The Role of Advertisers and Platforms in Monetizing Misinformation: Descriptive and Experimental Evidence

Abstract

We investigate how online misinformation is monetized by examining the role played by advertising companies and digital ad platforms in financing misinformation outlets. We find that advertising on misinformation outlets is pervasive for companies across several industries, and that companies using digital platforms for advertising are substantially more likely to appear on misinformation outlets than those not using digital platforms. Using an incentive-compatible information provision experiment with a representative sample of the U.S. population, we show that people exit, i.e. decrease their demand for a company's products or services upon learning about the company's practice of monetizing misinformation via advertising. This decrease in demand persists even when consumers learn about the substantial role played by digital platforms and other advertisers in monetizing misinformation. Consumers also voice concerns against both advertising companies and digital ad platforms for monetizing misinformation. Our second experiment with senior decision-makers and managers shows that they are ill-informed about their own company's role in monetizing misinformation. However, those uncertain about their role in financing misinformation increase their demand for a platform-based solution to reduce monetizing misinformation upon receiving an information treatment. Our results suggest that advertising companies may be financing misinformation inadvertently and upon access to the relevant information and the ability to choose ad platforms that reduce financing misinformation, decision-makers within companies are interested in reducing the monetization of misinformation.

Keywords: consumer behavior, platform strategy, programmatic advertising, misinformation, online experiments.

1 Introduction

The economic incentive to produce misinformation has been widely conjectured as one of the main reasons misinformation news outlets, masquerading as legitimate outlets, continue to be prevalent online (Hao, 2021; Giansiracusa, 2021).[1] Some recent industry estimates suggest that for every $2.16 in digital ad revenue sent to legitimate newspapers, U.S. advertisers send $1 to misinformation websites (Global Disinformation Index, 2019; NewsGuard, 2021). To tackle the problem of financing online misinformation outlets, it is important to understand the role of different entities within this ecosystem. To understand the scale of the problem, it is important to identify which outlets might propagate misinformation and who ends up advertising on these websites. We further need to establish whether companies directly place ads or use digital ad platforms (Google's Doubleclick, Microsoft's AppNexus) to automate website ad placement. Indeed, companies such as Google earn a majority of their revenue through their online ad network that automates the display ad placements across millions of websites.

The extent to which companies can be dissuaded from advertising on misinformation websites depends on how their customers would respond to information about such practices. As news of companies advertising on misinformation becomes known (Crovitz, 2020; Dua, 2021), consumers could reduce demand for the product or voice concerns against such practices online. Additionally, the extent to which key decision-makers within companies are aware of their ads appearing on misinformation outlets and have preferences to avoid doing so will also play an important role in curbing the financing of misinformation outlets. Existing work shows wide dispersion in firms' beliefs about key economic conditions such as inflation, unemployment, and exchange rate (Coibion, Gorodnichenko and Kumar, 2018; Link et al., 2020), which could be due to costly information acquisition (Ocasio, 1997). Such inattention describes decision-makers' behaviors across various settings (Kim, 2021; Hanna, Mullainathan and Schwartzstein, 2014; Bloom et al., 2013; Beaman, Magruder and Robinson, 2014). Recently, though, advertising companies have orchestrated boycotts of ad-driven social media platforms such as YouTube, Facebook, and Twitter, demanding more efforts from platforms to remove harmful content, including misinformation and hate speech since they do not want their ads appearing next to such content(D'Onfro, 2019; Hsu and Lutz, 2020; Brand Safety Institute, 2022).

In this paper, we first present novel descriptive evidence examining the relative roles played by advertising companies and digital ad platforms in placing ads on misinformation websites. To do so, we build a large-scale dataset of advertising activity across thousands of news outlets with over a million instances of advertising companies appearing on news websites. To measure the preferences and behaviors of consumers and decision-makers within companies regarding financing online misinformation, we conduct two survey experiments.

Our first experiment measures how people react to information about advertising on misinformation websites by changing their consumption ("exit") or voicing concerns ("voice") about such practices through online petitions on the Change.org platform (Hirschman, 1970). People may find out about companies financing

[1] "We've found that a lot of fake news is financially motivated. These spammers make money by masquerading as legitimate news publishers and posting hoaxes that get people to visit their sites, which are often mostly ads." See: `https://about.fb.com/news/2017/04/working-to-stop-misinformation-and-false-news/`; Also see: `https://support.google.com/adsense/answer/10502938?hl=en&visit_id=637717920975924126-977395725&rd=1`.

misinformation through news reports, watchdog groups or social media (Hsu and Lutz, 2020; Crovitz, 2020; Gomes Ribeiro et al., 2022). Since peoples' responses to companies advertising on misinformation websites could vary depending on the roles played by advertising companies and digital ad platforms, we randomly vary the pieces of factual information we provide to participants in this experiment. By simultaneously measuring how people change their consumption of a company's products and the types of actors (i.e. advertisers or digital ad platforms) people voice concerns about, we capture how consumer backlash changes as the degree to which advertisers and ad platforms are held responsible varies. Additionally, we study how consumer responses may vary depending on the intensity of a company's advertising on misinformation websites by providing company rankings on this dimension.

We also examine advertising companies' knowledge and preferences regarding financing misinformation websites due to ad revenue. The complexity of the online ad ecosystem may constrain the amount of control decision-makers have on where their ads appear online and leave them with little knowledge of whether their company's ads appear on misinformation websites. To measure decision-makers' beliefs within companies, we surveyed senior executives and managers using Executive Education lists from Stanford and Carnegie Mellon University. Using incentive-compatible behavioral measures, we also capture their revealed preferences. We conduct an information provision experiment to examine whether executive decision-makers would opt to receive information on a platform-based solution to avoid advertising on misinformation outlets when informed about the role played by digital ad platforms in monetizing misinformation.[2]

We report three sets of findings from our descriptive and experimental analyses. Our descriptive analysis shows that 74% of misinformation outlets were financed by advertising relative to only 2% that had paywalls. About 44% of the advertisers in our dataset and 55% of the top 100 most active advertisers appear on misinformation websites between 2019 and 2021. These advertising companies span multiple industries, such as online services, business solutions, household products, and financial and government institutions.[3] In examining the role of digital ad platforms among the top 100 advertisers, we find that companies using digital ad platforms were ten times more likely to appear on misinformation websites than companies that did not use ad platforms. [4]

Second, using an incentive-compatible survey experiment design, we find that consumers exit, i.e., switch away from using companies whose ads appear on misinformation outlets by 225% relative to the control group, which does not receive information on which companies advertised on misinformation. This switching effect persists at 150% and 75% relative to control even when consumers are told about the role played by digital ad platforms and other advertising companies in financing misinformation, respectively. When provided with ranking information, people increasingly switched their consumption away from companies that advertised more frequently on misinformation outlets towards companies that advertised less frequently. We also find

[2]More information in decision-making is associated with higher firm performance (Bloom, Sadun and Van Reenen, 2012; Brynjolfsson and McElheran, 2019; Bajari et al., 2019; Camuffo et al., 2020). Prior experimental evidence shows that firms respond to new information by changing pricing and other business decisions (Hanna, Mullainathan and Schwartzstein, 2014; Beaman, Magruder and Robinson, 2014; Kim, 2021).

[3]They include several well-known and commonly used companies like Amazon, Wendy's, and Deloitte.

[4]Additionally, misinformation websites served by digital ad platforms had approximately 7.7 times more advertisers on average than those not monetized by digital ad platforms.

heterogeneity in treatment effects with the magnitude of exit especially pronounced for women and left-leaning consumers. Consumers also increasingly voice concerns by signing online petitions against digital ad platforms by 36% for amplifying online misinformation financing when informed about their role. Overall, we find that financing misinformation via advertising can impose substantial costs on the companies and platforms involved once consumers find out about the roles they play.

Third, our survey for decision-makers shows that they overestimate the number of companies advertising on misinformation websites. However, 80% of senior managers and executives believe their company's ads did not appear on misinformation outlets. Despite their beliefs, approximately 81% of those in our advertising data appear on misinformation websites. When preferences are measured using incentive-compatible behavioral outcomes, our survey respondents exhibit a high demand for information on consumer reactions regarding advertising on misinformation (73%) and for learning whether their ads appeared on misinformation outlets (74%). Even when the cost of information acquisition is increased, 18% of senior decision-makers sign-up for a 15-minute information session on how companies can avoid advertising on misinformation websites. Finally, we find that decision-makers update their beliefs about the role played by digital ad platforms in placing companies' ads on misinformation websites after receiving our information treatment. Those uncertain whether their company's ads appear on misinformation outlets also increase their demand for a platform-based solution in response to our information treatment.

Together, our findings offer clear practical implications. Our descriptive evidence suggests that misinformation financing is widespread and amplified using digital ad platforms. Our analysis provides empirical evidence that companies whose ads appear on misinformation websites can face consumer backlash in terms of both exit and voice. The effects are particularly strong for women and people who voted for President Biden in the 2020 U.S. presidential election. Advertisers should exercise greater caution and reduce advertising on misinformation outlets to avoid alienating such consumers. Companies can now use lists of misinformation outlets provided by organizations such as NewsGuard and the Global Disinformation Index to limit ad dollars going to such outlets through online ad networks. Our decision-maker survey results suggest that advertising companies may be financing misinformation inadvertently and that there is room for decreasing the financing of misinformation by incorporating advertiser preferences in ad placement decisions.

Our work also provides empirical support for potential platform-level interventions that could reduce the financing of online misinformation. To accomplish this goal, digital ad platforms can increase the transparency of advertising on misinformation websites in two ways: First, digital ad platforms that run automatic auctions to place online ads across websites programmatically can make information about companies advertising on misinformation outlets available publicly. Our results show that consumers value such information and change their consumption behavior in response to it. Similar transparency features enable consumers to make more sustainable choices, e.g. Google Flights now provides users with carbon emissions data to categorize flights alongside cost data (Holden, 2021). [5] Secondly, digital ad platforms could enable advertisers to avoid ad

[5] Digital platforms have recently adopted features to increase transparency in advertising (e.g. the Google ad library and the Facebook ad library) to allow more oversight over political and social ads. Similarly, a public dashboard or tool enabling consumers to view where companies are advertising could help put public pressure on companies to ensure that their advertising practices reflect the values of their brands.

placement on misinformation websites more easily by increasing the visibility of where their ads appear online. Our results show that decision-makers within companies advertising online are ill-informed about their ads appearing on misinformation outlets, but have a high demand for such information. Allowing advertisers to have more easily access to data on whether their ads are appearing on misinformation outlets could enable them to make ad placement decisions consistent with their preferences, ultimately reducing the financing of misinformation.

The rest of this paper proceeds as follows. Section 2 describes our contributions to the academic literature. We outline the empirical context, data and descriptive findings in Section 3. In Section 4, we describe the design and results of our consumer experiment. Section 5 presents the design and results of our decision-maker survey. Finally, Section 6 concludes.

2 Related literature

Our paper contributes to several strands of academic literature. Prior research has alluded to the importance of the advertising business model in sustaining news outlets (Lazer et al., 2018; Gabszewicz, Resende and Sonnac, 2015; Casadesus-Masanell and Zhu, 2010, 2013; Goldfarb, 2004). Researchers have examined the types of ads appearing on misinformation websites by crawling the web for a few days (Papadogiannakis et al., 2022; Kohno, Zeng and Roesner, 2020). Scholars have also explored the infrastructure that supports misinformation websites (Han, Kumar and Durumeric, 2022), the structure of the programmatic advertising ecosystem (Braun and Eklund, 2019), and the connection between programmatic advertising and clickbait (Fenton and Freedman, 2017). We contribute to this literature by examining the relative roles of advertising companies and digital ad platforms in placing ads on misinformation websites. Moreover, to the best of our knowledge, we provide the first large-scale evidence of the business model sustaining online misinformation outlets and the role of different players in this ecosystem using fine-grained (monthly) advertising data on the same set of news websites over a three-year period.

Previous work has examined the conditions under which people react against companies for failing to operate up to their expectations (Hirschman, 1970; Broccardo, Hart and Zingales, 2022; Kitzmueller and Shimshack, 2012; Du, Bhattacharya and Sen, 2011; Ellen, Webb and Mohr, 2006). For example, empirical evidence has revealed that companies with poor social and environmental ratings alienate their buyers and suffer below-average market returns (Kempf and Osthoff, 2007). Others have examined the consequences on consumer responses when service quality deteriorates (Gans, Goldfarb and Lederman, 2021) or when a company or its leadership takes a political stance (Liaukonytė, Tuchman and Zhu, 2022; Copeland and Boulianne, 2020; Chatterji and Toffel, 2019). In the online advertising context, prior research has examined the effects of advertising on sales and consumer behavior under various scenarios such as companies reaching out to people via social media during high-stress times, debunking false claims in advertising and posting sensational content in ads (Fong, Guo and Rao, 2022; Bellman et al., 2018; Lull and Bushman, 2015). Analysis by Gomes Ribeiro, Horta Ribeiro, Almeida and Meira (2022) suggests that when an activist group targets companies for advertising on misinformation websites, tweets mentioning the company temporarily become more toxic and less positive. We contribute to this strand of research by conducting the first incentive-compatible experiment on how consumers might react to information about their preferred company's advertising practices. While prior experimental work uses self-reported purchase intentions or attitudes as outcomes, our work measures behavioral outcomes at the individual level using an incentive-compatible design to capture both "exit" and "voice" - the two types of potential consumer responses theorized in the literature (Hirschman, 1970). Our revealed preference approach allows us also to examine the characteristics of consumers engaging in exit and voice after receiving our information interventions. Additionally, we test how consumer reactions differ when informed about the different actors, such as digital ad platforms and other advertising companies, are involved in financing misinformation.

We also contribute to a literature strand showing how digital platforms create externalities for different players within the platform ecosystem. Prior research shows that platform and advertiser incentives are not aligned regarding ad effectiveness (Johnson and Lewis, 2015; Frick, Belo and Telang, 2022; Dalessandro et al., 2012; Agarwal and Mukhopadhyay, 2016). More broadly, digital platforms can create other negative indirect externalities in the advertising context, e.g., when more advertisers on a search engine platform decrease its value for searchers of independent advice (De Reuver, Sørensen and Basole, 2018). We extend this literature to show that ad platforms could create reputational externalities for advertisers since companies are about ten times more likely to appear on misinformation when they use digital ad platforms. Our experimental results show that appearing on misinformation websites harms advertising companies since it alienates their consumers. Even when informed about the role played by digital ad platforms in placing companies' ads on misinformation websites, people switch their consumption away from companies whose ads appear on such websites 2.5 times more than the control group.

More broadly, our research contributes to the literature on platform governance and regulation by information disclosure. Prior research shows that ratings and reviews affect consumer behavior, substituting for more traditional forms of reputation and acting as a disciplining force in the marketplace (Cabral and Hortaçsu, 2010; Luca, 2016). Different types of online disclosures related to advertising (Nair and Sahni, 2020), product characteristics (Gardete and Antill, 2019), product ranking (Baye, De los Santos and Wildenbeest, 2016), and the contractual parties involved in a transaction (Gaskell et al., 2020) have been shown to affect consumer behavior in terms of clicks, call rates, search behavior, and product selection. A related strand of this literature has tested various informational interventions to reduce the spread of misinformation on social media platforms. Prior research shows that making the concept of accuracy more salient reduces the sharing on misinformation (Pennycook et al., 2020, 2021; Pennycook and Rand, 2022; Andı and Akesson, 2020). Aslett et al. (2022) find that news credibility labels fail to reduce misperceptions since they only increase news diet quality among the heaviest misinformation consumers. Participants in our consumer experiment used company ranking information to shift their consumption away from companies that more frequently advertised on misinformation websites. This result implies that providing such information transparency at the point of product purchase could reduce the demand for such companies. Such a practice could incentivize such companies to reduce advertising on misinformation websites, potentially improving the quality of online content. Moreover, our decision-maker survey suggests that more control and information disclosure to companies that advertise will also allow them to curb expenditure on misinformation outlets.

There have also been a few supply-side policy interventions proposed to curb misinformation. Facebook's ban on the advertising of fake news on its platform resulted in a decline in the subsequent sharing of fake news on Facebook relative to Twitter (Chiou and Tucker, 2018). A policy proposal by economist Paul Romer advocates for a progressive, pigovian tax on the revenue digital platforms make from the sales of targeted digital ads to incentivize platforms to shift their business model from advertising towards a "healthier, more traditional" model (Paul Romer, 2019). Relative to these interventions, we take a middle path to suggest that accounting for advertisers' preferences could help counter the financing of online misinformation. Our results reveal a high demand for information among advertisers both regarding whether their ads appear on misinformation websites and platform-based solutions to avoid advertising on such outlets. Han, Kumar and Durumeric (2022) anecdotally observe that sites struggle when their monetization channels are removed. Instead of deciding which news types to demonetize, digital ad platforms could better inform companies where their ads appear online and let them choose which websites to advertise directly. Indeed, as mentioned above, smaller ad networks and companies advertising online have started using lists from organizations such as the Global Disinformation Index and NewsGuard to limit ads going to misinformation websites.

