a number of questions that motivate potential countermeasures and future work.

First, our results uncover the publishers and ad exchanges, such as justpremium.com (owned by GumGum), whose publisher IDs are being pooled and disproportionately abused by misinformation websites. We conclude that major ad exchanges such as google.com, freewheel.com, and openx.com that issue these publisher IDs need to do a better job of vetting their partners. We believe that the onus is on ad exchanges that support such pooling (e.g., Google MCM partner program [39]). They are best positioned to effectively put a stop to this abuse if they strictly vet their partners and also monitor the abuse of their issued publisher IDs.

Second, buyers should attempt to trace the provenance of the inventory through the Supply Chain Object (SCO). Unfortunately, our analysis of SCOs in §D shows that less than a quarter of bid requests actually include the SCO. And, even when bid requests do contain it, it never contains the full list of supply chain hops. As the compliance with SCO improves, we expect that buyers/DSPs would be able to conduct end-to-end supply chain validation of the ad impressions that they are planning to buy and thus avoid the misrepresented inventory.

Third, there are several organized efforts such as the Check My Ads Institute [79] that monitor ads on misinformation websites and call out reputable brands for unwittingly funding misinformation. Such public shaming efforts by activists seem to be somewhat successful in forcing the brands to fix the issue. Our data collection methodology can be used to provide an automated brand safety service that can systematically identify and report potential violations to brands. This could also be leveraged by ad exchanges to detect whether any of their partners enable dark pooling.

Fourth, we can track any additions/deletions of publishers by ad exchanges in their `sellers.json`. Such longitudinal analysis can provide insight into routine cleanups or one-off fixes. Our longitudinal analysis in §B uncovers evidence of significant cleanup of RevContent, an ad exchange known to be disproportionately used by misinformation websites [69]. Our longitudinal data collection and analysis can complement existing efforts to archive site metadata to track compliance with ad-tech standards [80].

Finally, our data collection and analysis suffers from completeness issues, some of which can be addressed in future work. While our data collection focused on misinformation websites, it can be easily repurposed for investigating other types of bogus or low quality websites. Due to the non-deterministic nature of RTB, our measurements of the prevalence of pooling and ads from reputable brands on misinformation websites are only a lower-bound for their actual prevalence. Also, we want to acknowledge that we can only observe false negatives of brand safety services in §5 – it is possible that brand safety services are somewhat successful in protecting reputable brands but we simply cannot publicly observe these true positives.

References

[1] Shuai Yuan, Jun Wang, and Xiaoxue Zhao. Real-time bidding for online advertising: measurement and analysis. In *Proceedings of the seventh international workshop on data mining for online advertising*, pages 1–8, 2013.

[2] OpenRTB Guidelines. IAB: https://www.iab.com/guidelines/openrtb/, 2022.

[3] Display ad-tech Lumascape. https://lumapartners.com/content/lumascapes/display-ad-tech-lumascape/.

[4] What's the Difference Between Waterfall Auctions & Header Bidding? https://clearcode.cc/blog/difference-waterfall-header-bidding/, 2022.

[5] Sumayah A. Alrwais, Alexandre Gerber, Christopher W. Dunn, Oliver Spatscheck, Minaxi Gupta, and Eric Osterweil. Dissecting ghost clicks: Ad fraud via misdirected human clicks. In *Proceedings of the 28th Annual Computer Security Applications Conference*, ACSAC '12, page 21–30, New York, NY, USA, 2012. Association for Computing Machinery.

[6] Brett Stone-Gross, Ryan Stevens, Apostolis Zarras, Richard Kemmerer, Chris Kruegel, and Giovanni Vigna. Understanding fraudulent activities in online ad exchanges. In *Proceedings of the 2011 ACM SIGCOMM Conference on Internet Measurement Conference*, New York, NY, USA, 2011. Association for Computing Machinery.

[7] Jonathan Crussell, Ryan Stevens, and Hao Chen. Madfraud: Investigating ad fraud in android applications. In *Proceedings of the 12th Annual International Conference on Mobile Systems, Applications, and Services*, MobiSys '14, page 123–134, New York, NY, USA, 2014. Association for Computing Machinery.

[8] Vacha Dave, Saikat Guha, and Yin Zhang. Measuring and fingerprinting click-spam in ad networks. In *Proceedings of the ACM SIGCOMM 2012 Conference on Applications, Technologies, Architectures, and Protocols for Computer Communication*, SIGCOMM '12, page 175–186, New York, NY, USA, 2012. Association for Computing Machinery.

[9] Apostolis Zarras, Alexandros Kapravelos, Gianluca Stringhini, Thorsten Holz, Christopher Kruegel, and Giovanni Vigna. The dark alleys of madison avenue: Understanding malicious advertisements. In *Proceedings of the 2014 Conference on Internet Measurement Conference*, IMC '14, page 373–380, New York, NY, USA, 2014. Association for Computing Machinery.

