
Is the Facebook Ad Algorithm a Climate Discourse Influencer?

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Abstract

1 Sponsored climate discourse, driven by both climate contrarians and advocates,
2 influences public attitudes towards climate change. We present an experimental
3 study suggesting that the Facebook advertisement algorithm also influences climate
4 discourse. The algorithm preferentially delivers ads to Facebook audiences in
5 certain locations and demographics, at least partially based upon the ad image.
6 Further, the algorithm is biased in terms of how it delivers ads featuring images of
7 non-renewable sources of energy, and does not always fulfill targeting intentions
8 as requested. This may result in inadvertent manipulation of ad delivery with
9 consequences for climate discourse and algorithmic fairness.

10 In 2022, the Intergovernmental Panel on Climate Change (IPCC) identified “rhetoric, misinformation,
11 and politicization of science” as key barriers to climate action, further stating that “vested economic
12 and political interests have organized and financed misinformation and contrarian climate change
13 communications”. Scholars across disciplines have documented the deceptive nature of contrarian
14 climate communications [41, 42, 43, 15, 17, 28, 29, 2, 19, 20, 22, 24, 31, 1, 4, 41, 42, 43], but the
15 roles of intermediary algorithms in delivering this content has been overlooked. These algorithms
16 comprise deep image networks and automated recommendation systems, and their implicit bias has
17 only recently begun to be studied by computer science researchers [8, 9, 7].

18 In 2022, Rolnick et al [36] presented a set of climate change issues that could be tackled by the
19 machine learning community. A missing item in their list is climate change disinformation and the
20 role of algorithmic bias in perpetuating it. To date, disinformation activities have been studied in
21 print and broadcast media, rather than social media platforms [11, 49, 32, 33, 12, 10, 25, 13]. This
22 blind spot is glaring given the volume of climate discourse on social media platforms. Analyzing this
23 data and reducing bias in these systems, could improve the effectiveness of online climate action
24 campaigns, support litigation[48] efforts, and advance inoculation and communication strategies
25 against climate disinformation [14, 44, 48, 35, 21], [47, 5, 40].

26 Current studies have restricted the notion of climate discourse influencers to commercial enterprises
27 (eg. fossil fuel companies), financial institutions (eg. banks), and lobby organizations (eg. think
28 tanks). However, the algorithmic systems on social media, such as Facebook’s ad algorithm, may
29 also deserve recognition. Among strong reasons for this are that it is possible that in the course of
30 providing maximum engagement for the cheapest cost, some inadvertent biases in other dimensions
31 have crept into these very large, highly complex, data driven and continuously updating ad delivery
32 systems [8, 9, 46, 39, 7].

33 In this study, we conduct an ad campaign, under controlled and ethical conditions, where we assume
34 the role of a Facebook advertiser. We design simple and informative experiments to uncover the
35 foundations of bias in the ad algorithm, based on ads that are primarily an image. Our experiment
36 supports the existence of algorithmic bias though more extensive studies are needed to gauge the
37 exact extent of such bias. We also discuss the implications of such algorithmic decision making on
38 the climate discourse.

39

1 Experiment

To isolate the algorithm’s influence, we do not use the targeting features provided to advertisers. Instead, we request the algorithm to impartially deliver ads to audiences in all U.S. states, and of all genders and ages. We launch the ads for a period of 24 hours, and further request Facebook to optimize delivery to reach audiences likely to click on them. This design is similar to the experiments found in prior research [8]. When a Facebook user clicks on an ad, they are taken to a website. At the end of the 24h experiment, ad delivery data is collected from Facebook and comparisons are made between the delivery information of contrarian and advocacy ads.

Ad delivery data Given that we cede full control over the ad targeting to Facebook, we use the Delivery Ratio (D) of advocacy and contrarian ads for each ad destination category c (U.S. state, gender category, age group category). D is a measure of delivery observed during the experiment and delivery expected, given Facebook’s ad audience estimates. The expected estimates are provided by Facebook at ad creation time (and only change minimally over several weeks or months). To calculate D , first the ‘Reach’ information is collected for each launched ad. This is a total count of unique Facebook accounts that were shown an ad, broken up by U.S. state, gender, and age group. Second, Facebook’s self-reported audience estimates are collected for each U.S. state, and age group. These provide a measure of the expected delivery count that is proportional to the audience size matching an ad destination. Facebook also advertises these population estimates as being the population sizes from which an ad audience sample will be drawn. The ‘Delivery Ratio’ (D) for an ad destination category c and an ad i is given by $D_i^c = \frac{O_i^c}{E_i^c}$. Here, $D \in \mathbb{R}^+$, and $O_i^c, E_i^c \in \mathbb{N}$. O_i^c is the unique number of times an ad i was shown in an ad destination (U.S. state, gender, or age) c , and E_i^c is Facebook’s estimated reach of the ad for the same category.

1.1 Experimental Groups



(a) Oil rigs (b) Solar cells (c) Controls (d) Oil rig + ExxonMobil logo (e) Solar cell + ExxonMobil logo (f) Oil rig + Greenpeace logo (g) Solar cell + Greenpeace logo

Figure 1: Examples of images without logo, and images with logos of ExxonMobil and Greenpeace representing contrarian and advocacy actors. Ads containing images without logos are launched twice to check whether Facebook delivery is consistent.

We create 650 ads containing images of solar cells and oil rigs, and the same neutral text. This sample size is chosen based on an *a priori* power analysis, indicating 65 images per group to uncover a small to moderate effect size of 0.25, with power=0.8. We design 3 experimental groups to investigate delivery dependence on ad images relevant to climate change.