3 Descriptive evidence

3.1 Empirical setting

We examine the role of advertising companies and digital ad platforms such as Google's DoubleClick and Microsoft's AppNexus in monetizing online misinformation. Such platforms serve as an intermediary connecting advertisers with independent websites that want to host ads. To do so, platforms run online auctions to algorithmically distribute ads over millions of websites, known as "programmatic advertising". For example, Google distributes ads in this manner to over 2 million non-Google sites in what is known as the Google Display Network. In this way, the websites receive payment from advertisers for hosting ads based on the number of views the ads receive, and they share a percentage of this payment with the platform. In the U.S., more than 80% of digital display ads are programmatic ads (Austin, Barnard and Hutcheon, 2019). [6]

While in other forms of (offline) media, advertisers typically have significant control over where their ads appear, ad placement through digital ad platforms is mainly automated. Since most companies do not have the capacity to participate in high-frequency ad auctions that require them to place individual bids for each ad slot they are interested in, they typically outsource the bidding process to an ad platform (Frick, Belo and Telang, 2022). Such programmatic advertising gives companies relatively less control over where their ads end up online. However, advertising companies can take steps to reduce advertising on misinformation websites, such as by only being part of ad auctions for a select list of credible websites. Digital advertising platforms can also remove harmful content, such as misinformation websites, from their publisher networks by directly not allowing any advertising on such websites or enabling advertisers to block ads from lists of misinformation

[6] Our empirical context is similar to other papers studying digital advertising such as Cowgill and Dorobantu (2020), Grewal, Stephens and Vana (2022), and Frick, Belo and Telang (2022).

outlets easily.

3.2 Data

To categorize whether a website contains misinformation, we compiled a list of misinformation domains using three different sources. First, we use a dataset maintained by NewsGuard. This company rates all the news and information websites that account for 95% of online engagement in each of the five countries where NewsGuard operates. Journalists and experienced editors manually generate these ratings by reviewing news and information websites according to nine apolitical journalistic criteria.[7] Recent research has used this dataset to identify misinformation websites (Edelson et al., 2021; Aslett et al., 2022; Bhadani et al., 2022). In this paper, we consider each website that NewsGuard rates as *repeatedly publishing false content* between 2019 and 2021 to be a misinformation website and all others to be non-misinformation websites, leading to a set of 1544 misinformation websites and 6809 non-misinformation websites.

In addition to the NewsGuard dataset, we use a list of websites provided by the Global Disinformation Index (GDI). This non-profit organization maintains a list of misinformation domains and updates them monthly. GDI provides ad tech platforms with these non-partisan and independent ratings to help reduce advertising on misinformation websites. The GDI list allows us to identify 1849 additional misinformation websites. Finally, we augment our list of misinformation websites with 415 additional ones used in prior work (Guess, Nyhan and Reifler, 2020; Allcott, Gentzkow and Yu, 2019). Our final dataset consists of 10,617 unique websites, of which 3808 are misinformation websites and 6809 are non-misinformation websites.

Remember that our final measure of misinformation is at the level of the website or outlet and not at the article level. The different organizations, such as NewGuard and GDI use article-level information and aggregate up to provide a metric at the website level. This is a meaningful approach since it will reduce noise exactly because of aggregation over a number of articles from every news outlet.

Our data on advertiser behavior comes from Oracle's Moat Pro platform, which includes data collected by crawling approximately ten thousand websites daily to create a snapshot of the advertising landscape and the players in the space. Moat's crawlers mirror a normal user experience and attempt to visit a representative sample of pages for each website at least once a day. We use the Moat platform to collect data from 2019 to 2021. For all the websites in our sample that get non-zero traffic between 2019 and 2021,[8], we collected the advertising companies and digital ad platforms used by the websites in each month.

Our final dataset, which has data on advertising and misinformation, consists of 5485 websites, of which 1276 are misinformation websites (445 identified by NewsGuard, 731 additional ones identified by the GDI and the remaining ones identified from prior work) and the remaining 4209 are non-misinformation websites. Additionally, for the most active 100 advertisers each year (as identified by Moat Pro based on the intensity of online advertising), we collected weekly data on the websites they appeared on and the digital ad platforms they used.

[7] https://www.newsguardtech.com/ratings/rating-process-criteria/
[8] We use data from SEMRush to determine the level of traffic received by each website during 2019, 2020 and 2021.

3.3 Descriptive results

Most misinformation websites in our sample (74%) were supported by advertising revenue between 2019 and 2021.[9] Moreover, a much smaller percentage of misinformation websites have a paywall (0.9% in the US and 2.1% globally) relative to non-misinformation websites (24.7% in the US and 25.1% globally). These findings suggest that misinformation websites are primarily financed via advertising and do not often rely on subscription-based business models. Next, we examine the roles played by advertising companies and digital ad platforms in financially sustaining misinformation news outlets.

3.3.1 The role of advertising companies

To examine the level of advertising on misinformation websites, we collect data on advertisers appearing on each of the 5485 websites in our dataset. Of the 42,595 unique advertisers on these websites, about 44% appear on misinformation websites. Focusing on the one hundred most active advertisers each year, we find that 55% of these appear on misinformation websites weekly.

Table 1: Number of Ad Appearances on News Websites

Industry	Misinformation		Non-misinformation	
	Appearances	Companies	Appearances	Companies
Holding Companies	19,649	6767	430,461	96,681
Online Services	37,035	5347	545,805	42,946
Media	35,796	4749	610,487	52,255
Technology	60,291	4157	943,453	37,606
Govt. or Religion	22,355	3851	340,549	47,062
Business Solutions	38,104	3848	615,006	37,480
Household	26,410	3644	445,357	35,137
Travel	29,284	3484	506,715	37469
Retail	28,577	3368	501,393	30,126
Apparel	31,306	3373	430,776	24,063
Insurance	19,982	3307	364,164	39,267
Telecommunications	13,132	3189	251,127	41,236
Digital Publishing	5921	3111	97,027	48,711
Print Publishing	4363	3103	70,987	48,206
Finance	44,772	3018	812,042	27,444
Health	27,412	2980	550,537	33,435
Babies & Kids	2589	2344	40,276	31,783
Automotive	19,578	1766	440,332	22,162
Food or Beverages	9269	1688	192,681	17,690
Industrial	2345	1180	29,067	12,611
Education	19,785	1032	307,558	9879
Dining	3753	1028	78,346	11,903
Unclassified	22,331	622	302,881	4085
Gas & Electric	5258	457	88,122	5421
Cosmetics	781	340	14,450	3781
Arms	45	28	125	111

Notes: Between 2019 and 2021, we record the advertising companies appearing on all 5485 websites in our sample per month (companies appearing on more than one website are counted each time they appear on a distinct website). Number of appearances records the total number of times companies in a given industry appeared on a website during these 36 months. For example, a company that appeared in each month from 2019 to 2021 on a website is said to have 36 appearances.

Table 1 shows the number of companies by industry and the number of times they appear on the websites in our dataset between 2019 and 2021. As shown in Table 1, advertising companies that appear on

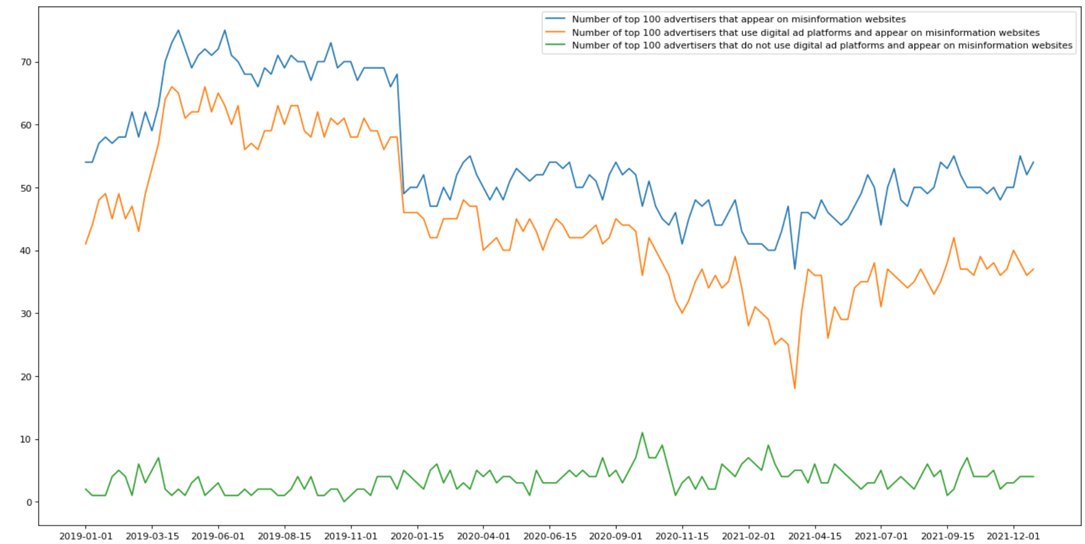
[9]Most non-misinformation websites in our sample (94%) also received advertising revenue during this period.

misinformation websites span a wide range of industries. These include several well-known brands among commonly used household products, technology products, and business services (e.g., Amazon, Adobe, DoorDash, Frigidaire, Roomba, etc.) as well as finance, health, government, and educational institutions (e.g., Barclays, KPMG, ACLU, YMCA, Stanford, etc.) among other industries.[10] The industries of companies that appear the most frequently in our full dataset are similar to those that appear most often on misinformation websites, which suggests that companies' ads appear on websites regardless of whether or not the website carries misinformation.

3.3.2 The role of digital ad platforms

For the one hundred most active advertisers in each year, we collected weekly data on which websites their ads appeared on and their use of digital ad platforms. The vast majority of advertisers that use digital ad platforms appear on misinformation websites, i.e. 80% of advertisers. In contrast to this figure, among companies that do not use digital ad platforms in a given week, only approximately 8% appear on misinformation websites. In other words, companies that used digital ad platforms were about 10 times more likely to appear on misinformation websites than companies that did not use digital ad platforms.[11] Figure 1 shows the number of the top 100 advertisers whose ads appear on misinformation websites based on weekly data from 2019 to 2021. As depicted in Figure 1, the number of advertisers who use digital ad platforms and appear on misinformation websites is much larger than those that do not use digital ad platforms and appear on misinformation websites throughout this period.

Figure 1: Number of Top 100 Advertisers on Misinformation Websites Based on Digital Ad Platform Usage



Notes: This figure shows the number of the top 100 advertisers (by advertising intensity) whose ads appear on misinformation websites based on weekly data from 2019 to 2021. We show trends in numbers of advertisers based on overall numbers of advertisers, those using digital ad platforms, and those not using digital ad platforms in a given week.

We next examine advertising on all websites in our sample using monthly data on advertisers and ad

[10]For select examples of companies whose ads appear on misinformation websites between 2019 and 2021, see Table A2 in the Appendix.

[11]For further details on the types of websites companies' ads appear on based on their usage of digital ad platforms, see Table A3 in the Appendix, which shows the mean results based on weekly data from 2019 to 2021. Companies may use one or several ad platforms in a given week. Our data shows different ad platforms placing ads on misinformation websites to varying extents as shown in Table A5.

exchange usage from 2019 to 2021. To allow us to compare how the number of advertisers per website changes both with and without the use of digital ad platforms for the same set of websites, we first select websites that both use digital platforms in certain months and don't use digital ad platforms in other months throughout this period. This results in a sample of 3441 websites, of which 514 are misinformation websites, and 2927 are non-misinformation websites. We then calculate the number of advertisers per website for misinformation and non-misinformation websites. In a month, we subdivided the sample into websites using digital ad platforms and those not using digital ad platforms. Our results show that misinformation websites served by digital ad platforms had approximately 7.7 times more advertisers than those not using digital ad platforms.[12]

4 Consumer experiment

4.1 Research design

We conducted an information provision survey experiment to measure how advertising on misinformation websites affects the advertising companies and digital ad platforms involved. Our survey experiment aims to determine potential changes in consumer behavior based on (experimentally varied) information about companies advertising on misinformation websites. Using the framework of Hirschman (1970), we measure how people 1) exit, i.e. decrease their consumption and 2) voice concerns about company or platform practices in response to the information provided in an incentive-compatible manner.

4.1.1 Setting and sample size

We recruit a representative sample of U.S. internet users via CloudResearch.[13] CloudResearch screened respondents for our study so that they are representative of the US internet population in terms of age, gender and race based on the US Census (2020). To ensure data quality, we include a screener in our survey to check whether participants pay attention to the information provided. Only participants who pass this screener can proceed with the survey. Our total sample includes approximately 4000 participants, who are randomized into five groups with about 800 participants per group.

The flow of the survey study is shown in Figure A8. We begin by asking participants to report demographics such as age, gender and residence. From a list of trustworthy and misinformation outlets, we then ask participants questions about their news preferences regarding the news outlets they have used in the past 12 months. Additionally, respondents report their trust in the media (on a 5-point scale), the online services or platforms they have used and the number of petitions they have signed in the past 12 months.

[12]Table A4 in the Appendix shows the descriptive statistics for the full period from 2019 to 2021. For trends on the mean number of advertisers per website for misinformation and non-misinformation websites, see Figure A1.

[13]CloudResearch is a data provider used in survey research that is more diverse and provide higher data quality than other providers such as MTurk (Chandler et al., 2019; Eyal et al., 2021).

4.1.2 Initial gift card preferences

We then inform participants that one in five (i.e. 20% of all respondents) who complete the survey will be offered a $25 gift card from a company of their choice out of six company options. Respondents are asked to rank the six gift card companies on a scale from their first choice (most preferred) to their sixth choice (least preferred). These six companies belong to one of three categories: fast food (Subway and Burger King), food delivery (DoorDash and Grubhub) and ride-sharing (Uber and Lyft). All six companies appeared on the misinformation websites in our sample during the past three years (2019-2021), offer items below $25, and are commonly used throughout the US. The order in which the six companies are presented is randomized at the respondent level. We then ask participants to confirm which gift card they would like to receive if they are selected to ensure they have consistent preferences regardless of how the question is asked.[14]

4.1.3 Information treatments

All participants in the experiment are given baseline information on misinformation and advertising as shown in Figure A10. This is meant to ensure that all participants in our experiment are made aware of how we define misinformation along with examples of a few misinformation websites (including right-wing, neutral and left-wing misinformation websites), how misinformation websites are identified, and how companies advertise on misinformation websites (via an illustrative example) and use digital platforms to automate placing ads.

Participants are then randomized into one control and four treatment groups, in which the information treatments are all based on factual information from our data and prior research. We use an active control design to isolate the effect of providing information relevant to the practice of specific companies on people's behavior (Haaland, Roth and Wohlfart, N.d.). Participants in the control group are given generic information based on prior research that is unrelated to advertising companies or platforms but relevant to topic of news and misinformation.

In our first "company only" treatment group (T1), participants are given factual information that ads from their top choice gift card company appeared on misinformation websites in the recent past. Our second "platform only" treatment group (T2) informs participants that companies using digital ad platforms were about 10 times more likely to appear on misinformation websites than companies that did not use such platforms in the recent past. These two information treatments measure the effects of a specific advertising company and digital ad platforms being involved in financing misinformation news outlets, respectively.

Because our descriptive data suggest that the use of digital ad platforms amplifies advertising revenue for misinformation outlets, we are interested in measuring how consumers respond to a specific advertising company appearing on misinformation websites when also informed of the potential role played by digital ad platforms in placing companies' ads on misinformation websites. For this reason, our third "company and platform" treatment (T3) combines information from our first two treatments (T1 and T2). Similar to T1, participants are given factual information that ads from their top choice gift card company appeared

[14] As a robustness check, we also ask respondents to assign weights to each of the six gift card options. This question gives respondents greater flexibility by allowing them to indicate the possibility of indifference or no preference (i.e., equal weights) between any set of options.

on misinformation websites in the recent past. Additionally, we informed participants that their top choice company used digital ad platforms and companies that used such platforms were about ten times more likely to appear on misinformation websites than companies that did not use digital ad platforms, as mentioned in T2.

Finally, since several advertising companies appear on misinformation websites, we would like to determine whether informing consumers about other advertising companies also appearing on misinformation websites changes their response towards their top choice company. In our fourth "company ranking" treatment (T4), participants are given factual information that ads from all six gift card companies appeared on misinformation websites in the recent past, along with a ranking based on the order of their intensity of advertising on misinformation websites. We personalize these rankings based on data from different years (i.e. 2019, 2020, or 2021) such that the respondents' top gift card choice company does not appear last in the ranking (i.e. is not the company that advertises least on misinformation websites) and in most cases, advertises more intensely on misinformation websites than its potential substitute in the same company category (fast food, food delivery or ride-sharing). Such a treatment allows us to measure potential differences in the direction of consumers switching their gift card choices, such as switching towards companies that advertise more or less intensely on misinformation websites.