[10] Gianluca Stringhini, Christopher Kruegel, and Giovanni Vigna. Shady paths: Leveraging surfing crowds to detect malicious web pages. In *Proceedings of the 2013 ACM SIGSAC Conference on Computer & Communications Security*, CCS '13, page 133–144, New York, NY, USA, 2013. Association for Computing Machinery.

[11] Kurt Thomas, Elie Bursztein, Chris Grier, Grant Ho, Nav Jagpal, Alexandros Kapravelos, Damon Mccoy, Antonio Nappa, Vern Paxson, Paul Pearce, Niels Provos, and Moheeb Abu Rajab. Ad injection at scale: Assessing deceptive advertisement modifications. In *2015 IEEE Symposium on Security and Privacy*, pages 151–167, 2015.

[12] Shishir Nagaraja and Ryan Shah. Clicktok: Click fraud detection using traffic analysis. In *Proceedings of the 12th Conference on Security and Privacy in Wireless and Mobile Networks*, WiSec '19, page 105–116, New York, NY, USA, 2019. Association for Computing Machinery.

[13] Suibin Sun, Le Yu, Xiaokuan Zhang, Minhui Xue, Ren Zhou, Haojin Zhu, Shuang Hao, and Xiaodong Lin. Understanding and detecting mobile ad fraud through the lens of invalid traffic. In *Proceedings of the 2021 ACM SIGSAC Conference on Computer and Communications Security*, CCS '21, page 287–303, New York, NY, USA, 2021. Association for Computing Machinery.

[14] Mobin Javed, Cormac Herley, Marcus Peinado, and Vern Paxson. Measurement and analysis of traffic exchange services. In *Proceedings of the 2015 Internet Measurement Conference*, IMC '15, page 1–12, New York, NY, USA, 2015. Association for Computing Machinery.

[15] Shehroze Farooqi, Guillaume Jourjon, Muhammad Ikram, Mohamed Ali Kaafar, Emiliano De Cristofaro, Zubair Shafiq, Arik Friedman, and Fareed Zaffar. Characterizing key stakeholders in an online black-hat marketplace. In *2017 APWG Symposium on Electronic Crime Research (eCrime)*, pages 17–27. IEEE, 2017.

[16] Manolis Chalkiadakis, Alexandros Kornilakis, Panagiotis Papadopoulos, Evangelos Markatos, and Nicolas Kourtellis. The rise and fall of fake news sites: A traffic analysis. In *13th ACM Web Science Conference 2021*, WebSci '21, page 168–177, New York, NY, USA, 2021. Association for Computing Machinery.

[17] Inside the Macedonian Fake News Complex. https://www.wired.com/2017/02/veles-macedonia-fake-news/, 2022.

[18] How teens in the balkans are duping trump supporters with fake news. https://www.buzzfeednews.com/article/craigsilverman/how-macedonia-became-a-global-hub-for-pro-trump-misinfo#.fu2okXaeKo.

[19] How Facebook powers money machines for obscure political news sites. https://www.theguardian.com/technology/2016/aug/24/facebook-clickbait-political-news-sites-us-election-trump, 2016.

[20] IAB Brand-safety. https://www.iab.com/topics/brand-safety/, 2022.

[21] Muhammad Ahmad Bashir, Sajjad Arshad, Engin Kirda, William Robertson, and Christo Wilson. A longitudinal analysis of the ads. txt standard. In *Proceedings of the Internet Measurement Conference*, pages 294–307, 2019.

[22] What is domain spoofing? https://www.adpushup.com/blog/what-is-domain-spoofing/, 2017.

[23] Domain spoofing remains a huge threat to programmatic. https://digiday.com/marketing/domain-spoofing-remains-an-ad-fraud-problem/, 2017.

[24] The Sentencing of The King Of Fraud and the Birth of Collective Protection. https://www.humansecurity.com/learn/blog/the-sentencing-of-the-king-of-fraud-and-the-birth-of-collective-protection, 2021.

[25] The four types of domain spoofing. https://integralads.com/insider/the-four-types-of-domain-spoofing/, 2018.

[26] IAB ads.txt Specifications. https://iabtechlab.com/ads-txt/, 2017.

[27] IAB sellers.json Specifications. https://iabtechlab.com/sellers-json/, 2019.

[28] Maciej Szpakowski and Renato. Fake news corpus. https://github.com/several27/FakeNewsCorpus, Feb 2018.

[29] Media Bias/Fact Check Team. Media bias/fact check: The most comprehensive media bias resource. https://mediabiasfactcheck.com.

[30] Austin Hounsel, Jordan Holland, Ben Kaiser, Kevin Borgolte, Nick Feamster, and Jonathan Mayer. Identifying disinformation websites using infrastructure features. In *10th USENIX Workshop on Free and Open Communications on the Internet (FOCI)*, 2020.

[31] Eric Zeng, Tadayoshi Kohno, and Franziska Roesner. Bad news: Clickbait and deceptive ads on news and misinformation websites. In *Workshop on Technology and Consumer Protection (ConPro). IEEE, New York, NY*, 2020.