1. **Images** - Solar cells (65 images) and oil rigs (65 images) unmodified. We add
 - (a) **Controls** - Control images (65 images)
 - (b) **Duplicates** - Duplicate ads using images from the *Images* and *Controls* group to check that delivery is consistent with ad content (65 images x 3).
2. **Images + Contrarian Logo** - Solar cells and oil rigs with the logo of ExxonMobil, an established contrarian organization [41, 42] on the top left (65 images x 2).
3. **Images + Advocacy Logo** - Solar cells and oil rigs with the logo of Greenpeace, an established advocacy organization [45, 16, 6] on the top left (65 images x 2).

We select images of oil rigs and solar cells in the experimental ads because these objects are found across the U.S., and featured in both contrarian and advocacy ads. While contrarians advertise oil rigs to highlight engineering capabilities and economic advantages, advocates use them to campaign

78 against drilling. Similarly, contrarian ads use solar cells to highlight their contributions to climate
79 action, and advocates use them to promote the use of renewable energy. 65 images featuring each
80 of these objects are selected. We launch ads with and without logos to investigate if the algorithm
81 decision making identifies and uses the advertiser information for delivery. A state-of-the-art image
82 classifier[34] is able to distinguish our probes with high accuracy. We also sample 65 controls from
83 the ImageNet-21K dataset, using a sampling process that excludes overlapping categories in the
84 dataset. This ensures that controls are also able to be distinguished by a machine classifier. The
85 algorithm to sample controls is provided in Appendix 6.3.

86 2 Research Questions

87 We pose the following research questions:

- 88 1. Can observed ad delivery be consistently attributed to the image?
- 89 2. Does ad delivery ratio, D , differ when logos are present on an ad image? Is the effect similar
90 for ads containing images of solar cells and oil rigs with logos?
- 91 3. Does ad delivery ratio, D , differ based on the ad image?
- 92 4. Is observed ad delivery proportional to Facebook’s population estimates across ad destina-
93 tions?

94 3 Results

95 3.1 Main takeaways

- 96 1. **Consistency** Ad delivery is consistent with ad image: The audience sizes of 90% of the
97 ads featuring the same image is consistent across U.S. states. The audience sizes of 100%
98 and 99% of the ads are consistent across audiences of the same gender and age group
99 respectively. See 6.4.1 for more details.
- 100 2. **Logo effects** The ad delivery ratio, D , is not significantly different for images featuring
101 ExxonMobil or Greenpeace logos. D is also not influenced by the presence or absence of a
102 logo in most ad destinations. We therefore combine images with and without logos when
103 studying image effects for additional statistical power. See 6.8.4 for more details.
- 104 3. **Image effects** The ad delivery ratio, D , is significantly different based on whether the ad
105 image features solar cells, oil rigs, or controls, in 46% of U.S. states, and in all gender and
106 age destinations. In states where See 6.8.5 for more details.
- 107 4. **Promised vs Fulfilled Delivery:** Observed audience sizes are not always proportional to
108 Facebook’s audience estimates. Across U.S. states, audience sizes for *Controls* are more
109 likely (64%) to be proportional to Facebook’s population estimates than for images of solar
110 cells and oil rigs (42.5%). Across males and females, audience sizes for solar cells and oil
111 rigs are more likely (67%) than controls (22%) to be proportional to Facebook’s population
112 estimates. Across audience age intervals, neither images of solar cells nor oil rigs (0%)
113 nor controls (0%), are proportional to Facebook’s population estimates. See 6.8.6 for more
114 details.

115 A detailed analysis of these results is provided in Appendix 6.4

116 4 Discussion

117 **Algorithmic bias** We show experimentally that climate ads featuring different content are con-
118 sistent delivered differently. This suggests that climate advertising is vulnerable to algorithmic
119 decision-making. We also find that delivery decisions made by Facebook’s advertising algorithm are
120 not proportional to Facebook’s ad audience estimates for U.S. states, males/females and different
121 age groups. This may also indicate that delivery skew is not arbitrary. While, we do not verify
122 this in our experiment, we note that past research has determined that delivery decisions are largely
123 driven by automated image classification on the algorithm’s side, and not due to interactions of ad
124 audiences with the ad. Startlingly, [8] showed that ads that appear invisible to a human (but visible to
125 an automatic image classifier system) are delivered similarly to ads that are fully visible to humans.

126 **Preferential Pricing** Our ad experiments set a common budget of \$1 on each ad. Our results
127 indicating preferential delivery, therefore, also indicate preferential pricing. It is ‘cheaper’ to advertise
128 images of oil rigs to males and older audiences and images of solar cells to females and younger
129 audiences. Advocacy organizations are cash strapped, with one dataset discovering that 15% of
130 advocacy ads request for donations or subscriptions [38]. Preferential pricing could therefore
131 adversely impact the advertising strategy employed by advocacy organizations.

132 **Audience impacts** Our results highlight how advertising algorithms may impact the consumption
133 of climate discourse by audiences with different psychological, cultural, and political responses
134 to the climate crisis. The Six Americas Report[27] segments the U.S. population into six groups
135 based on their response to climate action – Alarmed, Concerned, Cautious, Disengaged, Doubtful
136 and Dismissive. Communication studies have noted that these groups require different persuasion
137 strategies, and information channels, for climate engagement [37]. For example, audiences in the
138 Doubtful and Dismissive category are best engaged by adopting non-confrontational approaches, and
139 by framing messages in ways that are consistent with their values. Audiences in these groups are also
140 more likely to be older individuals and male and located in the interior regions of the U.S. [26, 30] –
141 demographics and regions where the algorithm preferentially delivers ads featuring pictures of an
142 oil rig. Advocacy ads featuring images of oil rigs are more likely to use these images to dissuade
143 audiences from fossil fuels and are more likely to be directed at male and older audiences who
144 are more likely to be in segments that are Doubtful or Dismissive about the climate crisis. Such
145 messaging from advocacy organizations may further alienate these groups from the climate cause.
146 Similarly, contrarian ads featuring renewable energy sources such as solar cells may sometimes be
147 used to promote an image of sustainable practice, a practice called greenwashing. Research is divided
148 on whether these ads lead individuals to view actors as being more [3] or less sustainable [23].
149 Therefore the implications of the algorithm’s recommendation of ads featuring solar cells to female
150 and younger audiences where solar cell ads were delivered preferentially) is unclear. However, our
151 experiment shows that these audiences may be more vulnerable to greenwashing ads from contrarian
152 actors, and may therefore need to be inoculated more frequently against the practice.