4.1.4 Outcome Measures

We measure two behavioral outcomes that collectively allow us to measure how people respond to our information treatments in terms of both voice and exit (Hirschman, 1970). After the information treatment, all participants are asked to make their final gift card choice from the same six options they were shown earlier. To ensure incentive compatibility, participants are told that those randomly selected to receive a gift card will be offered the gift card of their choice at the end of our study. As mentioned above, the probability of being randomly chosen to receive a gift card is 20%. We choose a high probability of receiving a gift card relative to other online experiments since prior work has shown that consumers process the choice-relevant information more carefully as realization probability increases (Cao and Zhang, 2021). Our main outcome of interest is whether participants switch their gift card preference, i.e. whether participants select a different gift card after the information treatment than their top choice indicated before the information treatment.[15]

Secondly, participants are given the option to sign one of several real online petitions that we made and hosted on Change.org. Participants can opt to sign a petition that advocates for either blocking or allowing advertising on misinformation or choose not to sign any petition. Further, participants could choose between two petitions for blocking ads on misinformation websites, suggesting that either 1) advertising companies or 2) digital ad platforms need to block ads from appearing on misinformation websites.[16] To track the number of petition signatures across our randomized groups, we provide separate petition links to participants in each

[15]We also use text analysis of the responses to a free-form question which helps identify the impact of the information intervention more directly.

[16]Participants select among the following five choices: 1. *"Companies like X need to block their ads from appearing on misinformation websites."*, where X is their top choice gift card company; 2. *"Companies like X need to allow their ads to appear on misinformation websites."*, where X is their top choice gift card company; 3. *"Digital ad platforms used by companies need to block ads from appearing on misinformation websites."*; 4. *"Digital ad platforms used by companies need to allow ads to appear on misinformation websites."*; and 5. *I do not want to sign any petition*.

randomized group.[17] Our petition outcome serves two purposes. While our gift card outcome measures how people change their consumption behavior in response to the information provided, people may also respond to our information treatments in alternative ways, e.g. by voicing their concerns or supplying information to the parties involved (Hirschman, 1970; Gans, Goldfarb and Lederman, 2021; Lenox and Eesley, 2009; Eesley and Lenox, 2006). Given that the process of signing a petition is costly, participants' responses to this outcome would constitute a meaningful measure similar to petition measures used in prior experimental work (Grigorieff, Roth and Ubfal, 2020; Haaland and Roth, 2020). Second, since participants must choose between signing either company or platform petitions, this outcome allows us to measure whether, across our treatments, people hold advertising companies more responsible than the digital ad platforms that automatically place ads for companies.

In addition to our behavioral outcomes, we also record participants' stated preferences. To do so, we ask participants about their degree of agreement with statements about misinformation on a seven-point scale ranging from "strongly agree" to "strongly disagree". These include whether they think 1) it is important to control the spread of misinformation, 2) companies have an important role in reducing the spread of misinformation through their advertising practices, and 3) digital platforms should give companies the option to avoid advertising on misinformation websites.

At the end of the survey, we measure further background characteristics such as race, household income, and political orientation along with participants' opinions on misinformation and feedback on the survey.

4.1.5 Dealing with Experimenter Demand Effects

In our incentivized, online setting that deals where we measure behavioral outcomes, we expect experimenter demand effects to be minimal as has been evidenced in the experimental literature (De Quidt, Haushofer and Roth, 2018). We take several steps to mitigate potential experimenter demand effects, including incorporating several suggestions by Haaland, Roth and Wohlfart (N.d.)

First, our survey experiment has a neutral framing from recruitment and throughout the survey. While recruiting participants, we invite them to "take a survey about the news, technology and businesses" without making any specific references to misinformation or its effects. While introducing misinformation websites and how they are identified by independent non-partisan organizations, we include examples of misinformation websites across the political spectrum (including both right-wing and left-wing sites) and provide an illustrative example of misinformation by foreign actors (Figure A10). In drafting the survey instruments, the phrasing of the questions and choices available were as neutral as possible.[18]

In our active control design, participants in all randomized groups are presented with the same baseline information about misinformation, given misinformation-related information in the information intervention

[17] We record several petition-related outcomes. First, we measure participants' intention to sign a petition based on the option they select in this question. Participants who pass our attention check and who opt to sign a petition are later provided with a link to their petition of choice to sign. This allows to track whether or not participants click on the petition link provided. Participants can also self-report whether they signed the petition. Finally, we track actual petition signatures for respondents in each randomized group.

[18] For example, while introducing our online petitions, we presented participants with the option to sign real petitions that suggest both blocking and allowing advertising on misinformation sites.

and asked the same questions after the information intervention to emphasize the same topics and minimize potential differences in the understanding of the study across treatment groups.

To maximize privacy and increase truthful reporting (Ong and Weiss, 2000), respondents complete the surveys on their own devices without the physical presence of a researcher. We also do not collect respondents' names or contact details (with the exception of eliciting emails to provide gift cards to participants at the end of the study).

Apart from making the above design choices to minimize experimenter demand effects, we measure their relevance using a survey question. Since demand effects are less likely a concern if participants cannot identify the intent of the study (Haaland, Roth and Wohlfart, N.d.), we ask participants an open-ended question "What do you think is the purpose of our study?". Following (Bursztyn et al., 2020; Song, 2021), we then analyze the responses to this question to examine whether they differ across treatment groups.

4.2 Results

4.2.1 Average Treatment Effects: Exit

Our primary outcome is whether respondents exit by switching their top choice of the gift card, which takes the value one for people who switch and the value zero for all other participants. To observe exit outcomes, we focus on company-related information treatments, i.e., all treatments (T1, T3 and T4) where respondents are informed that ads from their top choice gift card company appeared on misinformation websites in the recent past.

Table 2 shows the regression results for our behavioral outcomes measured after participants receive the information treatment. Column 1 of Table 2 shows that respondents increasingly exit (i.e., increase switching away or decrease demand) their first choice company by 13 percentage points ($p < 0.001$) relative to control in response to learning about their top choice gift card company's ads appearing on misinformation websites in the recent past (T1). This switch in preference represents a 225% decline in demand for the respondents' top choice gift card company. The effect persists when we control for both baseline demographic characteristics and behavioral characteristics ($p < 0.001$, Column 2 of Table 2). Respondents' text responses explaining their choice of gift card as shown in Figure 2 (a) reveal that misinformation concerns drive this switching behavior.[19]

Switching behavior also increases relative to the control group by ten percentage points ($p < 0.001$) or 150% when respondents are told about the substantial role played by digital ad platforms in placing companies' ads on misinformation websites (T3). This switching behavior persists even though respondents are more likely to state that digital ad platforms are responsible for placing companies' ads on misinformation websites by four percentage points ($p < 0.001$) relative to the control group (Figure 2b). This suggests that advertising companies can continue to experience a decline in demand for their products or services despite consumers knowing that digital ad platforms play a substantial role in placing companies' ads on misinformation websites.

When provided with a ranking of companies in order of their intensity of appearance on misinformation

[19]For more sample text responses and details about the text analysis methodology, see Table A9 in Appendix C.

Table 2: Average Treatment Effects on Exit and Voice

	Gift card switch ("exit")		Petition clicks ("voice")			
			Company		Platform	
	(1)	(2)	(3)	(4)	(5)	(6)
Company (T1)	0.13^{***}	0.13^{***}	0.02	0.03^{*}	-0.02	-0.01
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Platform (T2)	0.03^{***}	0.03^{**}	-0.01	-0.01	0.05^{***}	0.05^{***}
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Company and Platform (T3)	0.10^{***}	0.09^{***}	-0.00	0.01	-0.01	-0.00
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Company Ranking (T4)	0.08^{***}	0.07^{***}	0.04^{**}	0.04^{**}	-0.02	-0.02
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Control group mean	0.04	0.04	0.15	0.15	0.14	0.14
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Behavioral controls	No	Yes	No	Yes	No	Yes
Observations	4039	4039	4039	4039	4039	4039

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

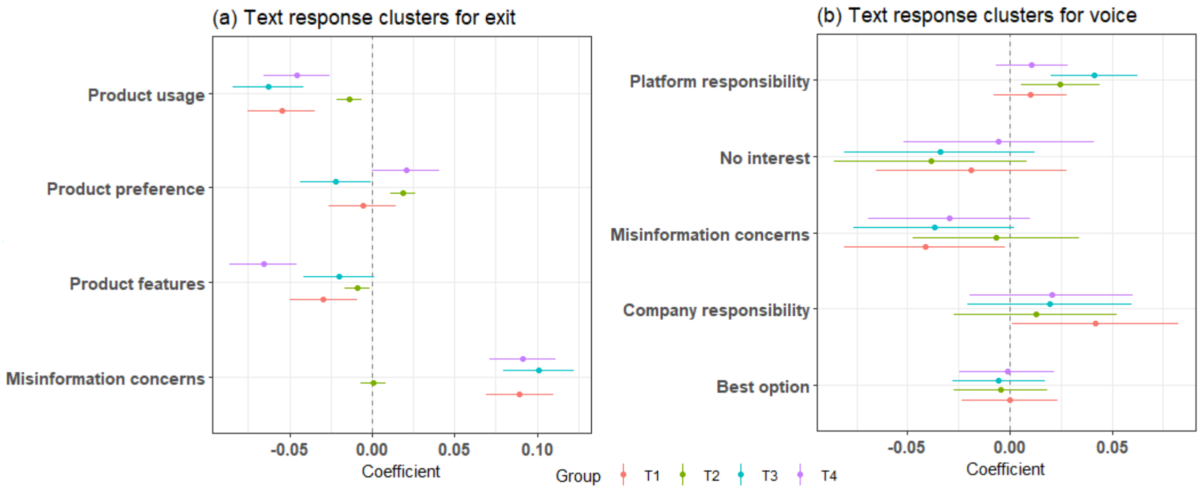
Notes: This table shows OLS regression results for each of the four treatment groups (T1, T2, T3 and T4). In columns 1 and 2, the dependent variable is switch in gift card choice from the respondent's top choice company (i.e. "exit") after receiving the information treatment. In columns 3 and 4, the dependent variable is clicking on a link to sign a petition that suggests that companies like the respondent's top choice gift card company need to block their ads from appearing on misinformation websites. In columns 5 and 6, the dependent variable is clicking on a link to sign a petition that suggests that digital ad platforms used by companies need to block ads from appearing on misinformation websites. We include baseline demographic controls in all specifications (including the respondent's age, gender, region of residence within the US, race, education level, employment status, household income and whether the respondent voted for President Joseph Biden in the 2020 U.S. Presidential election) and additional behavioral controls in columns 2, 4 and 6 (including the types of news sources consumed, whether the respondent had low trust in the news media, the number of online services used, whether the respondent had signed a petition in the past 12 months, whether the respondent reported using one or more misinformation news outlets from a list of 26 popular news outlets in the past 12 months, the respondent's top choice gift card and whether the respondent frequently uses their top choice gift card company). Robust standard errors in parentheses.

websites (T4), respondents switch away from opting for their top choice gift card company by seven percentage points ($p < 0.001$) or 75% relative to the control group. This result shows that advertising companies can expect to face a decrease in consumption for financing misinformation despite other companies also advertising on misinformation outlets. Respondents are less likely to mention product features relevant to the companies they are interested in, e.g. healthy food, good prices, availability in local area, etc. by 7 percentage points ($p < 0.001$, Figure 2a). Examining the direction of consumer switching shows that among those who switch their gift card preference, 84% of those given ranking information shifted their consumption to companies that less frequently advertised on misinformation websites - the largest percentage among all randomized groups.[20] This result suggests that providing a ranking of advertising companies transparently could steer consumer demand away from companies that advertise more frequently on misinformation websites.

While our primary exit outcome is the participants' switch in gift card choice, our results are robust to alternative measures as shown in Table A7. These exit outcomes, which include whether participants switch to a product they prefer less than their top choice one (Column 2, Table A7) and whether participants switch their choice across product categories (Column 3, Table A7), further indicate that our measures of exit are incentive-compatible since participants incur an actual cost of switching to a company that is not equivalent to their top-ranked one.

[20]The proportion of respondents who switched to a company that less frequently advertised on misinformation was 61% in the control group, 80% in T1, 74% in T2 and 78% in T3 among respondents who switched their gift card preference.

Figure 2: Text Explanation Clustering by Randomized Treatment Group



Notes: This figure plots regression coefficients from OLS regressions of an indicator for cluster membership on each randomized group. The horizontal bars represent 95% confidence intervals. The topics along the y-axes are binary variables that take value 1 if a participant's response is classified into the given topic and zero otherwise. Details about the text analyses are mentioned in Appendix C and sample text responses are shown in Tables A9 and A10. Figure (a) shows OLS regression results for text analysis on the open-ended reasons participants mentioned while explaining their choice of gift card. Figure (b) shows OLS regression results for text analysis on the open-ended reasons participants mentioned while explaining their choice of online petition to sign. In all specifications above, we control for the same baseline demographic characteristics and behavioral characteristics as in Table 2. Robust standard errors in parentheses.

4.2.2 Average Treatment Effects: Voice

Next, we examine how participants respond to our information treatments by voicing their concerns about advertising on misinformation websites by signing an online petition of their choice. While we observe actual petition signatures at the group level, we use clicks on petition links as our primary voice outcome, since this information is available at the individual level. Our results are robust to using alternative petition outcomes, such as intention to sign a petition, self-reported petition signatures, and actual signatures, as shown in Table A8 in Appendix C.

Relative to the control group, participants were significantly more likely to click on wanting to sign platform petitions when given information about the role of digital ad platforms in automatically placing ads on misinformation websites in the Platform (T2) treatment group, as seen in columns 5 and 6 of Table 2. Text analysis from respondents' explanation of their petition choice confirms that respondents hold digital ad platforms more responsible for financing misinformation in T2 relative to the control group (Figure 2). For example, one respondent stated, "Door Dash is not the only ad being put on misinformation sites. It is a larger issue that has to do with the platforms used to place ads." Another stated that, "I think that the digital ad platforms utilized by companies need to be more proactive in blocking ads from appearing on misinformation sites. In some (maybe even a majority) of cases, these companies that use the digital ad platforms in order to get advertising out probably do not even know exactly which sites their ads are going to appear on,, and having them appear on misinformation sites can be quite misleading for consumers- e.g: they may assume that the misinformation that appears on these sites is something that these brands agree with and it may lead to bad impressions, which leads to lower volume of sales."

Additionally, upon receiving information about all six gift card companies' ads appearing on misinformation websites (T4), participants are significantly more likely to click on petition links suggesting that advertising companies need to block their ads from appearing on misinformation websites (Columns 3 and 4, Table 2). Based on their open-ended text responses, respondents increasingly highlight misinformation-related concerns and place less emphasis on product usage and product features (Figure 2a).

4.2.3 Heterogeneous Treatment Effects

Next, we explore heterogeneity in treatment effects along four pre-registered dimensions: gender, political orientation, frequency of use of the company's products or services, and consumption of misinformation.

Prior research recognizes differences in the salience of prosocial motivations across gender (Croson and Gneezy, 2009; Falk et al., 2018) with women being more affected by social-impact messages than men (Guzman, Oh and Sen, 2020).[21] Given these findings, we could expect female participants to be more strongly affected by our information treatments. Indeed, while we observe positive treatment effects for both male and female participants, female participants exhibit greater switching or exit behavior by 5 percentage points ($p = 0.01$) in response to information about advertising on misinformation websites (Table 3, Column 1).

Responses to our information treatments may also differ by respondents' political orientation. According to prior research, conservatives are especially likely to associate the mainstream media with the term "fake news". These perceptions are generally linked to lower trust in media, voting for Trump, and higher belief in conspiracy theories (Van der Linden et al., 2020).[22] Moreover, the proportion of right-wing outlets is higher among misinformation outlets identified by third-party journalists relative to left-wing outlets.[23] Consequently, we might expect stronger treatment effects for left-wing respondents. Respondents who voted for both candidates (Joseph Biden and Donald Trump) reduced demand for their top choice in response to our information treatments. However, respondents who voted for President Biden in the 2020 US Presidential election are 3 percentage points more likely to exit ($p = 0.06$) and 5 percentage points more likely to voice concerns against company practices ($p = 0.04$) as shown in columns 2 and 6 of Table 3, respectively.

Consumers who more frequently use a company's products or services could be presumed to be more loyal towards the company that limits changes in their behavior (Liaukonytė, Tuchman and Zhu, 2022). Therefore, such consumers may have a smaller overall decrease in their demand for the company's products in response to our information treatments. Alternatively, more frequent consumers may be more strongly affected by our information treatments as they may perceive their usage as supporting such company practices to a greater extent than less frequent consumers. In our results, both frequent and infrequent users of a company's products or services exit in response to our information treatments. Still, we observe a negative and statistically significant interaction term for frequent users, revealing that frequent users were about 5 percentage points less likely to exit ($p = 0.01$) as shown in Column 3 of Table 3.

[21]Additionally, prior work has shown that female individuals were more likely to consume new media content critically and logically than male counterparts (Xiao et al., 2021)

[22]Previous research has found that the demand for fact-checking varies by ideological alignment, with a greater demand for fact-checking for politically non-aligned news (Chopra, Haaland and Roth, 2022).

[23]Indeed, in our website data from NewsGuard, the proportion of misinformation websites is greater among far right (83.9%) websites relative to far left (17.2%) websites and websites with a neutral political orientation (7.1%).