[32] Victor Le Pochat, Tom Van Goethem, Samaneh Tajalizadehkhoob, Maciej Korczyński, and Wouter Joosen. Tranco list. https://tranco-list.eu. Accessed on 27th Oct, 2021.

[33] Syed Suleman Ahmad, Muhammad Daniyal Dar, Zareed Zaffar, Narseo Vallina-Rodriguez, Rishab Nithyanand, et al. Apophanies or epiphanies: How crawlers can impact our understanding of the web. In *The Web Conference 2020 (WWW 2020)*, 2020.

[34] Jordan Jueckstock, Shaown Sarker, Peter Snyder, Aidan Beggs, Panagiotis Papadopoulos, Matteo Varvello, Benjamin Livshits, and Alexandros Kapravelos. Towards realistic and reproducibleweb crawl measurements. In *Proceedings of the Web Conference 2021*, pages 80–91, 2021.

[35] John Cook, Rishab Nithyanand, and Zubair Shafiq. Inferring tracker-advertiser relationships in the online advertising ecosystem using header bidding. *Proceedings on Privacy Enhancing Technologies*, 1:65–82, 2020.

[36] Maaz Bin Musa and Rishab Nithyanand. Atom: Ad-network tomography. a generalizable technique for inferring tracker-advertiser data sharing in the online behavioral advertising ecosystem. *Proceedings on Privacy Enhancing Technologies*, 4, 2022.

[37] Umar Iqbal, Peter Snyder, Shitong Zhu, Benjamin Livshits, Zhiyun Qian, and Zubair Shafiq. Adgraph: A graph-based approach to ad and tracker blocking. In *2020 IEEE Symposium on Security and Privacy (SP)*, pages 763–776. IEEE, 2020.

[38] Github | duckduckgo tracker-radar/entities. https://github.com/duckduckgo/tracker-radar/tree/main/entities.

[39] Overview of MCM - Google AdMob Help. https://support.google.com/admob/answer/9142605?hl=en.

[40] Misrepresentation - Advertising Policies Help. Google Advertising Policies, https://support.google.com/adspolicy/answer/6020955?hl=en&ref_topic=1626336, 2022.

[41] GumGum | Prohibited Content Policy for Buyers and Sellers. https://gumgum.com/terms-and-policies/buyer-policy, 2022.

[42] Supply policy. Pubmatic, 2022.

[43] Steven Bellman, Ziad HS Abdelmoety, Jamie Murphy, Shruthi Arismendez, and Duane Varan. Brand safety: the effects of controversial video content on pre-roll advertising. *Heliyon*, 4(12):e01041, 2018.

[44] Cyren url lookup api. https://www.cyren.com/security-center/url-category-check-gate, 2019 (accessed May 2, 2022).

[45] Steven Englehardt and Arvind Narayanan. Online tracking: A 1-million-site measurement and analysis. In *Proceedings of the 2016 ACM SIGSAC conference on computer and communications security*, pages 1388–1401, 2016.

[46] Abbas Razaghpanah, Rishab Nithyanand, Narseo Vallina-Rodriguez, Srikanth Sundaresan, Mark Allman, Christian Kreibich, Phillipa Gill, et al. Apps, trackers, privacy, and regulators: A global study of the mobile tracking ecosystem. In *The 25th Annual Network and Distributed System Security Symposium (NDSS 2018)*, 2018.

[47] Muhammad Ahmad Bashir, Sajjad Arshad, William Robertson, and Christo Wilson. Tracing information flows between ad exchanges using retargeted ads. In *25th USENIX Security Symposium (USENIX Security)*, pages 481–496, 2016.

[48] Aaron Cahn, Scott Alfeld, Paul Barford, and Shanmugavelayutham Muthukrishnan. An empirical study of web cookies. In *Proceedings of the 25th international conference on world wide web*, pages 891–901, 2016.

[49] Yash Vekaria, Vibhor Agarwal, Pushkal Agarwal, Sangeeta Mahapatra, Sakthi Balan Muthiah, Nishanth Sastry, and Nicolas Kourtellis. Differential tracking across topical webpages of indian news media. In *13th ACM Web Science Conference 2021*, pages 299–308, 2021.

[50] Marjan Falahrastegar, Hamed Haddadi, Steve Uhlig, and Richard Mortier. The rise of panopticons: Examining region-specific third-party web tracking. In *International Workshop on Traffic Monitoring and Analysis*, pages 104–114. Springer, 2014.

[51] S Tingleff. The Three Deadly Sins of Ads. Txt and How Publishers Can Avoid Them. https://iabtechlab.com/blog/the-three-deadly-sins-of-ads-txt-and-how-publishers-can-avoid-them, 2019.

[52] Antonio Pastor, Rubén Cuevas, Ángel Cuevas, and Arturo Azcorra. Establishing trust in online advertising with signed transactions. *IEEE Access*, 9:2401–2414, 2020.

