

Supplementary Materials:

Accepting Exclusion: Examining the (Un)Intended Consequences of Data-Driven Campaigns

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Supplementary Materials A: Measures and Descriptives

Supplementary Materials B: Codebook of targeting and exclusion criteria

Supplementary Materials C: Additional Results and Exploratory Analysis

Supplementary Materials A: Measures and Descriptives

Survey item to measure acceptability of exclusion criteria

The idea for this battery was based on Kozyreva et al (2021) and Dommett et al. (2022). but adapted to fit the context of excluding citizens rather than targeting them:

“Political campaigners sometimes try to target their online adverts and messages to different groups of voters during an election. Often this means they deliberately leave out certain voters. To decide who to exclude from their political messages and adverts, political campaigners consider what voters reveal online or they make inferences about voters based on their online interests and actions, for example through liking, commenting on, or sharing content.

How acceptable do you think it is for **your preferred political party** to use these different types of personal information **to exclude voters** from political messages and adverts online?”

1. age and gender
2. migration background
3. place of residence
4. political views
5. religious beliefs

Scale: [1 "Totally disagree" ... 7 "Totally agree"]

Budget Descriptives

We collected data from the Meta Ad Targeting Data Frame for the 2021 election between February 17th 2021 and March 17th 2021. For the 2023 election this is the timeframe between October 22nd 2023 and November 22nd 2023. Here we are interested in how much political parties are spending on exclusion strategies. Given that the Meta Ad Targeting dataset (just as the Meta Ad Library) provides spending only in large boundaries (e.g. 0 to 99 Euro spent on an individual ad), we take the median value between each spending pair. For example, if Party A spent a total of 1000 Euro and had only one ad excluding users based on their place of residence with a budget between 0 and 99 Euro, we estimate that 4.95% of its Meta ad budget was spent on excluding people based on place of residence (i.e. $1000/49.5 = 0.0495$). For detailed targeting and exclusion criteria, which often include dozens of them, we first divide ad budgets by the number of distinct target audiences and then divide within that by the number of targeting and exclusion criteria. This makes the assumption that each targeting and exclusion criterion received equal spending. Though in practice budget allocation could be unequally distributed across criteria it is a necessary assumption we have to make in order to calculate budget shares per criterion.

Table A1: Descriptives from Meta Ad Targeting Dataset

| Party | Number of Impressions (lower bound) | | Total Spent (mid-boundary estimate) | | Number of Ads | | % Spending on Implicit Exclusion | | % Spending on Explicit Exclusion | |
|---------|-------------------------------------|--------|-------------------------------------|--------|---------------|------|----------------------------------|-------|----------------------------------|------|
| | 2021 | 2023 | 2021 | 2023 | 2021 | 2023 | 2021 | 2023 | 2021 | 2023 |
| 50PLUS | 4.4m | 3.6m | 17.3k | 21.4k | 114 | 24 | 99.4 | 98.1 | 34.5 | 0.0 |
| BBB | 4.4m | 13.8m | 20.2k | 65.2k | 41 | 41 | 73.3 | 56.7 | 0.0 | 0.0 |
| BIJ1 | 7.0m | 1.1m | 41.9k | 10.7k | 166 | 20 | 91.5 | 85.1 | 0.0 | 0.0 |
| BVNL | 1.1m | 21.6m | 9.6k | 81.3k | 4 | 278 | 100.0 | 40.9 | 0.0 | 0.0 |
| CDA | 48.6m | 6.0m | 689.6k | 122.3k | 9.0k | 750 | 99.2 | 99.9 | 6.8 | 65.1 |
| CU | 3.1m | 4.0m | 36.7k | 23.6k | 172 | 95 | 40.6 | 77.0 | 0.0 | 0.0 |
| D66 | 41.8m | 18.2m | 261.9k | 166.8k | 1.1k | 334 | 49.1 | 68.3 | 52.4 | 69.1 |
| DENK | 4.2m | 8.5m | 31.1k | 49.5k | 183 | 182 | 61.8 | 89.5 | 0.0 | 6.7 |
| FvD | 36.7m | 16.0m | 278.9k | 149.1k | 157 | 204 | 37.6 | 81.5 | 0.0 | 0.0 |
| GL-PvdA | 38.7m | 50.7m | 374.9k | 313.0k | 3.8k | 590 | 49.8 | 51.0 | 36.1 | 7.9 |
| Ja21 | 13.9m | 3.8m | 57.6k | 27.4k | 87 | 205 | 47.9 | 35.7 | 0.0 | 2.0 |
| LP | 2.9m | 987.0k | 26.4k | 2.7k | 80 | 18 | 94.0 | 100.0 | 0.0 | 0.0 |
| PVV | 2.0k | 800.0k | 99 | 4.7k | 2 | 1 | 50.0 | 0.0 | 0.0 | 0.0 |
| PvdD | 8.4m | 10.7m | 86.6k | 101.7k | 253 | 139 | 74.7 | 94.7 | 66.4 | 19.2 |
| SGP | 489.0k | 1.3m | 5.0k | 15.5k | 59 | 51 | 56.5 | 95.2 | 1.0 | 0.0 |
| SP | 16.8m | 23.1m | 118.7k | 89.0k | 286 | 287 | 43.8 | 51.9 | 0.0 | 10.6 |
| VVD | 28.1m | 11.7m | 343.0k | 78.9k | 4.2k | 502 | 85.3 | 98.1 | 57.8 | 0.1 |
| Volt | 15.6m | 9.5m | 127.4k | 99.5k | 1.2k | 859 | 97.1 | 100.0 | 1.0 | 0.0 |