153

154 **5 Conclusion**

155 We find early evidence indicating that social media platforms are a set of new and constantly evolving
156 climate discourse influencers. While this study uncovers algorithmic influence, we cannot be fully
157 sure of the precise extent of the algorithm’s influence over ad delivery. One limitation of our study is
158 that we run experiments with a common budget of \$1. Experiments with higher ad budgets may reveal
159 if algorithmic decision making is conditional on ad budget. We urge social media and disinformation
160 scholars to not just study the proliferation of information on social media platforms but to also
161 account for information delivery patterns to engage diverse audiences towards climate action.

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284 6 Appendix

285 6.1 Metadata

286 The metadata that is most relevant to our analysis and work are the following:

- 287 • *ad_reached_countries* - Facebook delivered the ads in these countries. We use this
288 attribute to filter advertisements that were only shown in the United States.
- 289 • *delivery_by_region* - A state-wise breakdown of the ad delivery percentage.
- 290 • *demographic_distribution* - A gender and age wise breakdown of the ad delivery
291 percentage.
- 292 • *impressions* - A range representing the minimum/maximum number of non-unique Face-
293 book accounts that were shown an ad. The smallest bin represents ads that were shown to
294 between 0 - 999 Facebook accounts and the largest bin contains ads that were shown to >
295 1M Facebook accounts.
- 296 • *spend* - A range representing the minimum/maximum amount that was spent on an ad. The
297 smallest bin represents ads whose expenditure was between \$0 - \$100 and the largest bin
298 represents ads whose expenditure was >\$1M.

299 6.2 Ad Campaign Attributes

300 We briefly describe the attributes that were used for our ad campaigns.

- 301 • *Duration* - The 652 ad campaigns were run in 3 batches, such that each batch was run for a
302 period of 24h in order to reach all timezones of the U.S.¹
- 303 • *Ad media* We use images of oil rigs, solar cells or controls (Fig. ??). Each image was
304 modified with the logo of a contrarian or advocacy organization, depending on the treatment
305 group it was assigned to.
- 306 • *Ad text* For each ad, we included the text, "Use our website to tell us what you think about
307 this picture."
- 308 • *Desired audience attributes* - The ads were scheduled to be delivered to anyone in the United
309 States who belonged to the default age criteria on Facebook, irrespective of gender and
310 location. We did not use any additional micro-targeting features.
- 311 • *Ad placement* - We specified that the ads could only be shown on the Facebook platform,
312 and could only be situated on a user account's Facebook feed.
- 313 • *Ad budget* - We specified a daily ad budget of \$1/day.
- 314 • *Campaign Objective* - We specified that the ads' objective was to maximize audience traffic
315 to the website. This website collected opinions about the ad images, when shared by a
316 visitor. It did not contain content that revealed the intentions of our experiment, or a stance
317 on climate action or climate change.
- 318 • *Ad type* - We ran the ads under the 'Social issues, elections or political issues' category, in
319 accordance with Facebook's advertising guidelines.

320 6.3 Experiment: Sampling control images

321 To sample control images, we utilize the ImageNet-21k dataset [34] and the WordNet [18] hierarchy.
322 The ImageNet-21k dataset contains images grouped under 21,841 classes; WordNet is a large lexical
323 database of English. In WordNet, nouns, verbs, adjectives and adverbs are grouped into sets of
324 cognitive synonyms (synsets)[18], each expressing a distinct concept. The 21,841 labels in the
325 ImageNet-21k dataset are a direct mapping to the noun synsets in Wordnet. We devise a methodology

¹The 652 ads were run in 3 batches since Facebook has an upper limit of 250 concurrent ads that can be run by an advertiser whose advertising budget is less than \$1,000,000/month. Batch 1 (22 ads per campaign) was run from X to Y on Z. Batch 2 (22 ads per campaign) was run from X to Y on Z. Batch 3 (21 ads per campaign) was run from X to Y on Z. Since the ads are run simultaneously and run for a time period that spans all the timezones in the U.S, we minimize any market effects to the extent possible.

326 to randomly sample diverse ImageNet categories, such that a sampled category contains at least
327 one image of width and height greater than 600px, which is a criteria required by Facebook’s Ad
328 Platform.

329 **ImageNet Labels Tree** We begin by constructing the WordNet tree for all the labels (synsets)
330 in the ImageNet-21K dataset. The root of this tree is the synset, “entity”[18], level 1 of this tree
331 contains nodes that are descendants of the “entity” node, level 2 contains descendants of nodes in
332 level 1 and so on.

333
334 We then devise a methodology to randomly sample 300 different terminal nodes of this tree, such
335 that these nodes are not related to each other, and the ImageNet category associated with the node
336 contains images of width and height greater than 600px. We found, empirically, that it was necessary
337 to sample roughly 4x the number of images we needed, in order to gather images that satisfied the
338 Facebook Ad Platform’s size criteria. To select 65 control ad images, we therefore sampled 300
339 categories.

340
341 In order to gather diverse images, we started at a tree level that has > 300 nodes. Level 6 of the tree
342 is the highest level to have > 300 nodes at 1188. We begin by sampling a random category on level 6
343 of the WordNet tree. For each category sampled on level 6, we sample a random sub category on the
344 subsequent level, repeating this process until we sample a category that has no descendants. We
345 repeat this process 300 times, to sample 300 unique categories from the 21,841 synsets. From each
346 selected category, we sample a random image having at least 600px width and 600px height to satisfy
347 Facebook criteria for ad images; only 103 categories satisfy this condition. We randomly sample 65
348 categories from this filtered set to get 65 control images.