[53] Emmanouil Papadogiannakis, Panagiotis Papadopoulos, Evangelos P Markatos, and Nicolas Kourtellis. Who funds misinformation? a systematic analysis of the ad-related profit routines of fake news sites. *arXiv preprint arXiv:2202.05079*, 2022.

[54] Edlira Shehu, Nadia Abou Nabout, and Michel Clement. The risk of programmatic advertising: Effects of website quality on advertising effectiveness. *International Journal of Research in Marketing*, 38(3):663–677, 2021.

[55] Chunsik Lee, Junga Kim, and Joon Soo Lim. Spillover effects of brand safety violations in social media. *Journal of Current Issues & Research in Advertising*, pages 1–23, 2021.

[56] Sophie Bishop. Influencer management tools: Algorithmic cultures, brand safety, and bias. *Social Media+ Society*, 7(1):20563051211003066, 2021.

[57] Claudia Pereira Ferraz. Sleeping giants and indirect boycotts against the far right in united states of america. *Aurora.*, 14(40):28–47, 2021.

[58] Mike Hemmings. Ethical online advertising: Choosing the right tools for online brand safety. *Journal of Brand Strategy*, 10(2):109–120, 2021.

[59] Joshua A Braun and Jessica L Eklund. Fake news, real money: Ad tech platforms, profit-driven hoaxes, and the business of journalism. *Digital Journalism*, 7(1):1–21, 2019.

[60] Quan Minh Vo, Nhan Thi Cao, and An Hoa Ton-That. Unsafe image classification using convolutional neural network for brand safety. In *2020 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE)*, pages 1–4. IEEE, 2020.

[61] Doubleverify unveils expanded brand safety & brand suitability integration with facebook - doubleverify. https://doubleverify.com/newsroom/doubleverify-unveils-expanded-brand-safety-brand-suitability-integration-with-facebook/.

[62] Integral ad science | brand safety & suitability solutions. https://integralads.com/solutions/brand-safety-suitability/.

[63] Oracle moat measurement | oracle advertising. https://www.oracle.com/cx/advertising/measurement/.

[64] Nir Kshetri and Jeffrey Voas. The economics of “fake news”. *IT Professional*, 19(6):8–12, 2017.

[65] Arvind Hickman. Advertisers spend $2.6bn on misinformation websites, study finds. https://www.campaignlive.com/article/advertisers-spend-26bn-misinformation-websites-study-finds/1725293, Aug 2021.

[66] Global Disinformation Index. Cutting the funding of disinformation: The ad-tech solution. https://disinformationindex.org/wp-content/uploads/2019/05/GDI_Report_Screen_AW2.pdf, May 2019.

[67] Global Disinformation Index. The quarter billion dollar question: How is disinformation gaming ad tech? https://disinformationindex.org/wp-content/uploads/2019/09/GDI_Ad-tech_Report_Screen_AW16.pdf, Sep 2019.

[68] Augustine Fou. Big advertisers still fund hate and disinformation outside of facebook. https://www.forbes.com/sites/augustinefou/2020/07/06/big-advertisers-still-fund-hate-and-disinformation-outside-of-facebook/?sh=383aa3376f78, July 2020.

[69] Catherine Han, Deepak Kumar, and Zakir Durumeric. On the infrastructure providers that support misinformation websites. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 16, pages 287–298, 2022.

[70] Lia Bozarth and Ceren Budak. Market forces: Quantifying the role of top credible ad servers in the fake news ecosystem. In *The International AAAI Conference on Web and Social Media*, 2020.

[71] Joel Timmer. Fighting falsity: Fake news, Facebook, and the first amendment. *Cardozo Arts & Ent. LJ*, 35:669, 2016.

[72] Damian Tambini. Fake news: public policy responses. 2017.

[73] Norman Vasu, Benjamin Ang, Terri-Anne Teo, Shashi Jayakumar, Muhammad Raizal, and Juhi Ahuja. *Fake news: National security in the post-truth era*. S. Rajaratnam School of International Studies., 2018.

[74] Yelena Mejova and Kyriaki Kalimeri. Advertisers jump on coronavirus bandwagon: Politics, news, and business. *arXiv preprint arXiv:2003.00923*, 2020.

[75] Amelia M Jamison, David A Broniatowski, Mark Dredze, Zach Wood-Doughty, DureAden Khan, and Sandra Crouse Quinn. Vaccine-related advertising in the facebook ad archive. *Vaccine*, 38(3):512–520, 2020.

[76] Vanessa Boudewyns, Brian G Southwell, Kevin R Betts, Catherine Slota Gupta, Ryan S Paquin, Amie C O'Donoghue, and Natasha Vazquez. Two awareness of misinformation in health-related advertising: A narrative review of the literature. *Misinformation and mass audiences*, pages 35–50, 2021.

[77] Eric Zeng, Miranda Wei, Theo Gregersen, Tadayoshi Kohno, and Franziska Roesner. Polls, clickbait, and commemorative $2 bills: problematic political advertising on news and media websites around the 2020 us elections. In *Proceedings of the 21st ACM Internet Measurement Conference*, pages 507–525, 2021.