Table A2: Descriptives Survey Data

| Variable | N = 1,379 |
|---------------------------|-----------------------|
| Accepting Inclusion Index | Mean: 2.30 (SD: 1.45) |
| Age (5 Categories) | |
| 18-24 | 8.2% (113 / 1,379) |
| 25-34 | 13% (179 / 1,379) |
| 35-49 | 14% (196 / 1,379) |
| 50-64 | 31% (430 / 1,379) |
| 65+ | 33% (461 / 1,379) |
| Gender | |
| Man | 55% (761 / 1,379) |
| Woman | 45% (617 / 1,379) |
| X (Gender-Neutral) | <0.1% (1 / 1,379) |
| Education | |
| Low | 29% (399 / 1,379) |
| Middle | 32% (438 / 1,379) |
| High | 39% (542 / 1,379) |
| General Trust | Mean: 4.04 (SD: 1.32) |
| Left-Right Scale | Mean: 5.34 (SD: 2.77) |
| Note. N = 1379 | |

Supplementary Materials B: Codebook for targeting and exclusion criteria

The codebook serves to classify targeting and exclusion criteria found in the Meta Ad Targeting dataset, particularly focusing on the "detailed" criteria therein (which are listed under the "include" and "exclude" variables in the dataset). "Detailed" criteria are what Meta calls several criteria that include "behavior, field of study, education level, school, job title, and many more" (Meta, 2022). These lists of criteria are categorized by into five groups mirroring those used in our survey study: age and gender, migration background, place of residence, political views, and religious beliefs. Additionally, criteria are assigned to supplementary categories such as general political interest, demographic, and other, which were not included in the manuscript analysis. This approach aims to maintain clarity in categorization without overemphasising the presence of the five categories.

Instructions:

Is important to consider why politicians or campaigners would use a specific targeting criteria to tailor messages. It has to be noted that these criteria might align with multiple categories within the codebook. In such cases, the most relevant category should always be selected, taking into account the perspective of the campaigners.

Category: age and gender

This category aims to categorize individuals based on their age and gender demographics. Age Groups: Segmentation of individuals into predefined age ranges facilitates the analysis of age-related targeting criteria, such as content tailored for younger voters or seniors. Examples are: "Under 18," "18-24," "25-34," "35-44," "45-54," "55-64," and "65 and over,";

Gender: Identification of individuals based on gender identity allows for the examination of gender-specific targeting strategies, including messaging directed towards men, women, or non-binary individuals.

Examples are: women's clothing, men's clothing

Category: migration background

The "Migration Background" targeting category refers to criteria used to identify individuals based on their migration history or ancestry. This strategy involves customizing messaging in languages commonly spoken by immigrant communities, such as Spanish, Mandarin, or Arabic, to effectively communicate with them. The strategy also involves targeting people with specific interests commonly associated with immigrant communities; for example "Star TV Turkey" or "Surinam".