349
350 We use the *random* library on python for all our sampling needs.

351 6.4 Detailed Analysis

352 6.4.1 RQ1: Can observed ad delivery be consistently attributed to the ad image?

353 We test if the observed ad delivery can be consistently attributed to the ad image, by duplicating the
354 ads featuring images without logos. This includes images of solar cells, oil rigs, and controls without
355 logos. Since statistical tests that compare distributions of categorical variables rely on count values,
356 we compare the ‘Reach’ of an ad and its copy among various ad destinations (U.S. states, gender,
357 age).

358 **US states** Audiences in many U.S. states receive 0 views of some ads, and several states receive <
359 5 views. To satisfy the assumptions of the Fisher’s Test, we first group states based on Facebook’s
360 population estimates (See table 18). States that are expected to receive close to 0%, 1%, or 2% of the
361 ad are grouped together (and their reach counts are summed), while states expected to receive greater
362 than 2% of the ad are retained as is. This gives us 14 possible state destinations where an ad can be
363 distributed. We use Fisher’s Test to compare these observed delivery samples of an ad with its copy.
364 In 89.7% of the ads, we find that the observed delivery sample of an ad is not significantly different
365 from that of its duplicate ($N = 195$, $p < 0.05$). The exact values from our analysis are present in 4.

366 **Gender** Among gender-based destinations, we find that in 100% of the ads, the observed delivery
367 sample of an ad and its duplicate are not significantly different ($N = 195$, $p < 0.05$). The exact values
368 from our analysis are present in 5.

369 **Age** Among age-based destinations, we find that in 99% of the ads, the observed delivery sample
370 of an ad and its duplicate are not significantly different ($N = 195$, $p < 0.05$). The exact values from
371 our analysis are present in 6.

372 6.5 Additional Analyses: RQ1, Region axis

373 When we exclude the images containing logos from the groups considered above, the Kruskal-Wallis
374 test finds that in 35 states there is a statistically significant difference ($p < 0.05$) between the D^R of

375 ads featuring solar cells, oil fields, and controls. Within each state, we then investigate the pairwise
 376 differences between the 3 image groups using a Mann Whitney U Test with a Bonferroni correction,
 377 and find that in 17 states, there’s a statistically significant difference ($p < 0.05$) between the delivery
 378 of images showing solar cells and oil fields. In 24 states, there’s a statistically significant difference
 379 ($p < 0.05$) between the D^R of solar cell images and the control images and in 11 states there’s a
 380 statistically significant difference ($p < 0.05$) between the D^R of oil field images and the control
 381 images.

382 When we exclude the control images from our omnibus test, and directly investigate if there’s a
 383 difference between the solar cell images and the oil field images in different states in the U.S, we
 384 actually see that in 29 states, where there is a significant difference between the D^R of solar cells and
 385 oil fields.

386 6.6 Ad Delivery and Objects in an Ad Image

387 H-statistic and associated p-values from the Kruskal-Wallis test investigating if the population medians
 388 of ads featuring solar cells and oil rigs with no logo, logo of an advocacy organization and logo of
 389 a contrarian organization are significantly different. Results for U.S. State based ad destinations,
 390 gender based ad destinations and age based ad destinations are available in tables 1, 2, and 3.

391 6.7 Ad Delivery Attribution to Ad Image

392 p-values from Fisher’s exact test, comparing the delivery of two ads featuring the same image and
 393 running at the same time, for U.S. State based ad destinations, gender based ad destinations and age
 394 based ad destinations are available in tables 4, 5 and 6

395 6.8 Ad Delivery vs Facebook’s Population Estimates

396 6.8.1 Gender

397 χ^2 statistics and associated p-values for the 3 batches of ads in our experiment show whether observed
 398 ad delivery was proportional to Facebook’s population estimates. We find that in a majority of cases,
 399 the values were not proportional, as shown in tables 7, 8 and 9

400 6.8.2 Age

401 χ^2 statistics and associated p-values for the 3 batches of ads in our experiment show whether observed
 402 ad delivery was proportional to Facebook’s population estimates. We find that in a majority of cases,
 403 the values were not proportional, as shown in tables 10, 11 and 12

404 6.8.3 U.S. States

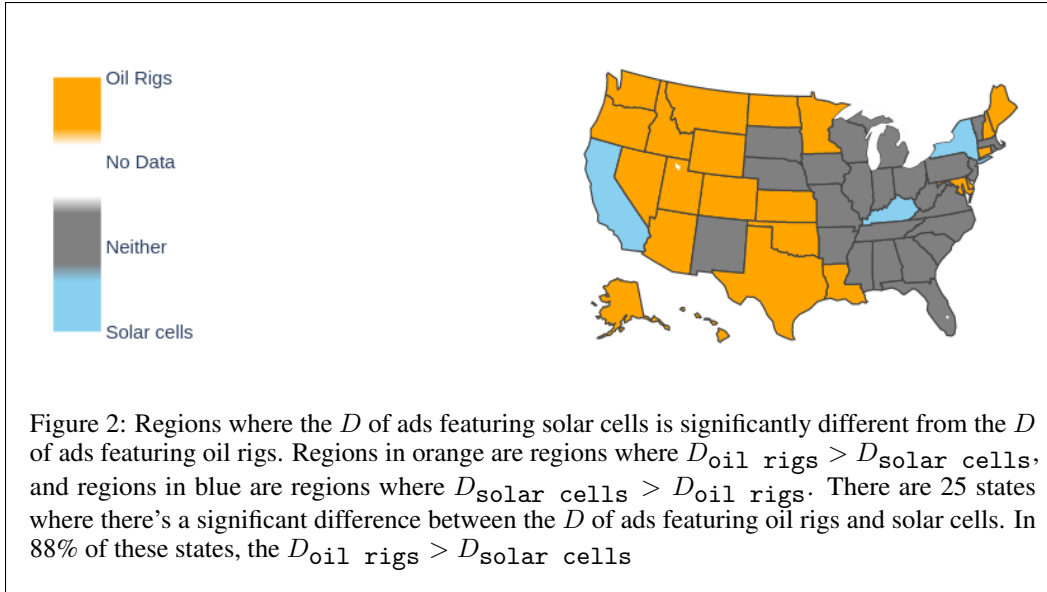
405 χ^2 statistics and associated p-values for the 3 batches of ads in our experiment show whether observed
 406 ad delivery was proportional to Facebook’s population estimates. We find that in a majority of cases,
 407 the values were not proportional, as shown in tables 13, 14 and 15

408 6.8.4 RQ2: Does ad delivery ratio, D , differ when logos are present on an ad image?