[78] Yingying Chen and Luping Wang. Misleading political advertising fuels incivility online: A social network analysis of 2020 us presidential election campaign video comments on youtube. *Computers in Human Behavior*, page 107202, 2022.

[79] Check My Ads Institute. https://checkmyads.org/, 2022.

[80] Well-known resource index. https://well-known.dev/, 2022.

Appendix

A Misrepresentations in `ads.txt` and `sellers.json`

Figures 8 and 9 depict all the possible cases of correct representations as well as minor/major misrepresentations cases that can be observed in `ads.txt` and `sellers.json` files, respectively. In Section §4.1, we only study major misrepresentations that result in the failure of end-to-end supply chain validation.

B Longitudinal Analysis of `sellers.json`

There have been various campaigns to highlight the role of AdXs in monetizing the misinformation ecosystem, pressuring them to remove their support for these domains [79]. To understand the effectiveness of these campaigns, we monitored changes to the `sellers.json` files present in our $\mathbf{D}^{\text{static}}_{.}$ dataset for a three-month period (from 10/21 to 2/22). Of the 470 AdXs found to support misinformation domains (by listing them as publishers) on 10/21, 39 (8.3%) AdXs delisted at least one misinformation domain.

It is important to understand whether the AdXs are delisting the misinformation content from their `sellers.json` files. Bashir et. al. [21] performed this analysis on `ads.txt` of Alexa Top-100K websites in their work. However, our study is on misinformation websites, whose `ads.txt` should not be trusted. Hence, we perform this analysis on `sellers.json` files of trusted AdXs.

We observed 470 `sellers.json` supporting at least 1 misinformation site as per the October's crawl. Out of 46 AdXs support 10 or more misinformation outlets. The one's that support the highest misinformation domains are *revcontent.com* (204), *liveintent.com* (56), *outbrain.com* (56), *pixfuture.com*

Figure 8: Correct representations (Case 1, 3), Misrepresentations (Case 2, 4, 5-8) and Problematic representations (Case 9, 10) used by publishers in their `ads.txt` implementations.