Table 3: Heterogeneous Treatment Effects for Exit and Voice

	Switch in gift card from top choice company ("exit")				Petition clicks on company petition ("voice")			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	0.07^{***}	0.07^{***}	0.12^{***}	0.10^{***}	0.02	0.00	0.03^{**}	0.03^{**}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)
Treatment $\times$ Female	0.05^{**}				0.00			
	(0.02)				(0.02)			
Treatment $\times$ Biden voter		0.03^{*}				0.05^{**}		
		(0.02)				(0.02)		
Treatment $\times$ Frequent user			-0.05^{***}				-0.02	
			(0.02)				(0.02)	
Treatment $\times$				-0.04^{*}				-0.03
Consumes misinformation				(0.02)				(0.03)
Female	0.00	0.03^{***}	0.03^{***}	0.03^{***}	0.00	0.01	0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Biden voter	0.01	-0.01	0.01	0.01	0.02^{*}	-0.01	0.02^{*}	0.02^{*}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Frequent user	-0.04^{***}	-0.04^{***}	-0.01	-0.04^{***}	0.03^{**}	0.03^{**}	0.04^{**}	0.03^{**}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Consumes misinformation	0.03^{**}	0.03^{**}	0.03^{**}	0.05^{***}	0.00	0.00	0.00	0.02
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Observations	4039	4039	4039	4039	4039	4039	4039	4039
Baseline and behavioral controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Notes: This table shows OLS regression results where *Treatment* is a binary variable that takes a value of 1 if a respondent is randomized into any of the company-specific treatment groups (T1, T3 or T4). In columns 1 to 4, the dependent variable is switch in gift card choice from the respondent's top choice company (i.e. "exit"). In columns 5 to 8, the dependent variable is clicking on a link to sign a petition that suggests that companies like the respondent's top choice gift card company need to block their ads from appearing on misinformation websites. *Female* is a binary variable that takes a value of 1 if a respondent reports being female and zero otherwise. *Biden voter* is a binary variable that takes a value of 1 if a respondent reported voting for President Biden in the 2020 US Presidential election and zero otherwise. *Frequent user* is a binary variable that takes a value of 1 if a respondent reported using their top choice gift card at least once a month. *Consumes misinformation* is a binary variable that takes a value of 1 if a respondent reported using one or more misinformation news outlets (out of a list of 26 popular news outlets) in the past 12 months and zero otherwise. In all specifications above, we control for baseline demographic characteristics and behavioral characteristics as in Table 2. Robust standard errors in parentheses.

Finally, we measure whether people's responses differ by whether they consume misinformation themselves. Consuming misinformation is a binary variable that takes the value of one when a respondent selects one of the misinformation outlets in the initial question asking them to select which news outlets they used in the past 12 months. We find that both types of participants (those who report using the misinformation outlets we identify and those who do not) exit in response to our information treatments, but participants who consume misinformation are 4 percentage points less likely to exit after receiving the information treatment, a decrease in demand that is significant at the 10% level ($p = 0.10$) as shown in Column 4 of Table 3. Respondents who do not consume misinformation also have a positive treatment effect of 3 percentage points higher than the control ($p = 0.01$) in terms of clicking on petitions suggesting that companies block their ads from appearing on misinformation websites. In contrast, respondents who do not report using misinformation outlets have a positive but statistically insignificant increase in clicks on the same petition links.

4.2.4 Comparing Stated and Revealed Preferences

We find stark differences between consumers' stated preferences as measured by their degree of agreement with specific statements and revealed preferences as measured by their choices. While 11% of our participants exit, a much larger percentage (68%) agree that companies have an important role in reducing the spread of misinformation through their advertising practices (Figure A2). Similarly, while 23% of our participants sign online petitions suggesting changes in company or platform practices, 76% agree that digital ad platforms should allow companies to avoid advertising on misinformation websites (v). Our stated preferences are consistent with recent industry reports that find that nearly two-thirds of consumers state that they would stop using a brand if its ad appeared next to fake or offensive content, and 62-70% of consumers want companies to take a stand on social, cultural environmental and political issues.[24] However, the contrast between stated and revealed preferences underscores the importance of eliciting revealed preferences via behavioral outcomes as consistent with prior research documenting hypothetical bias in the measurement of stated preferences (Cummings et al., 1995; List et al., 2001; Athey, Catalini and Tucker, 2017).

4.2.5 Experimenter Demand Effect

To minimize concerns about experimenter demand effects, we take several steps as part of our experimental design as described in Section 4.1, including using a neutral framing in our survey. We find that the vast majority of participants believe that the information provided in the survey was unbiased as shown in Figure A3.[25] We now consider the extent to which experimenter demand effects may be relevant in driving the results.

To measure potential differences in the respondents' perceptions of the study, we examine their open-ended text responses about the purpose of the study using a Support Vector Machine classifier.[26] We predict treatment status using the classfier, keeping 75% of the sample for the training set and the remaining 25% as the test set. We find that the classier predicts treatment status only slightly better than chance for each of the treatment groups relative to the control group, as shown in Table A12. These results suggest that our treatments do not substantially affect participants' perceptions about the purpose of the study. Therefore, although experimenter demand effects may still be present, our main experimental findings are not likely to be driven by these effects.

4.3 Economic implications

To evaluate the economic significance of our experimental results, the magnitudes of the treatment effect estimates in our consumer experiment can be benchmarked to other studies in the literature. The average treatment effects of 7 to 13 percentage points for people switching their gift card choice away from the company advertising on misinformation outlets is comparable to other studies that examine the reputational effects of information on sellers. For instance, Cabral and Hortaçsu (2010) find that when a seller on eBay receives negative feedback, their weekly sales growth rate drops by 13.2 percentage points. Akesson et al. (2022) find that fake reviews make people 12.6 percentage points more likely to purchase a low product product. Sim-

[24] https://doubleverify.com/newsroom/study-consumers-reject-brands-that-advertise-on-fake-news-and-objectionable-content-online/; `https://sproutsocial.com/insights/data/social-media-connection/`.

[25] About 77.8% of survey participants chose "unbiased" when asked to rate the political bias of the survey information provided from a seven-point scale ranging from "very right-wing biased" to "very left-wing biased". Additionally, 68.7% of the participants trust the information provided in the survey. Respondents' perceptions of survey information, misinformation websites, and journalists' ratings of websites are shown in Appendix Figures A3, A4, and A5, respectively.

[26] This classifier incorporates several features in text analysis, including word, character and sentence counts, sentiments, topics (using Gensim) and word embeddings.

ilarly, other studies have shown increases in revenue or sales based on positive feedback. Luca (2016) finds that a one-star increase in Yelp rating leads to a 5-9 percent increase in revenue. Jin and Leslie (2003) show that when restaurants are forced to post hygiene report cards, a grade of A leads to a 5% increase in revenue relative to other grades.

Our average treatment effects are larger than effects found in prior research for companies taking a social or political stance. Chatterji and Toffel (2019) find a 11.9% increase in purchase intentions when consumers were informed about CEO activism. Buell and Kalkanci (2020) show that providing transparency into a company's social responsibility practices increased the purchase probability by up to 46.3%. Liaukonytė, Tuchman and Zhu (2022) find a temporary net increase in sales of 22% for a brand engaging in political consumerism. Furthermore, the average treatment effects for consumers switching away from advertisers that appear on misinformation websites are also larger than the treatment effects for other interventions meant to counter misinformation. A meta-analysis of accuracy prompt interventions showed that they increase the quality of news that people share (sharing discernment) by 10% relative to control relative, primarily by reducing sharing intentions for false headlines (Pennycook and Rand, 2022). In testing how the demand for a newsletter among U.S. Democrats changes when its content is fact-checked, Chopra, Haaland and Roth (2022) find no significant increase in the overall demand for fact-checking with only a small significant increase of 4.5 percentage points among ideologically moderate Democrats in response to the fact-checking treatment. Aslett et al. (2022) also do not find statistically significant shifts in people's online news consumption away from unreliable publishers when providing randomized exposure to in-browser source reliability information. Relative to these interventions, our information intervention of disclosing advertisers that appear on misinformation websites shifts consumption away from such advertisers by 8-13 percentage points depending on the type of information disclosed.

Overall, our results suggest that providing consumers with information on companies advertising on misinformation websites can substantially decrease the revenue generated by such companies.

5 Decision-maker study

5.1 Research design

To examine the beliefs, preferences, and choices of decision-makers relevant to advertising on misinformation websites, we survey managers and executives within companies. This study addresses two research questions. First, we aim to pin down existing beliefs and preferences decision-makers have about advertising on misinformation websites, which will help examine whether companies may be inadvertently (or intentionally) sustaining online misinformation.

Secondly, we ask: how do decision-makers update their beliefs and demand for a solution to avoid advertising on misinformation websites in response to information about the extent of advertising on misinformation websites by digital ad platforms? To this end, we conduct an information provision experiment (Haaland, Roth and Wohlfart, N.d.). While past work has examined how firm behavior regarding market decisions changes in response to new information, it is unclear how information on the role of digital ad platforms in amplifying advertising on misinformation would affect decision-makers' non-market strategies (Lenox and Eesley, 2009; Eesley and Lenox, 2006).

5.1.1 Setting and sample size

We conduct an online survey experiment targeting senior decision-makers such as managers and executives within organizations who play a key role in strategic decision-making. Our sample of respondents mainly comes from the executive education alumni of the Graduate School of Business at Stanford University with a smaller sample of executive alumni from Heinz College at Carnegie Mellon University.

We first elicit participants' current employment status. All those working in some capacity are allowed to continue the survey, whereas the rest of the participants are screened out. After asking for participants' main occupation, all participants in the experiment are provided with baseline information on misinformation and advertising.

5.1.2 Eliciting baseline beliefs

First, we record participants' baseline beliefs. Specifically, participants are asked to estimate the number of companies among the most active 100 advertisers whose ads appeared on misinformation websites during the past three years (2019-2021). Additionally, we ask participants to report whether they think their company or organization had its ads appear on misinformation websites in the past three years. To measure participants' beliefs about the role played by digital ad platforms in placing ads on misinformation websites, we first inform participants that during the past three years (2019-2021), out of every 100 that did not use digital ad platforms, eight companies appeared on misinformation websites on average. We then asked participants to provide their best estimate for the number of companies whose ads appeared on misinformation websites out of every 100 companies that did use digital ad platforms.

5.1.3 Measuring preferences

In addition to recording participants' stated preferences using self-reported survey measures, we measure participants' revealed preferences. To ensure incentive compatibility, participants are asked three questions in a randomized order: 1) Information demand about consumer responses, i.e. whether they would like to learn how consumers respond to companies whose ads appear on misinformation websites (based on our consumer survey experiment), 2) Ad check, i.e. whether they would like to know about their own company's ads appearing on misinformation websites in the recent past, and 3) Demand for a solution, i.e. whether they would like to sign up for a 15-minute information session on how companies can manage where their ads appear online. Participants are told they can receive information about consumer responses at the end of the study if they opt to receive it whereas the ad check and solution information are provided as a follow-up after the survey.[27] Since all three types of information offered are novel and otherwise costly to obtain, we expect

[27] Participants are required to provide their emails and company name for the ad check. To sign up for an information session on a potential solution to avoid advertising on misinformation websites, participants sign up on a separate form by providing their emails.

respondents' demand for such information to capture revealed preferences.[28]

5.1.4 Information intervention

Participants are then randomized into a treatment and control group, which receives information about the role of digital ad platforms in placing ads on misinformation websites, and a control group, which does not receive this information. Based on the dataset we assembled, participants are given factual information that companies that used digital ad platforms were about ten times more likely to appear on misinformation websites than companies that did not use such platforms in the recent past. This information is identical to the information provided to participants in the T2 (i.e. platform only) group in the consumer experiment.

5.1.5 Outcomes

Following the information intervention, we measure three outcomes. First, we measure participants' posterior beliefs about the role played by digital ad platforms in placing ads on misinformation websites. Participants are told about the average number of advertising companies whose ads appear per month on misinformation websites that do not use digital ad platforms. They are then asked to estimate the average number of advertising companies whose ads appear monthly on misinformation websites that use digital ad platforms to understand whether participants believe that the use of digital ad platforms amplifies ads on misinformation websites.

We record two behavioral outcomes. Our main outcome of interest is the respondents' demand for a platform-based solution to avoid advertising on misinformation websites. Participants can opt to learn more about which platforms least frequently place companies' ads on misinformation websites. The other choices include learning about analytics technologies used to improve ad performance or opting not to receive any information. Participants are told that they will be provided the information they choose at the end of this study. Following the literature in measuring information acquisition (Capozza et al., 2021), we measure respondents' demand for solution information, which serves as a revealed-preference proxy for interest in implementing a solution for their organization (Hjort et al., 2021).

Additionally, to measure whether the information treatment increases concern for financing misinformation in general, we record a second behavioral measure. Participants are told that the research team will donate $100 to one of two organizations after randomly selecting one of the first hundred responses: 1) The Global Disinformation Index (GDI), and 2) DataKind, which helps mission-driven organizations increase their impact by unlocking their data science potential ethically and responsibly.

Next, participants interested in learning about survey findings are given the option to receive further information via a follow-up email. Finally, participants who opted to learn more in our information demand questions are provided with the requested information.

[28] For information demand about consumer responses, participants are told that they would be provided with this information at the end of our survey if they choose to receive it. For the ad check and demand for a solution, participants are told that they would receive this information in a follow-up email after survey completion if they opt to receive it.

5.2 Results

About 49% of the participants in our study are currently serving in a top executive role (e.g., chief executives, general and operations managers of multiple departments or locations, etc.). Table A13 summarizes the descriptive characteristics, beliefs, and preferences of our study participants.

5.2.1 Baseline beliefs and characteristics

The vast majority of decision-makers in our sample believe it is important to control the spread of misinformation in society (88%) and that digital platforms should give companies a way to avoid advertising on misinformation websites (86%). While most participants believe that companies have an important role in reducing the spread of misinformation through their advertising practices (76%), only 41% agree that consumers react against companies whose ads appear on misinformation websites. This suggests that decision-makers are unaware of how advertising on misinformation websites may provoke consumer backlash.

Participants beliefs about advertising on misinformation outlets are summarized in Table 4. When asked to estimate the number of companies among the 100 most active advertisers whose ads appeared on misinformation websites between 2019-2021, respondents' report an average of 64 companies, approximately 16% higher than the 55% of companies found in our data. However, respondents substantially underestimate their own company's likelihood of appearing on misinformation websites with only 20% of respondents believing that their own company's ads appeared on misinformation websites between 2019 and 2021. Among the subsample of participants who requested an ad check (by providing their company name and contact details) and whose companies appeared in our advertising data (N = 108), approximately 81% of companies appeared on misinformation websites between 2019 and 2021. These figures illustrate that executives and managers are uninformed about the likelihood of their company's ads appearing on misinformation websites.

Table 4: Decision-makers' Beliefs and Characteristics about Advertising on Misinformation Outlets

	Full sample	Certain		Uncertain	
	All	Yes	No	Yes	No
	(1)	(2)	(3)	(4)	(5)
Belief about % of Companies Advertising on Misinformation	0.64	0.75	0.61	0.70	0.66
Belief about Likelihood of Own Company Advertising on Misinformation	0.20	1	0	1	0
Advertised on Misinformation*	0.81	0.79	0.83	0.80	0.81
% of Correct Beliefs about Advertising on Misinformation*	0.40	0.79	0.17	0.80	0.19
Requested ad check	0.74	0.72	0.72	0.70	0.84
Observations	442	65	286	23	68

Notes: Column (1) shows results for the full sample. Columns (2) and (4) show results for the subsample who reported "yes" to the question "Do you think your company or organization had its ads appear on misinformation websites during the past three years (2019-2021)?". Columns (3) and (5) show results for the subsample who reported "No" to the same question. Columns (1)-(2) show results for participants who report being certain about their response to the aforementioned question (choosing "Somewhat sure", "Sure" or "Very sure") and Panel B shows results for participants who report being certain (choosing "Unsure" or "Very unsure"). The proportions in rows marked with an asterisk (*) are calculated based on the subsample of participants who requested an ad check and whose companies appeared in our advertising data (N = 106).

Moreover, decision-makers underestimate the role of digital ad platforms in placing companies' ads on misinformation websites. On average, respondents estimated that about 44.5% of companies using digital ad platforms appear on misinformation websites as opposed to the 79.8% of companies among the 100 most active advertisers that do so (Table A3). There is a wide dispersion in decision-makers' beliefs about the role of companies and platforms in financing misinformation as shown in Figures A6 and A7.

5.2.2 Preferences

The vast majority of participants requested an ad check by providing their company name and email address (74%). The demand for an ad check was high (70% or more) regardless of respondents' beliefs, suggesting a substantial interest in learning about whether their company's ads appeared on misinformation websites. Despite only 41% of respondents agreeing that consumers react against companies whose ads appear on misinformation websites, most participants opted to receive information on how consumers respond to companies whose ads appear on misinformation websites (73%). This suggests that while decision-makers may be unaware of how advertising on misinformation websites can provoke consumer backlash, most decision-makers are interested in learning about the degree of potential backlash. Most participants inquired about "exit" (58%), with only 15% inquiring about "voice".

Finally, for our most costly revealed preference measure, i.e. signing up to attend a 15-minute information session, a much lower but substantial proportion of participants (18%) responded.[29] For all three behavioral measures, demand was highest among participants who reported being uncertain about their belief that their company's ads did not appear on misinformation websites as shown in Table A13. The 18% rate of signing up for a 15-minute information session on learning how to avoid advertising on misinformation websites is arguably high given the value of a manager's time and the opportunity cost of attending the session. Concurrently, the difference in demand for our lower-cost information (73-74%) and higher-cost (18%) suggests that providing lower-cost interventions such as allowing advertisers to easily steer their ads across different types of news outlets could be more fruitful in aligning advertiser preferences with their algorithmically-driven ad placements.