409 We compare D samples of ads featuring images with a contrarian, advocacy, and no logos.

Gender	(H-statistic, p-value)
Female	(324.71, 0.0)
Male	(321.33, 0.0)
Unknown	(36.96, 0.0)

Table 1: H-statistic and p-values from the Kruskal-Wallis H-tests testing the null hypothesis that the population median of ads featuring solar cells, oil rigs, and controls are different.



410 RQ2a: Does D differ based on logos present in an oil rig images? We find that D samples of ads
 411 featuring oil rigs with different types of logos (contrarian, advocacy, none) are not significantly
 412 different in audiences of different genders, ages or those belonging to different locations.

413 RQ2b: Does the ad delivery ratio, D differ based on logos present in a solar cell image? We find
 414 that D samples of ads featuring oil rigs with different types of logos (contrarian, advocacy, none)
 415 are not significantly different in audiences of different genders, ages or those belonging to different
 416 locations.

417 **6.8.5 RQ3: Does ad delivery ratio, D , change based on the content of an ad image?**

418 We compare and investigate differences in the D samples of ads featuring solar cells, oil rigs and
 419 controls.

420 **U.S. states** In 38 states, the D sample of at least one of the three groups (Solar cells, oil rigs and
 421 controls) is significantly different from the others ($N=650$, $p < 0.05$, $k=3$). Upon investigating the
 422 pairwise differences, we find that, in 25 states, there's a significant difference ($N = 520$, $p < 0.05$)
 423 between the D samples of solar cells and oil rigs. In 30 states, there's a significant difference ($N=390$,
 424 $p < 0.05$) between the D samples of solar cells and controls and in 18 states there's a significant
 425 difference ($N=390$, $p < 0.05$) between the D samples of oil rigs and controls. See 2 for a map
 426 visualizing these states, and table 3 for the Kruskal-Wallis H Statistic and p values.

427 **Gender** In both male and female audiences, the D samples of the three groups (solar cells, controls,
 428 or oil rigs) are significantly different ($N=650$, $p < 0.05$, $k=2$) as seen in Fig. ???. Upon investigating
 429 the pairwise differences, we find that in both male and female audiences, the D samples of oil rigs

Age	(H-statistic, p-value)
18-24	(113.96, 0.0)
25-34	(73.85, 0.0)
35-44	(7.59, 0.02)
45-54	(6.29, 0.04)
55-64	(19.34, 0.0)
65+	(48.68, 0.0)

Table 2: H-statistic and p-values from the Kruskal-Wallis H-tests testing the null hypothesis that the population median of ads featuring solar cells, oil rigs, and controls are different.

430 and solar cells are significantly different ($N=520$, $p < 0.05$, $k=2$), and of oil rigs and controls ($N=390$,
431 $p < 0.05$, $k=2$) are significantly different. Further, ads featuring oil rigs are preferentially delivered
432 to males while ads featuring solar cells are preferentially delivered to females. The D samples
433 further reveal that male populations are over represented ($D > 1$) while female populations are under
434 represented in the ad audiences selected by Facebook ($D < 1$). See table 1 for the Kruskal-Wallis H
435 Statistic and p values.

436 **Age** The D samples of ads featuring solar cells, controls, or oil rigs (Fig ??) are significantly
437 different ($p < 0.05$, $N=650$, $k=3$) in audiences belonging to all age groups (18-24, 25-34, 35-44,
438 45-54, 55-64, 65+). Upon investigating the pairwise differences, we find that except for audiences
439 in the ages of 45-54, the D samples of solar cells and oil rigs are significantly different in all age
440 groups ($p < 0.05$, $N=520$, $k=2$). Ads featuring oil rigs are preferentially delivered to older audiences
441 while ads featuring solar cells are preferentially delivered to younger audiences. See table 2 for the
442 Kruskal-Wallis H Statistic and p values. Additional sub-analyses can be found in Appendix 6.5

443 **6.8.6 RQ4: Is the observed ad delivery proportional to Facebook's population estimates** 444 **within U.S. state, age, and gender-based ad destinations?**

445 **U.S. states** In 47% of all ads, the observed delivery matches Facebook's population esti-
446 mates ($N=650$, $p < 0.05$; See table 18 for population estimates by state.). The observed delivery of
447 64% of controls ($N=130$, $p < 0.05$), and 42.5% ($N=520$, $p < 0.05$) of non-control images (solar cells
448 or oil rigs) matches Facebook's population estimates. The exact H-statistics and p-values are provided
449 in tables 13, 14, and 15

450 **Gender** The observed delivery of 28% of non-control images (oil rigs or solar cells, $N = 520$, $p <$
451 0.05) and 54% of control images ($N=130$, $p < 0.05$) matches Facebook's population estimates (See
452 table 16 for population estimates by gender). The exact H-statistics and p-values are provided in
453 tables 7, 8, and 9

454 **Age** The observed delivery of none of the non-control images ($N=520$, $p < 0.05$) and none of
455 the control images ($N=130$, $p < 0.05$) matches Facebook's population estimates (See table 17 for
456 population estimates by age). The exact H-statistics and p-values are provided in tables 10, 11, and
457 12