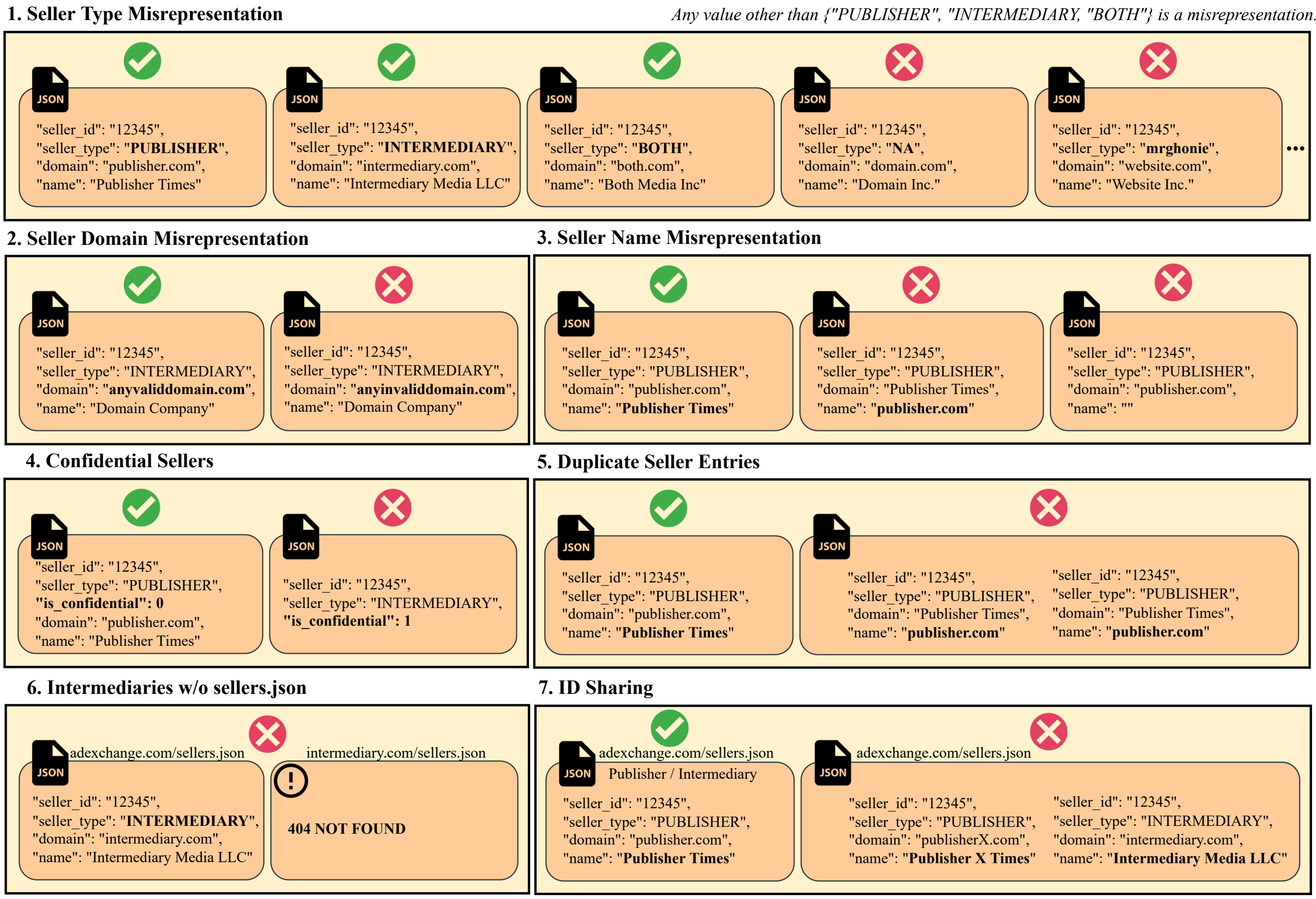

Figure 9: Correct representations and corresponding Misrepresentations employed by AdXs in their `sellers.json` implementations.

(39) and *lijit.com* (now part of *Sovrn*) (30). From October 2021 to February 2022, only 39 AdXs de-list atleast 1 misinformation website, while 53 `sellers.json` include atleast 1 misinformation domain in their files. Table 6 shows the top AdXs that added and removed the support for the highest number of misinformation sites in their `sellers.json` during the period of analysis.

Upon further investigation of RevContent, we observed that it dropped $\tilde{8}7\%$ of the total publisher domains from their `sellers.json` in mid December 2021 (Oct'21: 4727 domains to Feb'22: 621 domains) and we speculate that their primary aim might not have been to drop misinformation domains, but they ended up de-listing a few of misinformation outlets too as a result of their bulk drop. There has always been a constant peer-pressure and criticism from activists (e.g., [79]) forcing RevContent to remove their support for misinformation sites. There were active discussions on social media speculating RevContent's intent behind this massive drop. However, RevContent did this silently and never publicly addressed this action. It is surprising that eventhough

Ad-exchange	Misinformation Domain Counts			
	Oct'21	Feb'22	Added	Dropped
revcontent.com	204	73	2	133
outbrain.com	56	35	0	21
9mediaonline.com	20	1	0	20
stitchvideo.tv	14	1	0	13
adtelligent.com	26	28	13	11
infolinks.com	23	14	2	11
publisherdesk.com	14	3	0	11
mgid.com	20	32	13	1
nextmillennium.io	7	9	3	1
vidazoo.com	5	8	3	0
pixfuture.com	39	41	2	0
lijit.com	30	30	0	0

Table 6: AdXs that add and drop the highest number of misinformation outlets from their `sellers.json` during the period Oct'21 to Feb'22. The table is arranged in descending order of the Dropped counts.

RevContent dropped the maximum number of misinformation domains from its `sellers.json`, it still potentially funds the highest online misinformation. Other than RevContent, other AdXs that continued their support for the highest misinformation sites in Feb'22 are *LiveIntent* (56), *Pixfuture* (41), *Outbrain* (35) and *MGID* (32).

Additionally, the misinformation outlets which were added by the most AdXs are *rearfront.com*, *vidmax.com*, and *thetruereporter.com*. The former 2 outlets are agents of spreading viral and misleading content, while the latter publishes politicized news, commentary and analysis. These were added by 6 different AdXs. Similarly, *lifezette.com*, *waynedupree.com*, and *news18.co* were dropped by 6, 6, and 5 distinct AdXs respectively.

C Pooling

Different types of pooling scenarios studied in Section 4.2 are represented in the Figure 10. Figure 11 depicts the relationships between different entities of 297 unique pools observed in $\mathbf{D}^{\text{crawls}}$ dataset.

D Supply Chain Object Analysis

If adopted and implemented correctly, Supply Chain Objects (SCOs) can aid overall validation and provide transparency into all the entities involved in (re-)selling of a particular ad-inventory. In absence of this information, a buying entity's knowledge is just limited to the immediate upstream seller but not the entire path of (re-)sellers that were involved before the upstream seller. It is the job of the selling entity to append its seller object in the existing SCO and forward the bid request further. A buying entity extracts the SCO object from the bid request and parses the list of all seller nodes represented as key "nodes" (which contains a list of dictionaries). Lower the index of a node in this list, the more older the seller. When SSP forwards the bid request corresponding to the ad request received from the publisher, in the node dictionary it appends its website (represented by the key "asi") and account identifier for the given publisher in its network (represented by the key "sid").