5.2.3 Information intervention results

We report the results of our information treatment in Table 5. For the full sample of participants, we estimate positive and statistically significant effects on participants' posterior beliefs about the role of ad platforms in placing ads on misinformation websites (column 1), which is mainly driven by respondents who believe their company's ads do not appear on misinformation websites (Column 3).

We find a null effect overall of our information treatment on participants' demand for a platform-based solution (Columns (1)-(4) in Table 5). However, this result masks significant heterogeneity based on participants' prior beliefs. In Table 6, we report results based on subsamples of participants who are certain and uncertain about whether their company's ads recently appeared on misinformation websites, respectively. We find that

[29] For receiving an ad check, i.e., finding out whether their own company's ads appeared on misinformation websites in the recent past, we observed a close match between respondents' stated and revealed preferences with 76% of respondents stating that they would like to find out whether their company's ads appeared on misinformation websites and 74% of respondents providing their company's name and contact details to request an ad check. For solution information demand, however, there was a substantial gap between our stated and revealed preferences with 71% of respondents stating that they would recommend that their company adopt a product to avoid advertising on misinformation websites, but only 18% of respondents clicking on the form to sign up for a 15-minute information session on how their company can adopt a solution to avoid advertising on misinformation websites.

Table 5: Average Treatment Effects of Information Intervention

	Posterior beliefs			Platform solution demand		
	All	Yes	No	All	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	48.04^{***}	5.84	53.27^{***}	-0.03	-0.10	-0.03
	(15.83)	(43.59)	(17.88)	(0.05)	(0.13)	(0.05)
Observations	442	88	354	442	88	354
Controls	Yes	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Notes: This table shows OLS regression results where the dependent variables are posterior beliefs (columns 1 to 3), demand for platform solution (columns 4 to 6). We winsorize the posterior beliefs to remove outliers. Our platform solution demand outcome variable is a binary variable that takes a value of one when participants choose to receive information on which platforms least frequently place companies' ads on misinformation websites and zero otherwise. The columns are labelled "All", "Yes" and "No" similarly to Table 4. We control for baseline characteristics, beliefs and behavioral characteristics in all specifications except columns (2), (5) and (8) where the number of employees and industry dummies were not used as controls. Robust standard errors in parentheses.

Table 6: Treatments Effects on Platform Solution Demand Based On Prior Beliefs

	All	Yes	No
	(1)	(2)	(3)
Panel A: Uncertain			
Treatment	0.30^{**}	-0.00	0.40^{***}
	(0.12)	(0.45)	(0.12)
Observations	91	23	68
Panel B: Certain			
Treatment	-0.09^{*}	-0.31^{**}	-0.07
	(0.05)	(0.15)	(0.06)
Observations	351	65	286
Controls	Yes	Yes	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Notes: This table shows OLS regression where the dependent variable is platform solution demand from Table 5. Panel A (B) shows results for participants who report being (un)certain about whether their company's ads appeared on misinformation sites in the past 3 years. The columns are labeled similarly to Table 4. We use the same control variables as in Table 5. Robust standard errors in parentheses.

only participants who were uncertain about their own company's ads appearing on misinformation responded positively and significantly to our information treatment by increasing their demand for a platform-based solution (Panel A, Columns 1). This effect appears to be driven by participants who believe their company's ads did not appear on misinformation websites (Panel A, Column 3), for whom our treatment causes an increase in the proportion of participants who opt to receive information about which platforms least frequently place ads on misinformation websites by 40 percentage points ($p = 0.003$). This effect goes in the opposite direction when we consider participants who report being certain that their company's ads appeared on misinformation websites in the recent past (Panel B, Column 1).

Our results imply that the way participants respond to information about the role played by digital ad platforms in financing misinformation is highly dependent on their prior beliefs about their own company. For those uncertain about whether their company's ads appear on misinformation websites, providing such information can increase their demand for a platform-based solution, mainly if they believe their company's ads did not appear on misinformation websites. Such information could make companies switch ad platforms or pressure existing platforms to allow them to easily steer their ads away from misinformation outlets.

We did not find meaningful treatment effects for our donation preference outcome for the full sample or any subsamples based on participants' self-reported beliefs (Table A14). As previously mentioned, this outcome measures the proportion of respondents who prefer that we donate to the Global Disinformation Index (GDI) instead of DataKind. Since both organizations have similar goals of advancing technology's ethical and responsible use, respondents may have considered their missions interchangeable. Moreover, unlike our first behavioral outcome, respondents could have considered donating to the GDI less relevant to their own organizations' needs and more a matter of personal preference.

Similar to the analysis of potential experimenter demand effects in our consumer experiment described in Section 4.2, we examine respondents' perceptions about the purpose of the study using a Support Vector Machine classifier. We find that our classifier predicts treatment status slightly worse than chance as shown in Table A15. This result suggests that our information intervention results are not likely to be driven by experimenter demand effects.

6 Conclusion

Our descriptive and experimental results suggest that companies should exercise caution when incorporating automation in their business processes via digital ad platforms since it can lead to consumer backlash. Companies using digital ad platforms to place ads were about ten times more likely to appear on misinformation websites than those not using digital ad platforms. Consumers who find out about companies advertising on misinformation outlets exit by up to 225%. Even when informed of the role played by digital ad platforms in placing companies' ads on misinformation outlets and that other companies also advertise on such outlets, consumers continue to reduce demand by 150% and 75%, respectively. Overall, advertising companies and digital ad platforms face consumer backlash for monetizing misinformation outlets.

Our survey of decision-makers within companies reveals that they are ill-informed about their own company's role in monetizing misinformation outlets. Those uncertain about where their ads appeared also increased their demand for a platform-based solution to reduce advertising on misinformation websites upon learning how platforms amplify ad placement on such websites. These results suggest that some advertising companies may be financing misinformation inadvertently. Upon access to relevant information, decision-makers within companies are interested in reducing the monetization of misinformation. Altogether, our results suggest that there is room for decreasing the financing of misinformation by incorporating advertiser preferences in ad placement decisions.

Our results suggest that providing information to the public about the intensity or ranking of advertising on misinformation websites by companies could incentivize them to shift advertising away from misinformation websites. In the offline world, providing information to consumers on firms' social practices has incentivized changes in firm behavior. Various forms of information-based regulation, such as requirements that fast food restaurants include nutritional information on menus and that industrial facilities publicly disclose toxic chemical emissions and greenhouse gasses, have been shown to incentive improvements in firm performance based on the responses of consumers, investors, or other important stakeholders (Jin and Leslie, 2009; Dranove and Jin, 2010; Bollinger, Leslie and Sorensen, 2011). While prior work has examined how platforms use information such as reputation and feedback systems in e-commerce marketplaces to inform consumers about the quality of the goods and services available for purchase, the role of platforms in information disclosure to consumers about firms' social practices remains unexplored. Our work bridges the gap between the literature on information regulation by platforms and offline social information disclosure.

In the backdrop of mounting pressure from consumers and advertisers and the threat of government regulation, especially for transparency in the programmatic ad business (Allison Schiff, 2023; Horwitz and Hagey, 2021), digital ad platforms may benefit from self-regulation that reduces advertising on misinformation outlets (Cusumano, Gawer and Yoffie, 2021). Ad platforms are uniquely positioned to provide information about advertising on misinformation websites to consumers and advertisers. Such a practice would reduce information asymmetry for both parties and allow them to make more informed decisions. Moreover, this could limit backlash, both from the users as well as the regulatory agencies, against digital ad platforms.

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Appendix

Appendix A: Descriptive results

Table A1: Summary statistics for NewsGuard data

	US		Global	
	Misinformation	Non-misinformation	Misinformation	Non-misinformation
Average score	9.6	74.1	11.5	77.5
% of untrustworthy websites	100	29.2	100	21.8
% of right-wing websites	78.9	27.4	71.9	20.7
% of left-wing websites	7.0	1.7	2.8	7.7
% of websites with paywall	0.9	24.7	2.1	25.1
Observations	1131	4785	1578	7272

Notes: NewsGuard evaluates each news and information website on a set of nine journalistic criteria (does not repeatedly publish false content, gathers and presents information responsibly, regularly corrects or clarifies errors, handles the difference between news and opinion responsibly, avoids deceptive headlines, discloses ownership and financing, clearly labels advertising, reveals who's in charge of content, provides content creators' names and information). We use the first criterion of "*does not repeatedly publish false content*" to identify misinformation websites. NewsGuard assigns an aggregated score from 0 to 100 to each website based on a weighted average of how well it performs on the aforementioned criteria, and considers websites that receive a rating below 60 to be untrustworthy websites. This dataset is regularly updated to add new websites, remove inactive websites and update scores for any websites that have changed their practices along any of the above nine dimensions. (updated May 10, 2022).

Table A2: Number and examples of companies whose ads appear on misinformation websites

Industry	N	Examples
Holding Companies	6767	3M, AOL, Boeing, Colgate-Palmolive, Fox Entertainment Group, PepsiCo
Online Services	5347	Amazon, BBB (Better Business Bureau), Chegg.com, FlipKart, Goodreads
Media	4749	AMC Theatres, Al Jazeera, CBS, Getty Images, Hotstar, Oprah, Zynga
Technology	4157	Adobe, Apple, Bill.com, Casio, DoorDash, Hitachi, IBM, Lenovo
Govt., or Religion	3851	ACLU, Air National Guard, Democratic National Committee, YMCA
Business Solutions	3848	Accenture, Adweek, Bobcat Company, Deloitte, Forrester, GitHub, Oracle
Household	3644	Apartments.com, Big Ass Fans, Dyson, Frigidaire, Kohler, PetSmart, Roomba
Travel	3484	Amtrak, Big Bus Tours, Celebrity Cruises, Egencia, Greyhound, Zoo Miami
Apparel	3373	Abercrombie & Fitch, Aldo, Crocs, Eyebuydirect.com, Joie, Vera Wang
Retail	3368	1-800 Flowers.com, Costco Wholesale, Dollar Tree, Gamestop, Walmart
Insurance	3307	Aetna, Cigna, Fidelity, Liberty Mutual Group, Progressive Insurance
Telecommunications	3189	AT&T, Bell Canada Enterprises, Comcast, Ericsson, Sky, Vodafone
Digital Publishing	3111	Ars Technica, Daily Mail, MSN, Rollingstone, The Skimm, Women's Health
Print Publishing	3103	Arab News, Chicago Sun-Times, Denver Post, Forbes, Newsweek
Finance	3018	Bank of America, Bank of England, Barclays, Citadel, KPMG, Lendio
Health	2980	Astrazeneca, Bayer, California Psychics, Chesapeake Urology, Delta Dental
Babies & Kids	2344	Baby Jogger, Johnsons, Lego, Once Upon A Child, WaterWipes
Automotive	1766	America's Tire, Audi, BMW, Chevrolet dealerships, Denso, Mazda
Food or Beverages	1688	Annie's, Blue Bottle Coffee, Bordeaux Wines, Chobani, Goya, Lindt
Industrial	1180	84 Lumber, Big Tex Trailers, EcoLab, Kimber Manufacturing, Zippo
Education	1032	Arizona State University, GRE, Harvard University, MIT, Stanford
Dining	1028	Arby's, Chick-fil-A, Hooters, Panera, Nando's, Subway, Wendy's
Gas & Electric	457	AmeriGas, BP (British Petroleum), Chevron, Citgo, Exxonmobil, Shell
Cosmetics	340	Curology, Fresh.com, Massage Heights, RevitaLash Cosmetics
Arms	28	Beretta, Silencer Shop, Smith & Wesson, The Range LLC

Notes: This table shows the number of unique companies whose ads appear on misinformation websites between 2019 and 2021 for each of the 25 industries in the Moat Pro dataset along with select examples of companies in each industry.

Table A3: Descriptive statistics for the one hundred most active advertisers between 2019 and 2021

	Companies using digital ad platforms	Companies not using digital ad platforms	Overall
Misinformation websites	79.8	7.7	54.9
Non-misinformation websites	20.2	92.3	45.1
Total	100.0	100.0	100.0

Notes: This table shows the mean percentages of advertising companies that both appear and do not appear on misinformation websites on misinformation websites based on weekly data for the one hundred most active advertisers in each year from 2019 to 2021. The first two columns show the average percentages of advertising companies that appear on such websites among companies that were found to use digital ad platforms and those not found to use digital ad platforms, respectively. The last column reports the overall mean percentages of companies whose ads appeared and did not appear on misinformation websites.

Table A4: Descriptive statistics for the websites in our sample

		Uses digital ad platforms	Does not use digital ad platforms	Total
Misinformation	Number of websites	514	514	514
	Number of advertisers	256,817	33,517	290,334
	Advertisers per website	500	65	565
Non-misinformation	Number of websites	2927	2927	2927
	Number of advertisers	2,555,153	258,614	2,813,767
	Advertisers per website	873	88	961

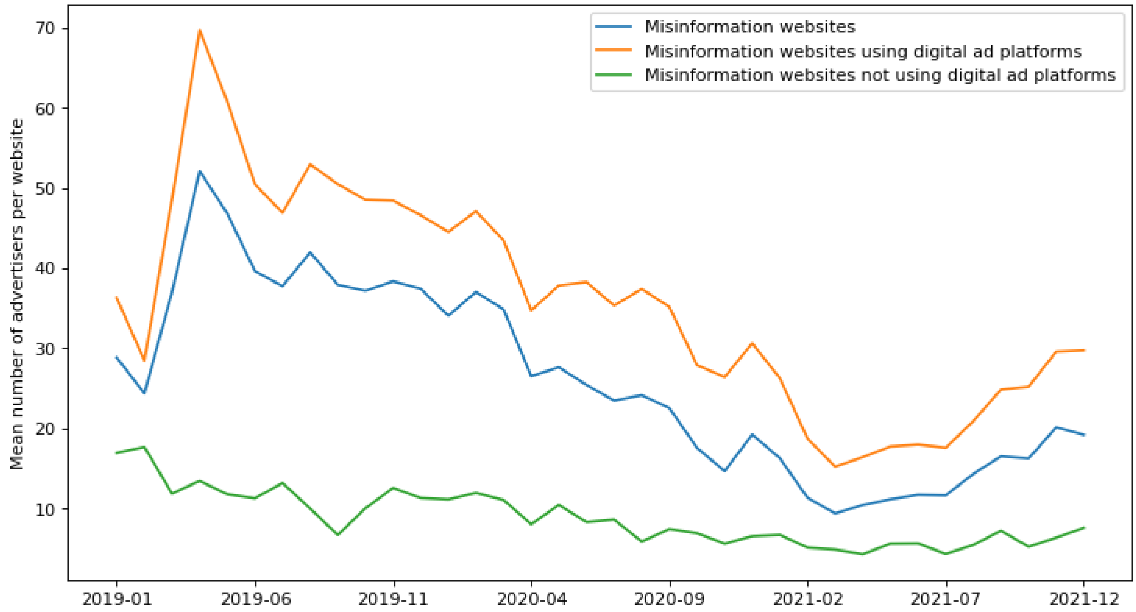
Notes: This table shows descriptive statistics for the sample of 3,441 websites that both use digital ad platforms in certain months and do not use digital ad platforms in other months during 2019-2021.

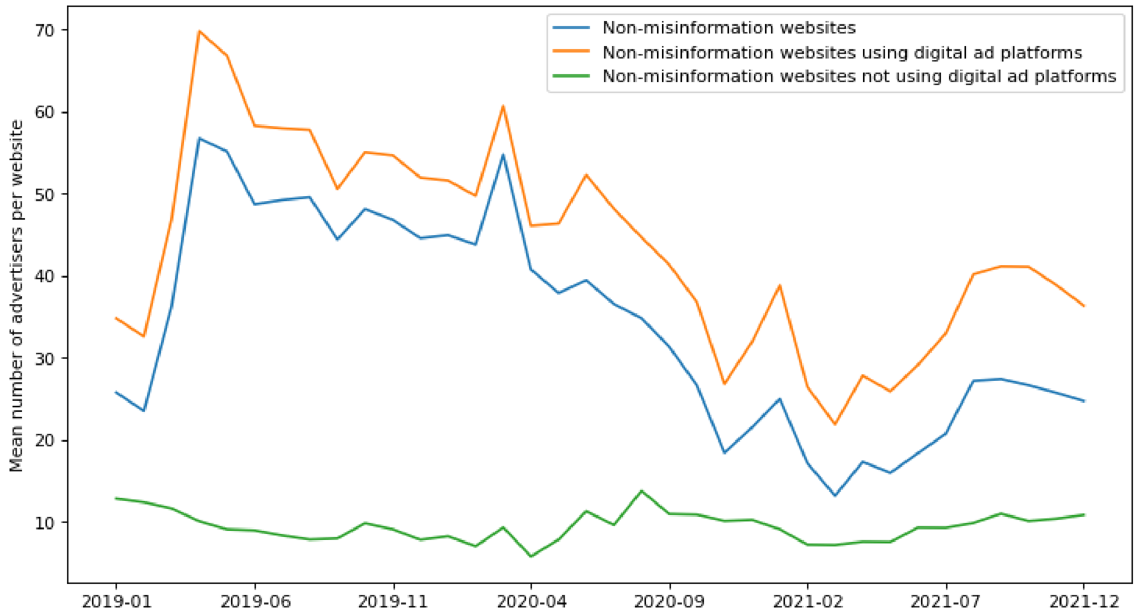
Table A5: Misinformation amplification ratios for digital ad platforms

Ad platform	Misinformation amplification ratio (1)	(2)
AppNexus	5.77	7.26
Google DoubleClick	5.11	6.11
OpenX	3.42	5.59
Any ad exchange	10.31	10.31

Notes: This table shows the ratio of the percentage of the top 100 most active advertisers that use the specified digital ad platform and appear on misinformation websites to the percentage of the same advertisers that do not use the specified digital ad platform and appear on misinformation websites for all weeks from 2019 to 2021. In column (1), the ratio is calculated in comparison with companies that do not use the given ad platform. In column (2), the ratio is calculated in comparison with companies that do not use any ad platform.