458 **6.9 Facebook Estimated Audience Size Estimates**

459 Facebook's estimated audience size estimates are available in tables 16, 17, and 18.

U.S. State	H-statistic, p-value
Alabama	(10.38, 0.01)
Alaska	(20.63, 0.0)
Arizona	(41.19, 0.0)
Arkansas	(0.7, 0.71)
California	(13.54, 0.0)
Colorado	(41.2, 0.0)
Connecticut	(31.24, 0.0)
Delaware	(21.66, 0.0)
Florida	(3.23, 0.2)
Georgia	(1.01, 0.6)
Hawaii	(13.36, 0.0)
Idaho	(10.49, 0.01)
Illinois	(9.74, 0.01)
Indiana	(4.66, 0.1)
Iowa	(10.03, 0.01)
Kansas	(8.49, 0.01)
Kentucky	(14.16, 0.0)
Louisiana	(8.67, 0.01)
Maine	(27.79, 0.0)
Maryland	(31.25, 0.0)
Massachusetts	(43.94, 0.0)
Michigan	(4.73, 0.09)
Minnesota	(13.15, 0.0)
Mississippi	(4.1, 0.13)
Missouri	(1.42, 0.49)
Montana	(18.5, 0.0)
Nebraska	(7.93, 0.02)
Nevada	(29.7, 0.0)
New Hampshire	(29.08, 0.0)
New Jersey	(13.19, 0.0)
New Mexico	(13.23, 0.0)
New York	(20.47, 0.0)
North Carolina	(2.52, 0.28)
North Dakota	(26.96, 0.0)
Ohio	(12.55, 0.0)
Oklahoma	(32.05, 0.0)
Oregon	(22.74, 0.0)
Pennsylvania	(11.89, 0.0)
Rhode Island	(11.39, 0.0)
South Carolina	(2.54, 0.28)
South Dakota	(10.34, 0.01)
Tennessee	(5.81, 0.05)
Texas	(42.88, 0.0)
Utah	(20.56, 0.0)
Vermont	(21.09, 0.0)
Virginia	(5.12, 0.08)
Washington	(15.18, 0.0)
West Virginia	(1.08, 0.58)
Wisconsin	(7.83, 0.02)
Wyoming	(16.69, 0.0)

Table 3: H-statistic and p-values from the Kruskal-Wallis H-tests testing the null hypothesis that the population median of ads featuring solar cells, oil rigs, and controls are different.

Ad ID	Solar Cells			Oil rigs			Controls		
	Batch 1	Batch 2	Batch 3	Batch 1	Batch 2	Batch 3	Batch 1	Batch 2	Batch 3
1	0.12	0.56	0.53	0.01	1.0	0.34	1.0	0.73	0.55
2	1.0	0.06	1.0	0.49	0.01	1.0	0.53	1.0	0.15
3	1.0	1.0	0.54	0.01	0.77	0.37	0.56	0.19	0.28
4	0.5	1.0	0.23	0.46	0.36	0.69	0.11	0.63	0.26
5	1.0	0.67	0.52	0.63	0.56	1.0	0.65	0.02	0.23
6	1.0	1.0	0.44	0.69	0.13	0.48	0.41	0.02	0.76
7	0.6	1.0	0.31	1.0	1.0	0.14	0.39	0.76	0.34
8	1.0	0.17	0.42	1.0	1.0	0.9	1.0	0.27	1.0
9	1.0	0.36	0.53	0.03	0.73	1.0	0.14	0.07	0.2
10	1.0	0.92	0.22	1.0	0.34	0.04	0.06	1.0	1.0
11	0.59	1.0	0.09	1.0	0.77	0.06	0.63	0.58	0.02
12	0.25	0.17	1.0	0.53	0.0	0.2	0.54	0.74	1.0
13	0.1	1.0	0.26	0.64	1.0	0.85	0.42	0.71	0.75
14	0.3	0.03	0.03	0.54	0.33	0.89	0.54	0.06	1.0
15	0.38	1.0	0.73	0.25	0.14	0.9	0.12	0.11	0.12
16	0.08	0.48	0.0	0.73	0.0	1.0	0.48	0.44	0.91
17	1.0	1.0	0.04	0.35	1.0	0.1	0.06	0.57	0.35
18	0.04	1.0	0.09	0.04	0.69	1.0	0.76	0.02	1.0
19	0.49	1.0	0.03	0.27	0.45	0.08	0.55	0.51	0.5
20	0.12	0.64	1.0	1.0	0.0	0.48	0.81	1.0	0.71
21	1.0	0.55	1.0	0.51	0.0	0.5	1.0	0.59	0.32
22	0.46	0.06		0.51	0.08		0.14	1.0	

Table 4: Table showing p-values for the Two Sided Fisher’s Exact Test. The test measures if observed ad delivery in different U.S. state based ad destinations was consistent between 2 ads featuring the same image and run at the same time. p-values were calculated using the exact test, without using Monte-carlo simulations. Confidence intervals, and an estimate of the odds ratio are not available since this is a 14x2 dataset. Delivery of 65 associated solar cell, oil rig and control ad pairs split into 3 batches were compared.

Ad ID	Solar Cells			Oil rigs			Controls		
	Batch 1	Batch 2	Batch 3	Batch 1	Batch 2	Batch 3	Batch 1	Batch 2	Batch 3
1	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
2	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
3	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
4	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
5	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
6	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
7	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
8	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
9	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
10	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
11	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
12	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
13	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
14	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
15	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
16	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
17	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
18	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
19	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
20	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
21	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
22	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0

Table 5: Table showing p-values for the Two Sided Fisher’s Exact Test. The test measures if observed ad delivery in different gender based ad destinations was consistent between 2 ads featuring the same image and run at the same time. p-values were calculated using the exact test, without using Monte-carlo simulations. Confidence intervals, and an estimate of the odds ratio are not available since this is a 3x2 dataset. Delivery of 65 associated solar cell, oil rig and control ad pairs split into 3 batches were compared.