In order to analyze the adoption and correctness of SCOs in our data, we use our custom SCO-parser (written as per the IAB guidelines) on all the bid requests captured in the $\mathbf{D}^{\text{crawls}}$ dataset. We observed that although SCOs have been introduced by IAB since July 2019, only 20.5% (3796) bid requests have included SCOs, all of which comprised of only a single seller node. To verify correctness of SCOs, we extracted 'sid' and 'asi' associated with the seller node and performed a lookup of the 'sid' in the `sellers.json` file of the 'asi' to obtain the upstream website with which the ad-inventory is associated as per the SCO. Next, we matched if this website domain matched the actual domain on which the current bid request was captured during the dynamic crawl. Lets call this boolean result as A. We, also generated a dynamic path based on the SCO object as follows: upstream website → asi seller → domain of the ad-request. We obtain the ground truth from the sellers.json, using which we also generated all 3-hop static paths for each misinformation domain in our dataset. Next, we checked each of the 3796 dynamic paths among all the static paths of the associated misinformation domain. Let's call this boolean result as B. The cases where A and B were True are cases where we could verify the correctness of the SCOs. The rest were the cases where SCOs were misrepresented. We observed only 18.94% (719) bid requests with correct SCOs.

E Display Ads on Misinformation Websites

We show some example display ads observed from a few brands on misinformation websites – GoDaddy and Amazon (Figure 12), Harvard Medical and Let's Go Brandon (Figure 13). Top brands in different categories are listed in Table 7.

Figure 12: GoDaddy ad (Left) observed on `breitbart.com`. Amazon ad (Right) for a shady book promoting conspiracy theories on `illuminatiwatcher.com`

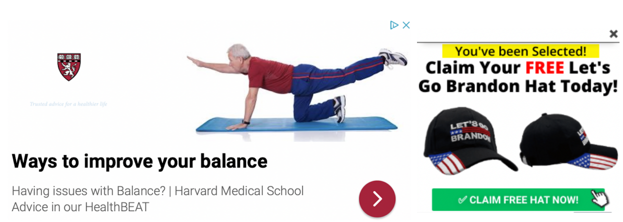

Figure 13: Ad from Harvard Medical (Left) seen on `darkpolitricks.com` and Lets Go Brandon ad (Right) politicizing hat sales on `clashdaily.com`

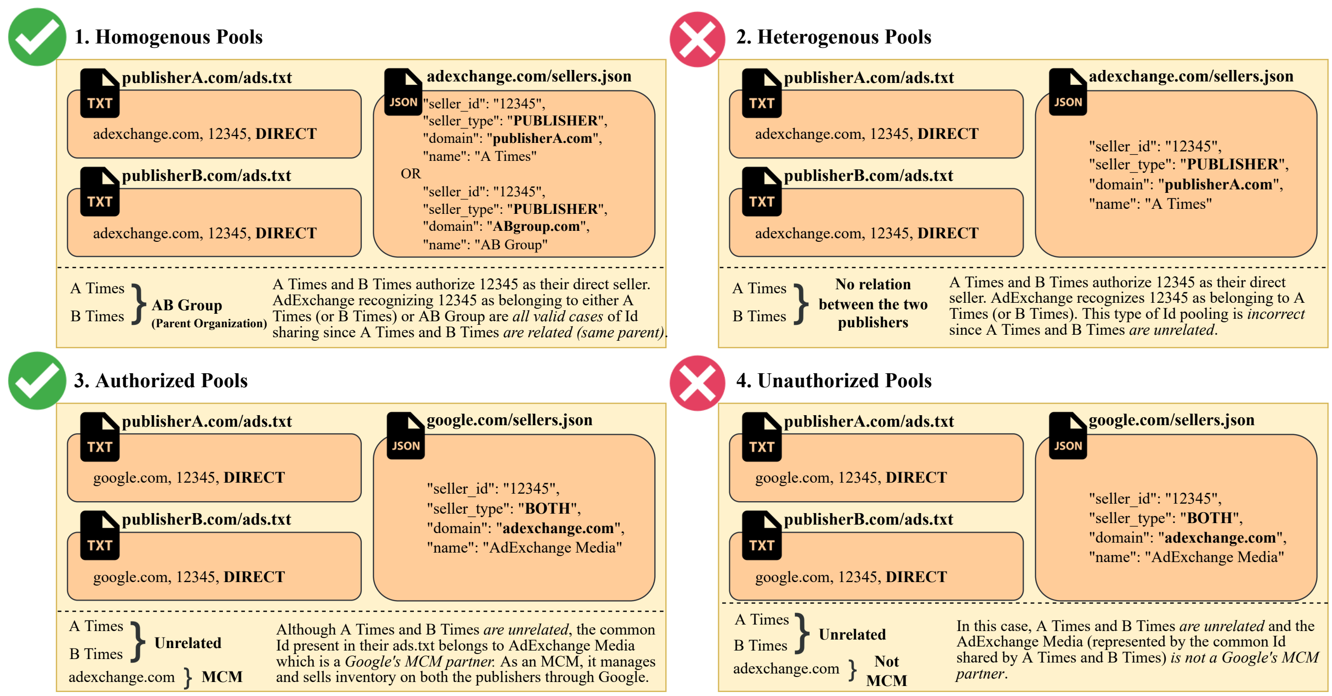

Figure 10: Classification of different types of Pooling.