Figure A1: Mean number of advertisers per website based on monthly data from 2019 to 2021





Appendix C: Consumer study results

Table A6: Summary statistics and balance across treatment arms for the consumer survey.

	All	Information treatments					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Control	T1	T2	T3	T4	p-value
Duration (in seconds)	1185	1005	1095	1032	1669	1122	0.14
Gender (Female)	0.52	0.53	0.50	0.53	0.55	0.49	0.17
Gender (Male)	0.47	0.46	0.49	0.46	0.45	0.51	0.13
Race (White)	0.78	0.82	0.78	0.77	0.77	0.77	0.07
Age (Below 45)	0.45	0.44	0.46	0.44	0.46	0.45	0.90
Residence (North East)	0.18	0.18	0.19	0.20	0.18	0.17	0.52
Residence (Midwest)	0.21	0.20	0.21	0.20	0.21	0.22	0.85
Residence (South)	0.40	0.40	0.41	0.39	0.39	0.40	0.90
Residence (West)	0.21	0.22	0.19	0.20	0.22	0.21	0.58
Household income ($<$ 50K)	0.46	0.48	0.48	0.46	0.44	0.46	0.49
Education (No degree)	0.47	0.48	0.48	0.47	0.45	0.46	0.85
Education (At least college)	0.41	0.40	0.40	0.41	0.44	0.40	0.43
Employment (Working)	0.52	0.50	0.51	0.52	0.52	0.53	0.69
Employment (Not working)	0.47	0.49	0.48	0.46	0.47	0.46	0.76
Partisanship (Democrat)	0.44	0.42	0.43	0.47	0.47	0.42	0.12
Partisanship (Republican)	0.32	0.33	0.33	0.31	0.30	0.33	0.51
Vote (Trump)	0.32	0.33	0.33	0.31	0.30	0.35	0.14
Vote (Biden)	0.47	0.47	0.47	0.49	0.48	0.42	0.10
Vote (Other)	0.03	0.02	0.04	0.03	0.03	0.05	0.13
Vote (None)	0.18	0.17	0.17	0.17	0.19	0.18	0.75
Frequent user	0.57	0.53	0.57	0.58	0.56	0.61	0.03
Infrequent user	0.18	0.20	0.19	0.17	0.18	0.18	0.53
Prior petitions signed	0.35	0.35	0.33	0.37	0.35	0.36	0.64
Consumes misinformation	0.30	0.28	0.30	0.29	0.29	0.32	0.48
Media trust (Low)	0.34	0.36	0.33	0.33	0.33	0.34	0.78
Media trust (High)	0.25	0.25	0.27	0.25	0.24	0.24	0.50
First choice (Subway)	0.35	0.36	0.33	0.38	0.32	0.35	0.11
First choice (Burger King)	0.27	0.28	0.29	0.25	0.28	0.26	0.41
First choice (Uber)	0.10	0.08	0.09	0.11	0.09	0.11	0.14
First choice (Lyft)	0.04	0.03	0.05	0.04	0.05	0.03	0.04
First choice (DoorDash)	0.18	0.18	0.18	0.15	0.20	0.19	0.12
First choice (Grubhub)	0.06	0.07	0.06	0.07	0.06	0.06	0.57
Observations	4039	806	808	802	809	814	

Table A7: Comparison of responses across exit outcomes

	Switch in Preference (1)	Switch to Lower Preference (2)	Switch in Category (3)
Company (T1)	0.13^{***}	0.08^{***}	0.05^{***}
	(0.01)	(0.01)	(0.01)
Platform (T2)	0.03^{**}	0.01	0.01
	(0.01)	(0.01)	(0.01)
Company and Platform (T3)	0.10^{***}	0.06^{***}	0.04^{***}
	(0.01)	(0.01)	(0.01)
Company Ranking (T4)	0.08^{***}	0.06^{***}	0.02^{**}
	(0.01)	(0.01)	(0.01)
Control group mean	0.04	0.02	0.03
Baseline and behavioral controls	Yes	Yes	Yes
Observations	4039	4039	4039

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Notes: This table shows OLS regression results for each of the four treatment groups (T1, T2, T3 and T4). In column (1), the dependent variable is a binary variable that takes the value 1 when a participant switches their gift card choice from their top choice company after receiving the information treatment and is zero otherwise. In column (2), the dependent variable is a binary variable that takes the value 1 when a participant switches their gift card choice from their top choice company to a company they prefer less (as measured by how participants assign weights to each of the six gift card choices that must all sum up to 100) and is zero otherwise. In column (3), the dependent variable is a binary varaible that takes the value 1 when a participant switches their gift card choice across product categories (e.g. from ridesharing gift cards like Uber or Lyft to a fast food gift card like Subway or Burger King) and is zero otherwise. As detailed in Table 2, we include baseline demographic and behavioral controls in all specifications. Robust standard errors in parentheses.

Table A8: Comparison of responses across all petition outcomes.

	Company				Platform			
	Intention (1)	Clicks (2)	Reported (3)	Signed (4)	Intention (5)	Clicks (6)	Reported (7)	Signed (8)
T1	0.04^{*}	0.02	0.03	0.02	-0.02	-0.02	-0.02	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
T2	0.01	-0.01	0.01	-0.01	0.05^{**}	0.05^{***}	0.04^{**}	0.03^{**}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
T3	0.01	-0.00	0.01	-0.01	0.03	-0.01	0.03	0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
T4	0.05^{**}	0.04^{**}	0.04^{*}		-0.03	-0.03^{*}	-0.03	
	(0.02)	(0.02)	(0.02)		(0.02)	(0.02)	(0.02)	
Control mean	0.22	0.21	0.15	0.14	0.21	0.20	0.12	0.10
Controls	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Observations	4039	4039	4039	4039	4039	4039	3225	3225

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Notes: This table shows OLS regression results for each of the four treatment groups (T1, T2, T3 and T4) across all of our petition outcomes. Columns (1) to (4) refer to company-specific petitions suggesting that companies like the respondent's top choice gift card company need to block their ads from appearing on misinformation websites. Columns (5) to (8) refer to platform-specific petitions suggesting that digital ad platforms used by companies need to block ads from appearing on misinformation websites. In columns (1) and (5), the dependent variable is the intention to sign a petition, a binary variable that takes the value 1 when a participant indicates wanting to sign a given petition and zero otherwise. In columns (2) and (6), the dependent variable is a click on the petition link that takes the user to the Change.org platform to sign a petition, a binary variable that takes the value 1 when a participant clicks on the link and zero otherwise. In columns (3) and (7), the dependent variable is the self-reported petition signature, a binary variable that takes the value 1 when a participant reports having signed a given petition and zero otherwise. We record actual petition signatures in columns (4) and (8). We omit signatures for the T4 group since these petitions were accidentally deleted by Change.org. Since we only observe actual signatures on the treatment group level, we cannot include controls and run regressions for these outcomes. To do testing, we calculate standard errors using the standard formula for proportion tests. For the remaining columns, we apply robust standard errors in parentheses and use the same baseline and behavioral controls as in Table 2.

Analysis of text responses

In our consumer survey, we ask our survey participants to briefly state the reason behind their choice of gift card and choice petition using an open-ended text field. we analyzed participants' text responses in order to understand their responses to each of these two behavioral outcomes. To do so, we first removed the names of companies from the text responses and then used the top2vec algorithm (Angelov, 2020), which automatically outputs the number of clusters and assigns. Top2vec uses word embeddings that account for the context of a word in a document, which is an advantage this method has over bag-of-word approaches like Latent Dirichlet Allocation (Blei, Ng and Edu, 2003).

For our exit outcome, we observe six topics emerge from the algorithm. We manually inspect the responses and find responses in these clusters correspond to responses that mainly mention misinformation-related concerns, how much they like a given company's products, how much they love products from a given company, how much they use a given company, how frequently they use a given company and specific features of a company's products. We further cluster together responses that mention how much they like a company and how much they love a given company's products together into a single "product preference" cluster. Similarly, we merge together responses in the use and frequency of use clusters into a single "product usage" cluster. We end up with four main clusters as shown in Figure 2. Table A9 shows sample text responses belonging to each cluster. These clusters are as follows:

1. Misinformation: a binary variable that takes a value of 1 if a participant indicated companies ads appearing on misinformation websites as being a factor contributing to their final gift card choice and zero otherwise.
2. Product usage: a binary variable that takes value 1 when a participant mentions their use or frequency of use of the product and zero otherwise.
3. Product preference: a binary variable that takes value 1 if a respondent mentions how they or their family like, enjoy or love the product they chose and zero otherwise.
4. Product features: a binary variable that takes a value of 1 if a participants refers to specific features such as how convenient, healthy or close to home the product they chose is and zero otherwise.

For our voice outcome, we take the same approach as above. This process results in five key clusters, which are shown in Figure 2 with select sample text responses in Table A10. These clusters are as follows:

1. Company responsibility: a binary variable that takes a value of 1 if a participant's response indicated that companies are responsible for their ads appearing on misinformation websites and zero otherwise.
2. Platform responsibility: a binary variable that takes value of 1 if a participant's response indicated that digital ad platforms are responsible for companies' ads appearing on misinformation websites and zero otherwise.
3. Misinformation concerns: a binary variable that takes value 1 if a participant's response mentions being concerned about misinformation and zero otherwise.
4. Best option: a binary variable that takes a value of 1 if a participant's explanation for their choice mentions the option they chose as being the best available option in their opinion and zero otherwise.
5. No interest: a binary variable that takes a value of 1 if a participant's response indicates that they would not like to sign an online petition and zero otherwise.

Table A9: Sample text responses from participants explaining their choice of gift card.

Sample	Text classification	Text response
1.	Misinformation	I will use a food delivery service more than using a driver service. I changed to grub hub because door dash allows their ads on websites with incorrect information.
2.	Misinformation	I first chose Uber as my choice because it is the only one that I use from the choices. However, I would happily switch to Lyft if their practices are more ethical.
3.	Misinformation	Subway was not a company that advertised on misinformation websites.
4.	Misinformation	I feel guilty about taking the burger king card if it is being used to further false information.
5.	Misinformation	I don't want to support the spread of misinformation.
6.	Misinformation	It was not listed among the sites that were linked to a misinformation site.
7.	Misinformation	I equally like door dash and grub hub but don't want to support a business business associated with misinformation.
8.	Product usage	I can use this to go to work.
9.	Product usage	Doordash is the only company out of these choices that I use on a regular basis.
10.	Product usage	I chose this card because over the past two years I have bought more subs then other food places.
11.	Product usage	Because i would most likely use this gift card on my next visit to Burger King and it is less likely that i would use the others.
12.	Product usage	I chose Burger King because it's the only restaurant and service I actually use from the above list.
13.	Product usage	I frequent this restaurant quite a bit, so it would be a good fit for me.
14.	Product usage	I chose the above gift card because it's the one that I'd get the most utility from.
15.	Product preference	This is one of my favorite fast food restaurants.
16.	Product preference	I love Burger King. There plenty of items on menu that are worth getting excited about. Yummy food.
17.	Product preference	I eat at Subway and I like the food.
18.	Product preference	The have a selection that I like with fast delivery.
19.	Product preference	I would like Doordash because it is my go to food app. I love that I get to choose from a variety of food restaurants and even for beverages. My children love it as well and that gift card is going to go to them.
20.	Product preference	This gift card is the one that will be most beneficial for my family.
21.	Product preference	Subway is mine and my children's favorite local restaurant. We love to "eat fresh" and at subway everything is always fresh and delicious!
22.	Product features	subway is good to eat because of the calories that are in the food.
23.	Product features	I personally use door dash quite a bit and it fits into the convenience of my life.
24.	Product features	Health choice and trying to be healthy.
25.	Product features	Subway has convinient locations and great food at good prices.
26.	Product features	I chose this one because it is a lot closer and there is a person at burger king i am trying to become friends with.
27.	Product features	I am in a rural area now where food delivery is non exsistent so I would like it only to take my family out.
28.	Product features	I chose this gift card because there is a Subway close enough that i can walk to. I dont have a vehicle to drive to burger king and I dont believe lyft and uber are offered here.

Table A10: Sample text responses from participants explaining their choice to sign an online petition.

Sample	Text classification	Text response
1.	Company responsibility	Companies like Subway absolutely should do this. The war on disinformation requires private and government action.
2.	Company responsibility	I think they should block their ads because of these misinformation sites causing their reputation harm.
3.	Company responsibility	Because it gives a bad reflection on the company and their brand if their ads are on websites that share misinformation.
4.	Company responsibility	All companies should be mindful of how they gain revenue and operate in society. Being ethical should always be at the forefront of their mission.
5.	Company responsibility	It can taint a company's image to be seen on misinformation websites.
6.	Platform responsibility	Because companies like subway depend on digital ad platforms to place their ads the responsibility lies with the ad platforms.
7.	Platform responsibility	Digital ad platforms should accept responsibility for placing ads on inappropriate and misleading sites.
8.	Platform responsibility	I feel like if we stop the use of ad platforms on misinformation sites in the first place then it would help out more in the long run.
9.	Platform responsibility	Digital ad platforms seem to make it easier to allow ads on misinformation websites.
10.	Platform responsibility	I feel that the onus is on digital ad platforms.
11.	Misinformation concerns	Supporting misinformation websites is horrible.
12.	Misinformation concerns	I do not want any misinformation sites to show ads.
13.	Misinformation concerns	Ads shouldn't help pay for misinformation.
14.	Misinformation concerns	I've always gotten misleading infotmation on multipule occasions and needs to stop.
15.	Misinformation concerns	No one should be supporting misinformation.
16.	Best option	It eliminates more of the problem than the others.
17.	Best option	sounded like the most plausible choice.
18.	Best option	It is the best way to cancel out their problem
19.	Best option	It is the right thing to do.
20.	Best option	This statement seems to address the problem on a more widespread basis.
21.	No interest	I have not seen any of these ads we are taking the survey about.
22.	No interest	Freedom of speech. Up to consumers to educate themselves via various platforms.
23.	No interest	Who decides what is misinformation. Today these claims may be true, but if legistaltion is enacted and it becomes what corporations or government disagree with, this subverts the first amendment.
24.	No interest	I am not interested in governing what people or companies advertise or report as news. They are within their right to do so. This is America and in America people have the right to be wrong. If they don't want to do the research to find if the information they are getting is false than that's also people's right to be lazy. It's unfortunate but true.
25.	No interest	I don't want to sigh the petition because its not for me to tell a company how or who to run their company ads whether i agree with it or not.