Ad ID	Solar Cells			Oil rigs			Controls		
	Batch 1	Batch 2	Batch 3	Batch 1	Batch 2	Batch 3	Batch 1	Batch 2	Batch 3
1	1.0	1.0	1.0	1.0	1.0	1.0	0.2	1.0	1.0
2	0.07	1.0	1.0	1.0	1.0	0.5	0.07	1.0	0.5
3	1.0	1.0	1.0	1.0	0.4	0.2	1.0	1.0	0.2
4	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.5	0.07
5	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.07	0.05
6	1.0	0.2	1.0	0.2	1.0	1.0	1.0	1.0	0.13
7	0.2	1.0	1.0	1.0	1.0	1.0	1.0	0.4	1.0
8	1.0	1.0	1.0	1.0	1.0	0.5	1.0	0.07	1.0
9	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
10	1.0	0.4	1.0	0.5	1.0	1.0	0.13	1.0	1.0
11	1.0	1.0	1.0	1.0	1.0	0.07	1.0	1.0	0.4
12	1.0	1.0	1.0	1.0	1.0	0.4	1.0	0.07	1.0
13	1.0	0.2	0.2	0.2	0.4	1.0	1.0	0.2	1.0
14	1.0	1.0	1.0	0.07	0.5	1.0	1.0	0.4	1.0
15	1.0	1.0	1.0	1.0	0.2	1.0	1.0	1.0	0.2
16	1.0	1.0	1.0	1.0	1.0	1.0	0.07	0.2	1.0
17	1.0	0.4	1.0	1.0	1.0	1.0	1.0	0.2	1.0
18	1.0	1.0	1.0	1.0	1.0	0.02	0.4	0.2	0.07
19	0.2	1.0	1.0	1.0	0.13	1.0	1.0	1.0	1.0
20	1.0	1.0	1.0	0.07	1.0	1.0	1.0	1.0	1.0
21	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
22	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0

Table 6: Table showing p-values for the Two Sided Fisher’s Exact Test. The test measures if observed ad delivery in different age based ad destinations was consistent between 2 ads featuring the same image and run at the same time. p-values were calculated using the exact test, without using Monte-carlo simulations. Confidence intervals, and an estimate of the odds ratio are not available since this is a 6x2 dataset. Delivery of 65 associated solar cell, oil rig and control ad pairs split into 3 batches were compared.

Ad ID	Solar Cells	Solar Cells (Copy)	Solar Cells + Contrarian Logo	Solar Cells + Advocacy Logo	Oil rigs	Oil rigs (Copy)	Oil rigs + Contrarian Logo	Oil rigs + Advocacy Logo	Controls	Controls (Copy)	df
1	(16.12, 0.0)	(9.14, 0.01)	(25.14, 0.0)	(23.77, 0.0)	(40.83, 0.0)	(88.08, 0.0)	(40.3, 0.0)	(39.07, 0.0)	(35.92, 0.0)	(87.77, 0.0)	2.0
2	(16.26, 0.0)	(3.78, 0.15)	(23.31, 0.0)	(38.66, 0.0)	(51.36, 0.0)	(58.89, 0.0)	(36.93, 0.0)	(44.47, 0.0)	(41.48, 0.0)	(41.88, 0.0)	2.0
3	(52.66, 0.0)	(30.63, 0.0)	(22.8, 0.0)	(2.86, 0.24)	(47.2, 0.0)	(42.7, 0.0)	(45.58, 0.0)	(3.24, 0.2)	(65.37, 0.0)	(65.76, 0.0)	2.0
4	(10.44, 0.01)	(2.9, 0.23)	(30.92, 0.0)	(16.03, 0.0)	(50.83, 0.0)	(42.58, 0.0)	(45.95, 0.0)	(74.85, 0.0)	(53.74, 0.0)	(79.24, 0.0)	2.0
5	(1.19, 0.55)	(49.32, 0.0)	(42.23, 0.0)	(53.32, 0.0)	(32.22, 0.0)	(43.06, 0.0)	(65.23, 0.0)	(53.24, 0.0)	(50.53, 0.0)	(56.01, 0.0)	2.0
6	(4.16, 0.12)	(12.13, 0.0)	(28.86, 0.0)	(30.81, 0.0)	(37.3, 0.0)	(62.94, 0.0)	(40.67, 0.0)	(60.41, 0.0)	(1.53, 0.47)	(3.64, 0.16)	2.0
7	(10.62, 0.0)	(6.41, 0.04)	(0.72, 0.7)	(0.74, 0.69)	(54.86, 0.0)	(67.38, 0.0)	(41.88, 0.0)	(88.93, 0.0)	(7.36, 0.03)	(10.93, 0.0)	2.0
8	(7.4, 0.02)	(3.78, 0.15)	(18.41, 0.0)	(2.33, 0.31)	(49.35, 0.0)	(49.09, 0.0)	(33.42, 0.0)	(56.85, 0.0)	(3.99, 0.14)	(6.35, 0.04)	2.0
9	(15.09, 0.0)	(7.28, 0.03)	(39.72, 0.0)	(9.25, 0.01)	(39.34, 0.0)	(30.29, 0.0)	(52.75, 0.0)	(56.22, 0.0)	(15.46, 0.0)	(16.45, 0.0)	2.0
10	(11.11, 0.57)	(6.8, 0.03)	(14.66, 0.0)	(23.27, 0.0)	(45.81, 0.0)	(43.08, 0.0)	(64.21, 0.0)	(22.19, 0.0)	(4.92, 0.09)	(0.73, 0.69)	2.0
11	(2.87, 0.24)	(2.33, 0.31)	(44.44, 0.0)	(8.53, 0.01)	(76.58, 0.0)	(71.44, 0.0)	(56.23, 0.0)	(72.08, 0.0)	(0.87, 0.65)	(1.39, 0.5)	2.0
12	(28.08, 0.0)	(25.09, 0.0)	(19.99, 0.0)	(5.91, 0.05)	(55.93, 0.0)	(20.08, 0.0)	(36.31, 0.0)	(74.86, 0.0)	(82.86, 0.0)	(58.39, 0.0)	2.0
13	(14.94, 0.0)	(24.7, 0.0)	(26.21, 0.0)	(35.05, 0.0)	(46.47, 0.0)	(51.3, 0.0)	(77.6, 0.0)	(81.78, 0.0)	(2.65, 0.27)	(2.21, 0.35)	2.0
14	(22.26, 0.0)	(1.62, 0.45)	(26.61, 0.0)	(3.17, 0.21)	(16.75, 0.0)	(28.12, 0.0)	(25.21, 0.0)	(21.38, 0.0)	(6.75, 0.03)	(5.92, 0.05)	2.0
15	(8.83, 0.01)	(11.26, 0.0)	(11.46, 0.0)	(4.67, 0.1)	(35.61, 0.0)	(42.25, 0.0)	(29.25, 0.0)	(48.21, 0.0)	(2.74, 0.25)	(7.94, 0.02)	2.0
16	(15.65, 0.0)	(15.55, 0.0)	(22.97, 0.0)	(17.2, 0.0)	(21.59, 0.0)	(10.91, 0.0)	(28.34, 0.0)	(72.67, 0.0)	(8.19, 0.02)	(2.16, 0.34)	2.0
17	(22.58, 0.0)	(48.87, 0.0)	(32.43, 0.0)	(23.99, 0.0)	(53.51, 0.0)	(46.78, 0.0)	(39.3, 0.0)	(56.97, 0.0)	(3.21, 0.2)	(0.75, 0.69)	2.0
18	(12.19, 0.0)	(6.63, 0.04)	(21.28, 0.0)	(15.05, 0.0)	(39.62, 0.0)	(60.54, 0.0)	(40.06, 0.0)	(66.24, 0.0)	(32.08, 0.0)	(28.26, 0.0)	2.0
19	(2.34, 0.31)	(7.41, 0.02)	(1.5, 0.47)	(1.68, 0.43)	(50.19, 0.0)	(39.69, 0.0)	(46.12, 0.0)	(86.43, 0.0)	(11.26, 0.0)	(4.6, 0.1)	2.0
20	(5.01, 0.08)	(0.16, 0.92)	(15.55, 0.0)	(9.31, 0.01)	(71.32, 0.0)	(65.09, 0.0)	(58.39, 0.0)	(69.39, 0.0)	(70.2, 0.0)	(78.02, 0.0)	2.0
21	(29.55, 0.0)	(16.22, 0.0)	(35.49, 0.0)	(8.66, 0.01)	(89.27, 0.0)	(63.42, 0.0)	(31.57, 0.0)	(61.9, 0.0)	(0.75, 0.69)	(1.08, 0.58)	2.0
22	(1.76, 0.41)	(2.07, 0.20)	(6.02, 0.05)	(0.81, 0.67)	(63.2, 0.0)	(64.18, 0.0)	(63.98, 0.0)	(93.0, 0.0)	(23.03, 0.0)	(30.34, 0.0)	2.0