Category: place of residence

The "Place of Residence" category refers to targeting criteria based on individuals' geographic locations or living arrangements. Examples could be targeting criteria aiming at addressing the distinct needs of urban and rural communities, references to specific neighbourhoods or villages in general.

Category: political views

The "Political Views" category involves targeting criteria based on individuals' ideological leanings, party affiliations, or specific political beliefs. This category enables politicians or campaigners to tailor messaging and outreach efforts to align with the preferences, values, and priorities of targeted individuals. Examples could be: veganism, feminism, gay-friendly, organic food, animal rights movement, Intensive pig farming. Interests in politics in general are not coded as "political views".

Category: religious beliefs

The "Religious Beliefs" category involves targeting criteria based on individuals' religious affiliations, practices, or beliefs. This category enables politicians or campaigners to tailor messaging and outreach efforts to resonate with the values, traditions, and priorities of specific religious communities. Examples are: Halal, Christian Church, Christian Music.

Category: general political interest

Targeting criteria that imply that someone pays attention to politics, for example, people interested in politics, public news broadcasters, current events, government, or elections, or city council.

Category: Demographic

Refers to targeting criteria using demographics like education levels, employment (except employment at a political or religious organisation), whether people are parents or not, whether they are in relationships or not. People interested in education in general. This category excludes targeting age and gender.

Category: Other

Targeting criteria that do not fit in any of the categories: "age & gender", "place of residence", "migration background", "religious beliefs", "political views", "general political interest, "demographics"

Supplementary Materials C: Additional Results and Exploratory Analyses

As an exploratory analysis we test multiple linear regressions predicting the percentage of party budgets spent by left-right ideology and controlling for election year with fixed effects. Figure C1 in the appendix shows the coefficients for left-right orientation and its influence on spending. Notably, there is a distinct lack of statistically significant results, with the one exception of sending messages via custom audiences which seems to be slightly more used by left-leaning parties. However, none of the models themselves are statistically significant (p-value for F-scores are all larger than 0.05). With this, we can conclude that there is no evidence for H1.