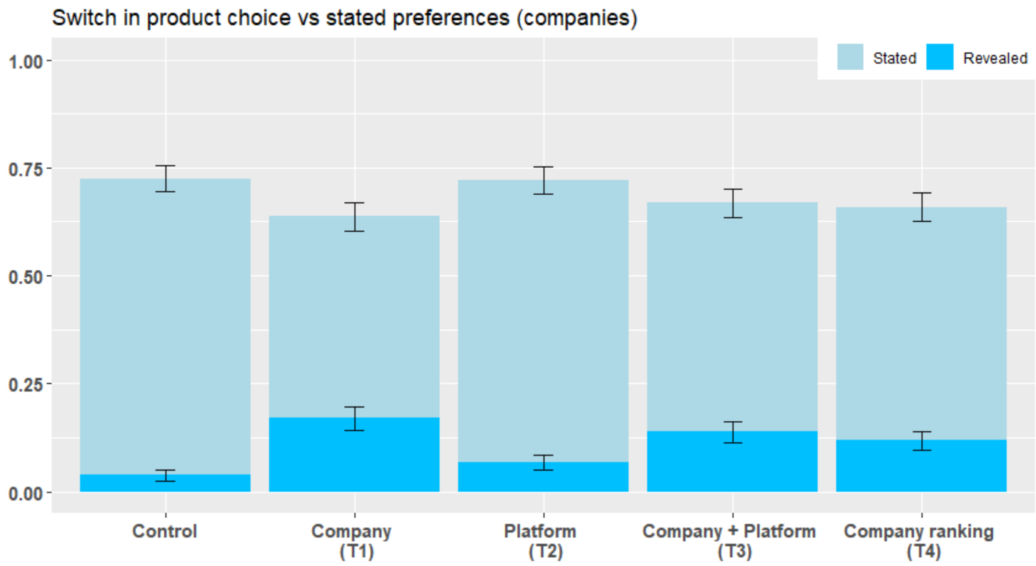
Table A11: Attitudes of Participants Engaging in Exit and Voice

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Exit						
Treatment	0.03	0.04^{***}	0.01	0.15^{***}	0.17^{***}	0.13^{***}
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Treatment × Misinformation (General)	0.08^{***}					
	(0.02)					
Treatment × Misinformation (Company)		0.08^{***}				
		(0.02)				
Treatment × Misinformation (Platform)			0.11^{***}			
			(0.02)			
Treatment × Company (Trust)				-0.12^{***}		
				(0.02)		
Treatment × Company (Recommend)					-0.13^{***}	
					(0.02)	
Treatment × Company (Responsible)						-0.10^{***}
						(0.02)
Panel B: Voice						
Treatment	-0.01	-0.00	0.00	0.04^{***}	0.05^{***}	0.04^{***}
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Treatment × Misinformation (General)	0.05^{**}					
	(0.02)					
Treatment × Misinformation (Company)		0.05^{**}				
		(0.02)				
Treatment × Misinformation (Platform)			0.03			
			(0.02)			
Treatment × Company (Trust)				-0.03		
				(0.02)		
Treatment × Company (Recommend)					-0.04^{*}	
					(0.02)	
Treatment × Company (Responsible)						-0.02
						(0.02)
Observations	4039	4039	4039	4039	4039	4039
Baseline and behavioral controls	Yes	Yes	Yes	Yes	Yes	Yes

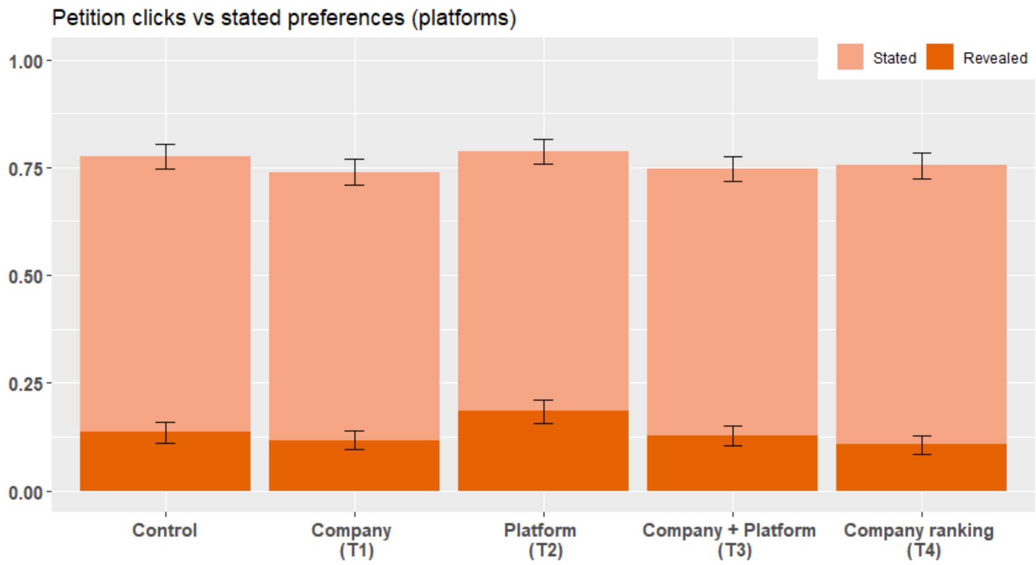
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Notes: This table shows OLS regression results where *Treatment* is a binary variable that takes a value of 1 if a respondent is randomized into any of the company-specific treatment groups (T1, T3 or T4). In Panel A, the dependent variable is switch in gift card choice from the respondent's top choice company (i.e. "exit"). In Panel B, the dependent variable is clicking on a link to sign a petition that suggests that companies like the respondent's top choice gift card company need to block their ads from appearing on misinformation websites. *Misinformation (General)* is a binary variable that takes a value of 1 if a respondent agrees or strongly agrees that *"It is important to control the spread of misinformation in society"* and zero otherwise. *Misinformation (Company)* is a binary variable that takes a value of 1 if a respondent agrees or strongly agrees that *"Companies have an important role to play in reducing the spread of misinformation through their advertising practices"* and zero otherwise. *Misinformation (Platform)* is a binary variable that takes a value of 1 if a respondent agrees or strongly agrees that *"Digital platforms should give companies the option to avoid advertising on misinformation websites"* and zero otherwise. *Company (Trust)* is a binary variable that takes a value of 1 if a respondent agrees or strongly agrees that *"I believe X is trustworthy company"*, where X is the respondent's top choice gift card company, and zero otherwise. *Company (Recommend)* is a binary variable that takes a value of 1 if a respondent agrees or strongly agrees that *"I would recommend X to someone else"*, where X is the respondent's top choice gift card company, and zero otherwise. *Company (Responsible)* is a binary variable that takes a value of 1 if a respondent agrees or strongly agrees that *"I believe X is a socially responsible company"*, where X is the respondent's top choice gift card company, and zero otherwise.

Figure A2: Participants' stated and revealed responses in terms of (a) exit and (b) voice.



(a) This figure shows participants' revealed preferences against their stated preferences regarding the role of advertising companies in financing misinformation. Revealed preferences are measured by the proportion of participants in each group who switch their gift card choice (i.e. "exit") after receiving the information treatment. Stated responses show the proportion of participants' who agree or strongly agree with the statement "Companies have an important role to play in reducing the spread of misinformation through their advertising practices". The vertical bars represent 95% confidence intervals.

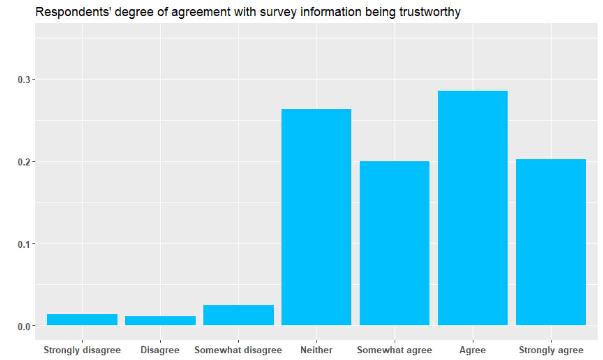


(b) This figure shows participants' revealed preferences against their stated preferences regarding the role of digital ad platforms in financing misinformation. Revealed preferences are measured by the proportion of participants in each group who click on a link to sign a petition suggesting that digital ad platforms should block ads on misinformation websites. Stated responses show the proportion of participants' who agree or strongly agree with the statement "Digital platforms should give companies the option to avoid advertising on misinformation websites." The vertical bars represent 95% confidence intervals.

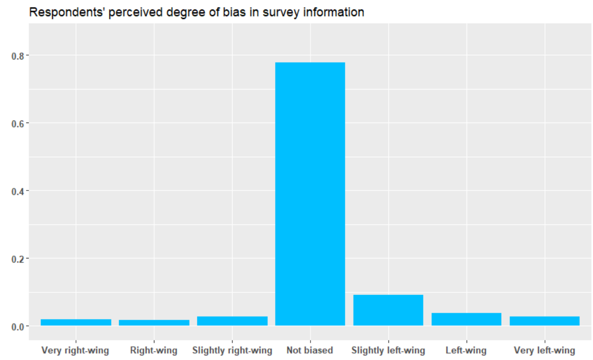
Table A12: Treatment prediction confusion matrices for the consumer experiment

	Predicted Control	Predicted Treated
Panel A: Control vs. T1		
True Control	99	97
True Treated	98	110
		Overall accuracy: 51.7%
Panel B: Control vs. T2		
True Control	110	100
True Treated	93	99
		Overall accuracy: 52.0%
Panel A: Control vs. T3		
True Control	125	81
True Treated	96	102
		Overall accuracy: 56.2%
Panel A: Control vs. T4		
True Control	94	99
True Treated	99	113
		Overall accuracy: 51.1%

Notes: This table presents the confusion matrices for the study purpose responses by participants in our consumer experiment. Each cell counts the number of participants assigned to the randomized group in the row and classified by the Support Vector Machine to be in the randomized group in the column.

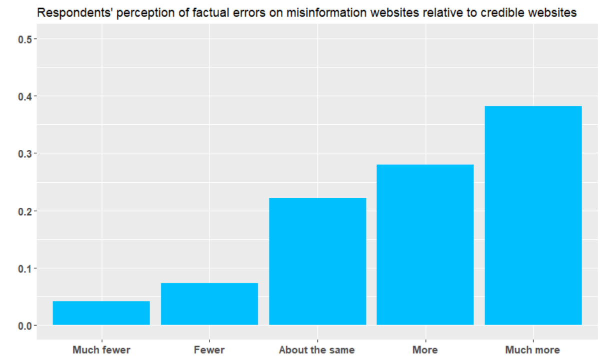


(a) Distribution of participants' responses to the question "The information provided in this survey is trustworthy."

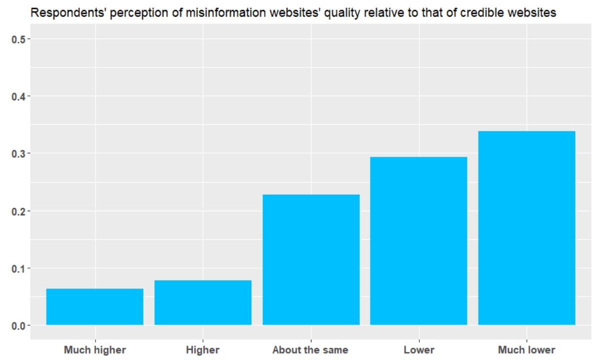


(b) Distribution of participants' responses to the question "Do you think that this survey was biased?"

Figure A3: Participants' perception of survey information.

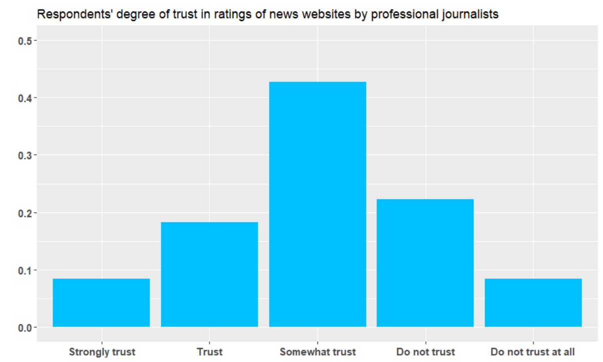


(a) Distribution of participants' responses to the question "Relative to credible websites, how many factual errors do you expect misinformation websites to have?"

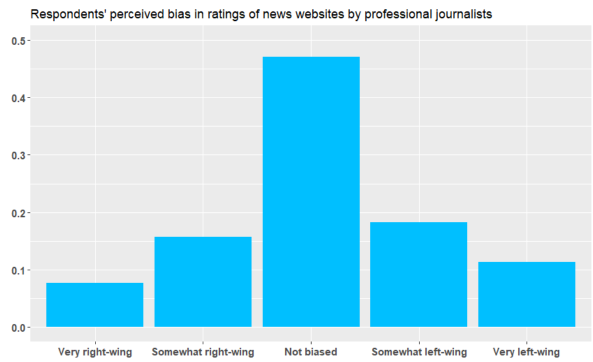


(b) Distribution of participants' responses to the question "Relative to credible websites, what quality do you expect misinformation websites to have?"

Figure A4: Participants' perception of misinformation websites.



(a) Distribution of participants' responses to the question "How much do you trust the ability of independent third party professional journalists to rate news websites?"



(b) Distribution of participants' responses to the question "What kind of political bias do you expect third party ratings of news websites by professional journalists to have?"

Figure A5: Participants' perception of website ratings by journalists.

Appendix D: Decision-maker study results

Table A13: Characteristics and Preferences of Decision-makers in Our Sample

		Full sample	Certain		Uncertain	
			Yes	No	Yes	No
Characteristics	Top executive role	0.49	0.45	0.52	0.39	0.43
	Duration in role (> 5 years)	0.58	0.63	0.59	0.48	0.54
	Number of employees (> 100)	0.59	0.75	0.50	0.83	0.71
	Headquartered in the U.S.	0.43	0.41	0.40	0.57	0.56
Stated preferences	Misinformation control	0.88	0.88	0.90	0.78	0.84
	Company responsibility	0.76	0.68	0.80	0.61	0.75
	Platform responsibility	0.86	0.88	0.87	0.70	0.84
	Consumer backlash	0.41	0.52	0.39	0.30	0.43
Revealed preferences	Consumer information demand	0.73	0.74	0.70	0.70	0.87
	Requested ad check	0.74	0.72	0.72	0.70	0.84
	Solution demand*	0.18	0.15	0.18	0.17	0.21
Survey feedback	Unbiased survey information	0.65	0.77	0.65	0.48	0.57
	Trustworthy survey information	0.65	0.71	0.68	0.48	0.54
Observations		442	65	286	23	68

Notes: Misinformation control is a binary variable that takes the value 1 if a participant agrees or strongly agrees that "It is important to control the spread of misinformation in society" and zero otherwise. *Company responsibility* is a binary variable that takes the value 1 if a participant agrees or strongly agrees that "Companies have an important role to play in reducing the spread of misinformation through their advertising practices" and zero otherwise. *Platform responsibility* is a binary variable that takes the value 1 if a participant agrees or strongly agrees that "Digital platforms should give companies the option to avoid advertising on misinformation websites" and zero otherwise. *Consumer backlash* is a binary variable that takes the value 1 if a participant agrees or strongly agrees that "Consumers react against companies whose ads appear on misinformation websites" and zero otherwise. The revealed preference variables are those described in Section 5.1.3. The proportions for "solution demand" are calculated based on the subsample of participants whose click data was recorded (N = 363). *Unbiased survey information* is a binary variable that takes value 1 if a participant chooses "unbiased" when asked to rate the political bias of the survey information provided from a seven-point scale ranging from "very right-wing biased" to "very left-wing biased" and zero otherwise. *Trustworthy survey information* is a binary variable that takes the value 1 when a participant agrees or strongly agrees that he survey information provided was trustworthy and zero otherwise.

Figure A6: Distribution of Beliefs About Advertising Companies

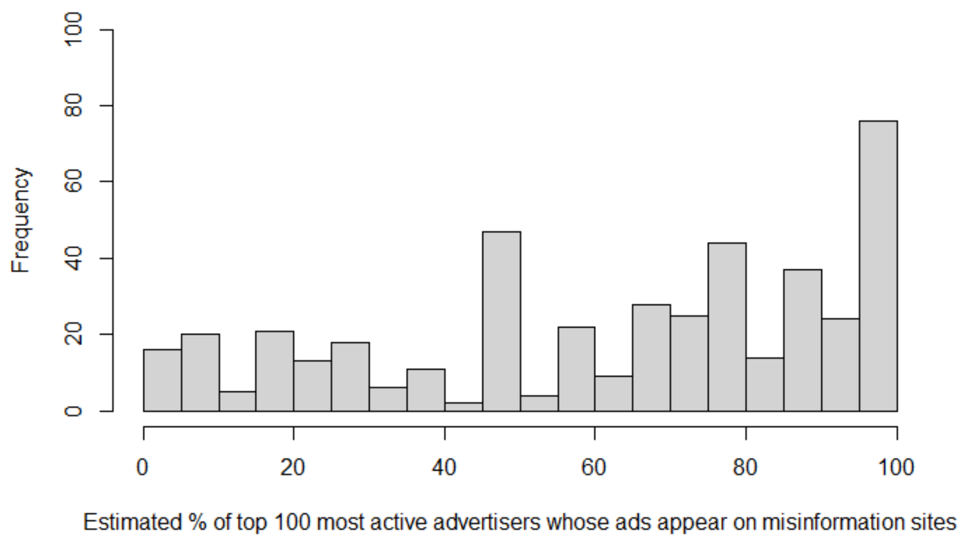


Figure A7: Distribution of Beliefs About Digital Ad Platforms

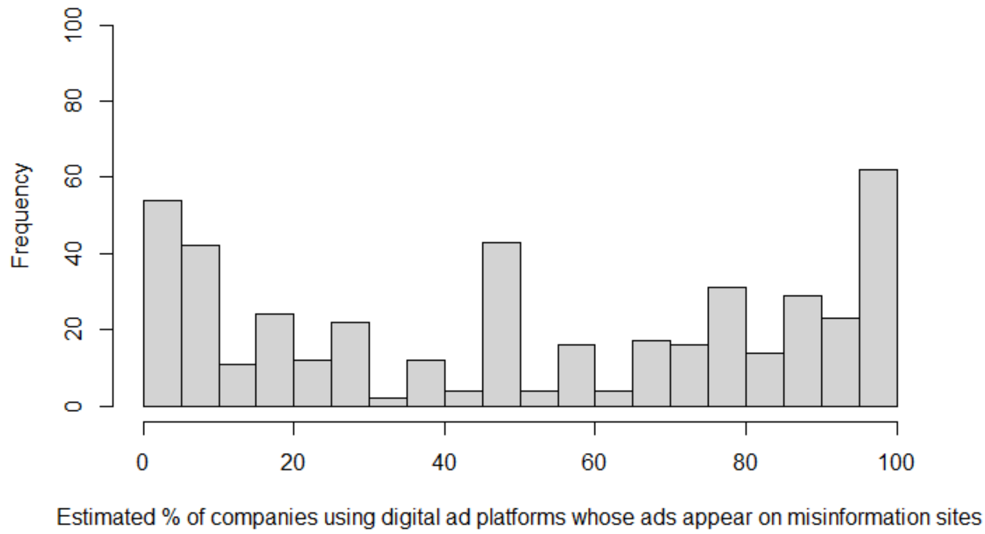


Table A14: Treatments Effects on Donation to GDI Based On Prior Beliefs

	All (1)	Yes (2)	No (3)
Panel A: Full sample			
Treatment	−0.01	−0.06	−0.00
	(0.05)	(0.12)	(0.05)
Observations	442	88	354
Panel B: Uncertain			
Treatment	−0.04	−0.14	0.07
	(0.13)	(0.25)	(0.17)
Observations	91	23	68
Panel C: Certain			
Treatment	−0.04	−0.09	−0.02
	(0.06)	(0.20)	(0.06)
Observations	351	65	286
Controls	Yes	Yes	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Notes: This table shows OLS regression results where the dependent variable is donation to the Global Disinformation Index or GDI, a binary variable that takes a value of one when a participant chooses to donate to GDI and zero when a participant chooses to donate to DataKind, the alternative charity option provided. Column (1) shows results for the full sample of participants, column (2) shows results for the subsample of participants who reported "yes" to the question "Do you think your company or organization had its ads appear on misinformation websites during the past three years (2019-2021)?", and column (3) show results for the subsample who reported "No" to the same question. Panel A shows results for the full sample of participants. Panel B shows results for participants who report being uncertain about their response to the aforementioned question (choosing "Unsure" or "Very unsure") and Panel C shows results for participants who report being certain about their response to the aforementioned question (choosing "Somewhat sure", "Sure" or "Very sure"). We control for baseline characteristics, beliefs and behavioral characteristics in all specifications except column (2), where the number of employees and industry dummies were not used as controls. Robust standard errors in parentheses.