Table 7: Batch1: χ^2 statistic and p values to test the hypothesis that the observed ad delivery in different gender based ad destinations is proportional to the population estimates provided by Facebook. In a majority of ads, the observed ad delivery is not proportional to the population estimates from Facebook.

Gender	Estimated Audience Size (Lower Bound)	Estimated Audience Size (Upper Bound)
male	100725600	118361400
female	121112000	142313900
unknown	1997800	3190900

Table 16: Estimated Facebook ad audience size estimates for different genders

Ages	Estimated Audience Size (Lower Bound)	Estimated Audience Size (Upper Bound)
18-24	42538900	50135000
25-34	55250800	65054000
35-44	42453300	50032600
45-54	31922400	37540100
55-64	26205100	30632600
65+	26166800	30603100

Table 17: Estimated Facebook ad audience size estimates for different age groups

State	Estimated Audience Size (Lower Bound)	Estimated Audience Size (Upper Bound)
Alabama	3400000	4000000
Alaska	530500	624100
Arizona	4900000	5800000
Arkansas	2000000	2400000
California	27200000	32000000
Colorado	3800000	4400000
Connecticut	2400000	2800000
Delaware	644900	758700
Florida	16500000	19400000
Georgia	7500000	8900000
Hawaii	978900	1200000
Idaho	1200000	1400000
Illinois	8200000	9600000
Indiana	4400000	5200000
Iowa	2000000	2300000
Kansas	1900000	2300000
Kentucky	3000000	3500000
Louisiana	3200000	3700000
Maine	889400	1000000
Maryland	4100000	4800000
Massachusetts	4700000	5600000
Michigan	6300000	7500000
Minnesota	3400000	4100000
Mississippi	1900000	2300000
Missouri	3900000	4600000
Montana	656300	772100
Nebraska	1200000	1500000
Nevada	2300000	2700000
New Hampshire	895800	1100000
New Jersey	6200000	7300000
New Mexico	1200000	1400000
New York	13800000	16300000
North Carolina	7300000	8600000
North Dakota	493100	580100
Ohio	7500000	8800000
Oklahoma	2700000	3200000
Oregon	2700000	3200000
Pennsylvania	8000000	9400000
Rhode Island	761100	895400
South Carolina	3500000	4200000
South Dakota	548100	644900
Tennessee	4800000	5600000
Texas	21300000	25100000
Utah	2200000	2500000
Vermont	392800	462100
Virginia	5800000	6900000
Washington D. C.	694200	816700
Washington	4800000	5700000
West Virginia	1100000	1300000
Wisconsin	3700000	4300000
Wyoming	350300	412100

Table 18: Estimated Facebook ad audience size estimates for different U.S. states