Figure C1: Linear Regression Results for Party Budget Spending on Exclusion

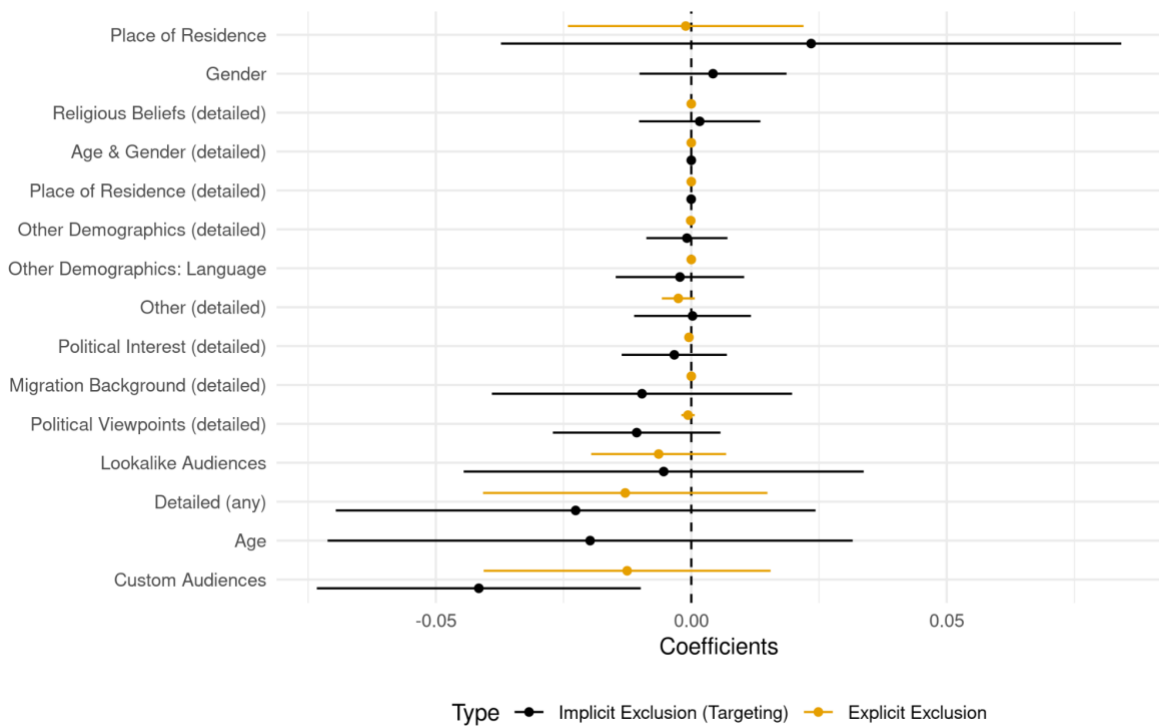


Figure C2: Election Budgets spent on (Additional) Exclusion Strategies

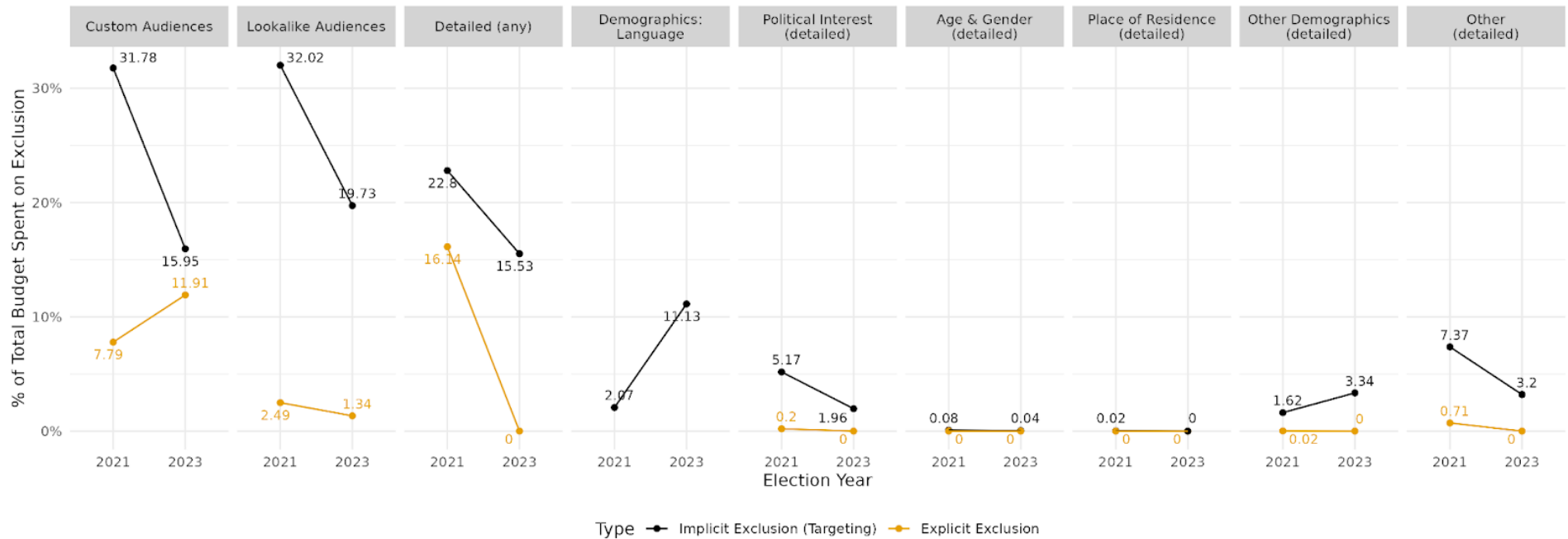


Figure C2. Election Budgets spent on (Additional) Exclusion Strategies. This graph shows additional targeting and exclusion criteria that are not reported in the main analysis, as the manuscript focuses on criteria that overlap with the survey questions. The label “age & gender” are coded from the proxies included in the “detailed” target and exclusion categories as opposed to age and gender reported in the manuscript (Figure 2 and 3), which only includes the direct usage of age and gender as target audiences. Custom audiences include lists of information such as phone numbers, or e-mail addresses which can be matched with the Meta user base in order to find these particular individuals on the platform to target or exclude them from political messages. Lookalike audiences are algorithms employed by Meta in order to find users with similar characteristics as the provided custom audiences to target or exclude them (Bossetta, 2018).

References

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