Table A15: Treatment prediction confusion matrices for the consumer experiment

	Predicted Control	Predicted Treated
Panel A: Control vs. T1		
True Control	22	23
True Treated	23	21
		Overall accuracy: 48.3%

Notes: This table presents the confusion matrix for the study purpose responses by participants in our decision-maker experiment. Each cell counts the number of participants assigned to the randomized group in the row and classified by the Support Vector Machine to be in the randomized group in the column.

Appendix D: Design of survey experiments

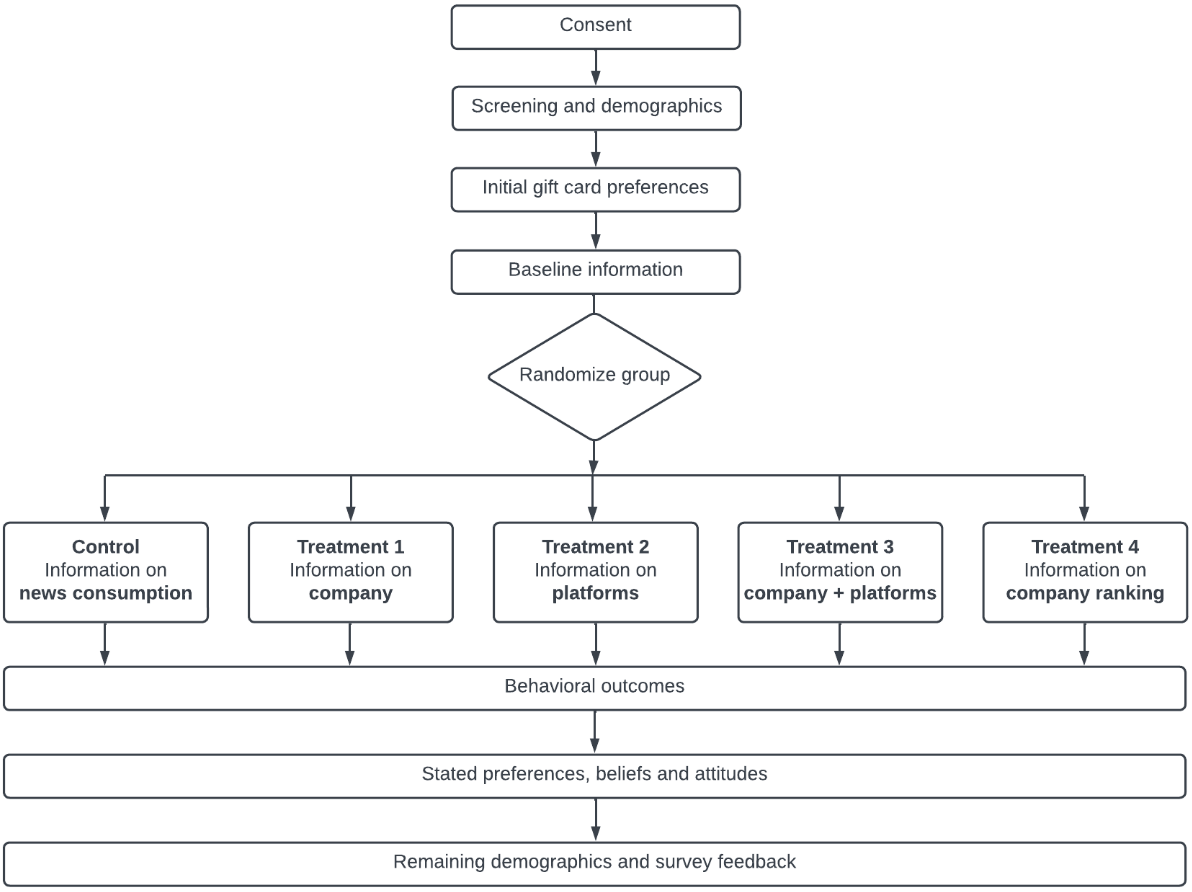


Figure A8: Design of the consumer survey experiment.

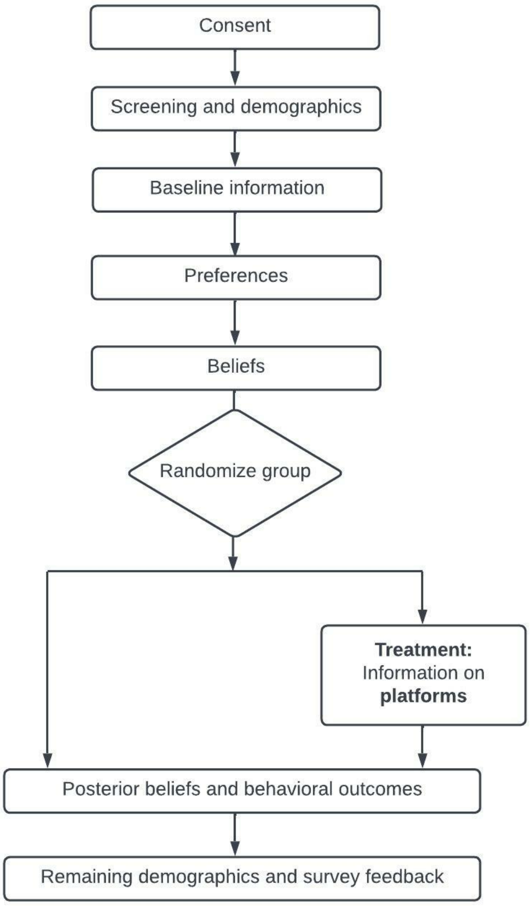


Figure A9: Design of the decision-maker survey experiment.

6.1 Baseline information

Misinformation websites repeatedly present incorrect or misleading information as fact. Examples of misinformation websites identified in this way include: thegatwaypundit.com, infowars.com, rt.com, sputniknews.com, palmerreport.com, etc. These misinformation websites are identified by trained non-partisan professionals at independent organizations.

Ads from companies appear on various websites, some of which are misinformation websites. These ads are how news websites make money.

In the below example, ads from athletics company Puma appear on zerohedge.com, a website that frequently spreads misinformation (e.g. misinformation about the Russia-Ukraine war) according to trained journalists. Thus, ads such as the one shown below by Puma contribute towards financially sustaining this misinformation website.

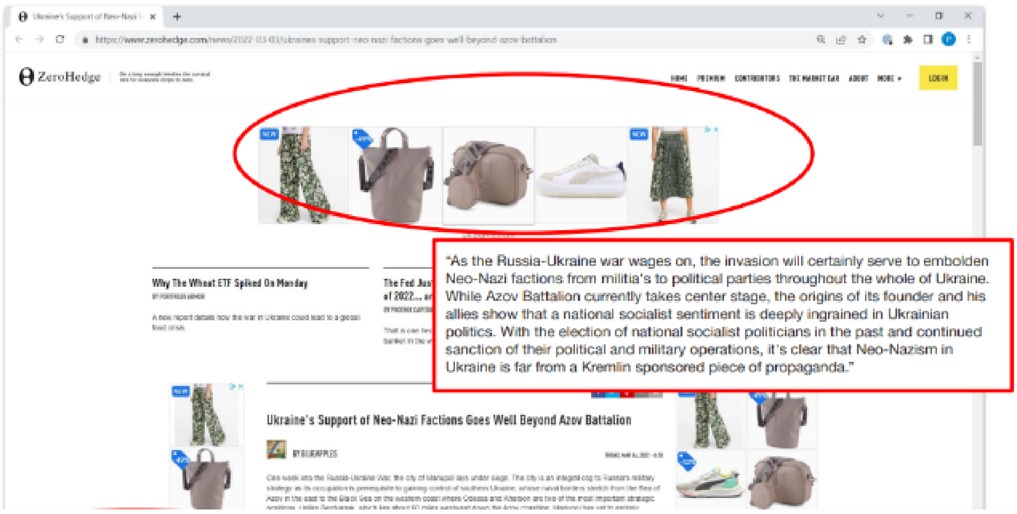


Figure A10: Participants in both experiments are given the above baseline information on misinformation and advertising prior to receiving randomized information treatments.

6.2 Randomized information treatments

A recent study found that Americans consume about five times more news from television than from online sources. Some of these news sources may include misinformation whereas others are trustworthy sources.

Figure A11: Information provided to the control group in the consumer experiment.

In the recent past, ads from X repeatedly appeared on misinformation websites. To provide more context, companies can adopt tools to control which websites their ads appear on.

Figure A12: Information provided to the "Company" treatment group (T1) in the consumer experiment. "X" is the top choice company chosen by the respondent prior to the information treatment.

Digital platforms (e.g., Google's DoubleClick platform, Microsoft's AppNexus platform, etc.) can be used to automatically place ads on different websites. In the recent past, companies that used digital ad platforms were about 10 times more likely to appear on misinformation websites than companies that did not use digital ad platforms as shown below:

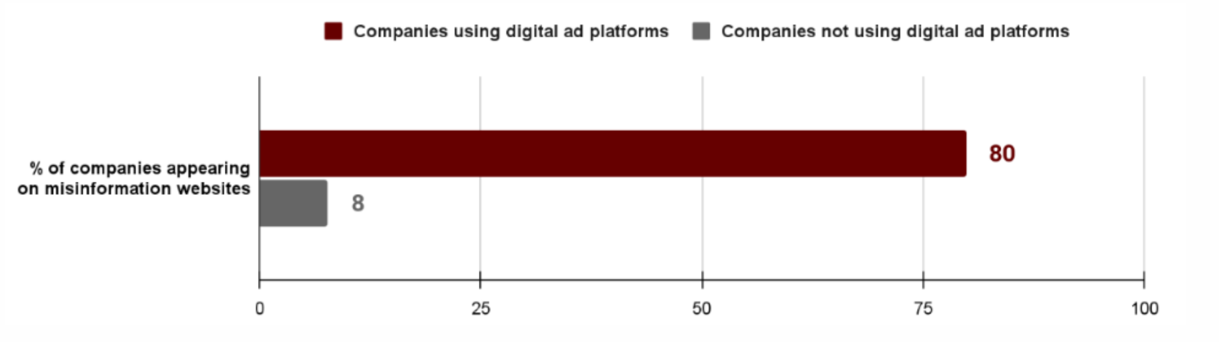


Figure A13: Information provided to the "Platform" treatment group (T2) in the consumer experiment. This information is also provided to treated participants in the decision-maker experiment.

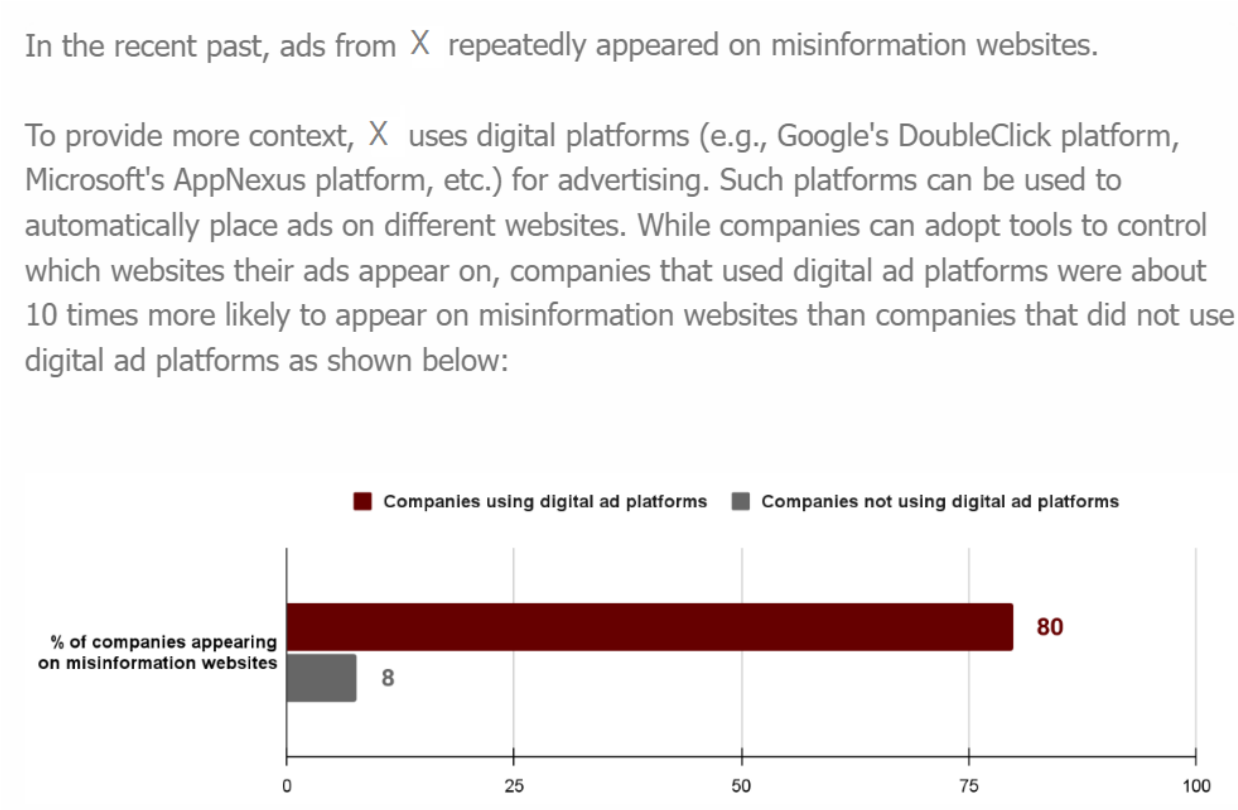


Figure A14: Information provided to the "Company and Platform" treatment group (T3) in the consumer experiment. "X" is the top choice company chosen by the respondent prior to the information treatment.

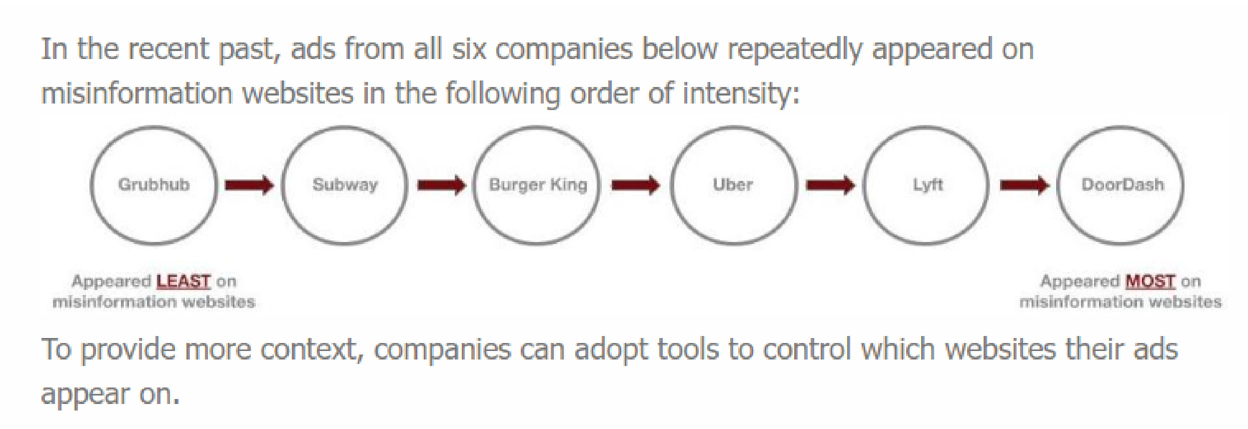


Figure A15: Information provided to the "Company ranking" treatment group (T4) in the consumer experiment.