Brand Category	Example Brands (# sites advertised on)
Business	Cotosen (22), Elkay (18), BusinessFocus (12)
Shopping	Amazon (21), Harbor Freight (18), Alibaba (10)
Computers & Technology	ManageEngine (12), GoDaddy (8), McAfee (1)
Health & Medicine	HealthiNation (19), Rocket Facts (17), Onnit (7)
Finance	Wall Street Watchdogs (42), Good Homeowner (21), LendingTree (19)
Education	Hillsdale College (21), MyHeritage (21), Harvard University (3)

Table 7: Examples of Top-3 brands that are observed advertising across misinformation websites in the Top-6 brand categories returned by Cyren.

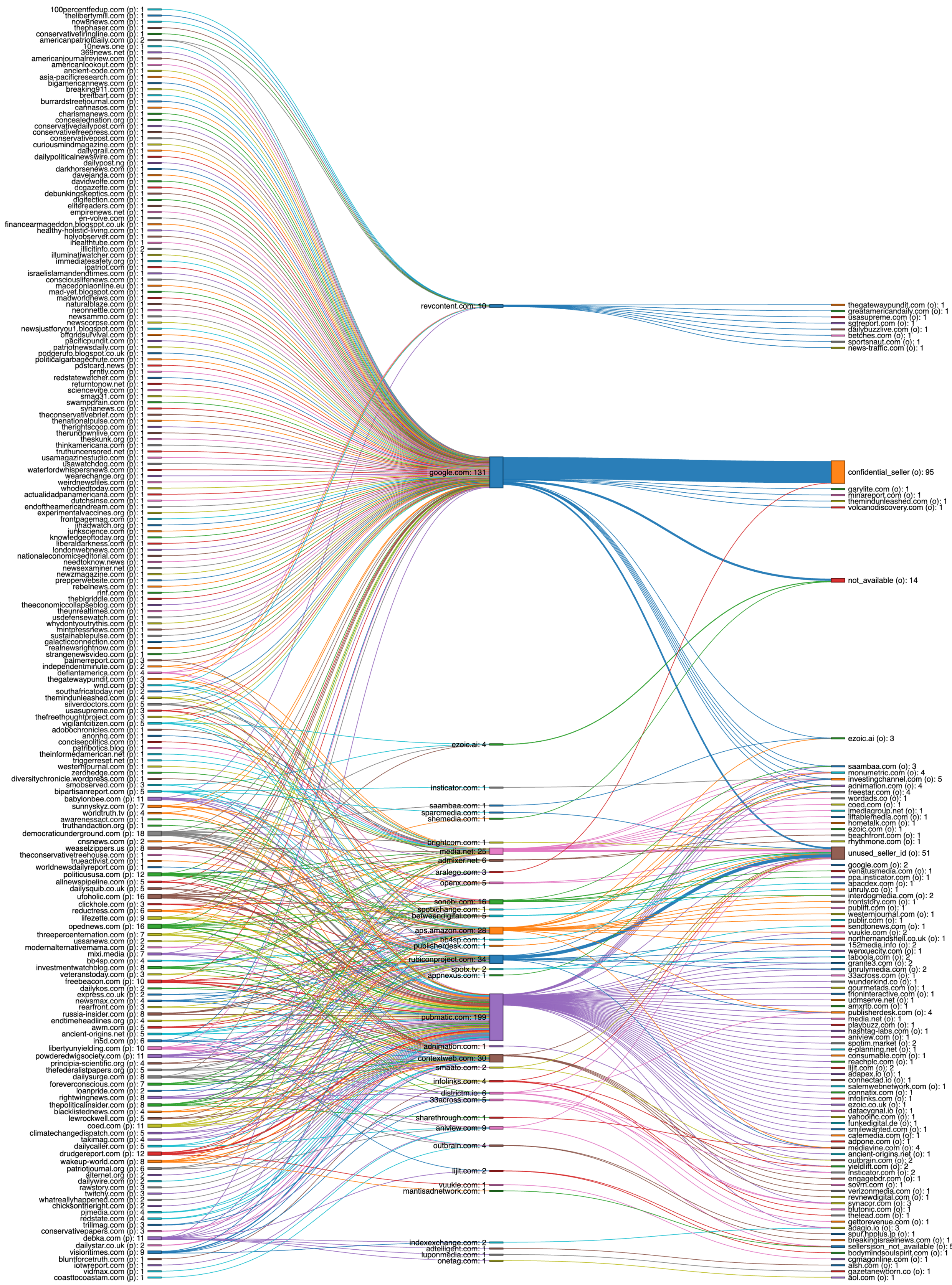

Figure 11: Pooling relationships between different entities of triplets in $\mathbf{D}^{\text{crawls}}$ dataset. Leftmost portion ((p): publisher) shows the misinformation domains and the rightmost portion ((o): owner) represents owner domains whose seller IDs or publisher IDs associated with the AdXs (represented as intermediary connections between the entities on extremes) are pooled and abused by these publisher domains. Count represents pooled IDs.