Null effects of news exposure: A causal test of the (un)desirable effects of a 'news vacation' and 'news binging'

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Null effects of news exposure: A causal test of the (un)desirable effects of a 'news vacation' and 'news binging'

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This preregistered project examines the general belief that news has a beneficial impact on society. We test news exposure effects on desirable outcomes, i.e., political knowledge and participation, and detrimental outcomes, i.e., attitude and affective polarization, negative system perceptions, and worsened individual well-being. We rely on two complementary over-time experiments that combine participants' survey self-reports and their behavioral browsing data: one that incentivized participants taking a 'news vacation' for a week (N = 797; 30M visits) in the US, the other of 'news binging' for two weeks (N = 828; 17M visits) in Poland. Across both experiments, we demonstrate that reducing or increasing news exposure has little – if any – impact on the positive or negative outcomes tested. These robust null effects emerge irrespective of participants' prior levels of news consumption and whether prior news diet was like-minded, and regardless of compliance levels. We argue that these findings reflect the reality of limited news exposure in the real world, with news exposure comprising roughly 3.5% of citizens' online information diet.

News exposure | Political Polarization | Computational Social Science | News media | Democratic Attitudes

Introduction

Democratic theorists view news media as normatively beneficial (1). Thus, observers worry about decreasing news use (2) and the underfunding of media organizations (3, 4), and survey respondents over-report news exposure, underscoring its perceived desirability among the public (5). Some research confirms democratic benefits of news media. By covering the issues of the day and providing information about opportunities for political involvement, news media increase knowledge and stimulate participation (6–11). And yet, the vast 'minimal effects' literature clearly shows that citizens' prior predispositions (12), interpersonal contacts (13), and media fragmentation (14) lead to non-existent or very small media effects (see (15)).

Furthermore, there are reasons to believe that news exposure may have a wide range of largely overlooked *adverse* effects. After all, negativity is one of core journalistic values (16), and so news media tend to focus on clashes between political groups, feature uncivil debates (17–19), and cover politics as a game or a horse-race (20). This may lead people to see the system at large as failing, the elites as evil, and society as sharply divided, and also make individuals anxious, worried, or angry. Longstanding theories of public opinion formation also establish that elite cues distort citizens' policy preferences (21–23) and make people's partisan identities more salient. Because citizens are exposed to these cues and elite communication via news media, news exposure can polarize attitudes (21, 24) and intensify out-group hostility (18, 25), among other side-effects that have received little attention.

Realistic estimates of these positive and negative outcomes are missing. Previous work has been unable to identify causal effects of news exposure, let alone in naturalistic settings. Correlational evidence of its link to political engagement cannot establish causality and relies on largely unreliable (5) survey self-reports of news use. Although controlled experiments address these limitations, they often 'force' people to watch certain - often partisan - content (24). Even those experiments that allow for some selection (26–28) cannot approximate actual exposure contexts, where users can tune in to a nearly unlimited number of sources.

Addressing this gap, we use two unique pre-registered experiments on non-probability-based but representative on key census demographics samples in the United States (US) and Poland (see SI B.2 for a description of the samples). The first experiment examines the effects of taking a seven-day 'news vacation' ($N = 803$) in the US. In this experiment, we incentivized participants to *not* consume any news. The second experiment tests the effects of 'news binging' in Poland ($N = 936$), where we incentivized participants to *increase* their news consumption for 14 days. Both experiments are part of an international panel project that studies changes in attitudes and behaviorally tracked online exposure.

Our study offers several key advantages. For one, we maximize ecological validity by embedding the treatments in participants' real life rather than in a controlled and isolated context. As importantly, we move beyond reliance on self-reports by analyzing participants' online browsing data comprising over 47 million visits, collected via our open-source tool Web Historian (see SI A.1). We use these behavioral data to measure compliance, establish floor and ceiling effects, and examine heterogeneity in treatment effects by prior levels of news consumption *and also* the congeniality thereof. Toward this end, we create a comprehensive list of news domains in both countries (4,683 in the US, 301 in Poland, of which 944 and 212, respectively, were visited by our final samples). We match 702 of the visited US news domains with a list of ideology scores

Fig. 1. Research design

(29) and also develop an open-source ideology categorization for 133 of the visited news domains in Poland (see SI A.2). We guard against several threats to our conclusions (e.g., attrition bias) and account for differential levels of compliance measured using both self-reported and online behavioral data.

We find a robust pattern of near-zero effects. Neither taking a week-long news vacation nor increasing news consumption for two weeks influenced the tested outcomes, beneficial (e.g., political engagement) or not (e.g., polarization, attribution of malevolence to out-party). These null effects emerged consistently regardless of one's prior levels of news exposure, the extent to which one's news diet was like-minded, and one's compliance with the treatment. Because our designs had sufficient statistical power to detect effects and these effects emerged in two different countries, we see them as accurate representations of reality. News media have a central role in society. Yet, our evidence suggests that their contributions (often detected cross-sectionally) may be more limited than generally believed, with news domains comprising only 3.5% of the overall browsing of our respondents.

Research Design

Fig. 1 provides an overview of our pre-registered design. Both experiments were embedded in a larger international 3-wave panel study, in which, every three months, the same participants completed 20-minute surveys and submitted - after extensive informed consent - their browsing data via Web Historian, our open-source tool that allows transparent data sharing.[1] We use these data in conjunction with a comprehensive list of news websites and machine learning algorithms to construct sophisticated behavioral compliance and (like-minded) news consumption measures (see SI A.2 for a list of news domains and details on the ideological classification).

The 'news vacation' experiment was embedded in Wave 3 of the US panel survey. The 872 respondents who took part in Wave 3 were invited to take part in the experiment and 803 agreed to participate (92%) and were randomly assigned to an experimental or control condition (probability of assignment

[1] Web Historian is a web browser plug-in that accesses respondents' browser history stored on their computers, displays it to them using visualizations (e.g. network graph of websites visited, word cloud of used search terms, searchable table of browser history), and allows them to submit it to researchers following an extensive informed consent. SI A.1 contains more details and shows screenshots of the interactive informed consent process

to treatment: 60%). The treatment participants ($N = 457$) were incentivized to stop following the news for one week, while the control ($N = 346$) received no instruction. The 'news binging' experiment was embedded in Wave 2 of the Polish part of the project. Out of 976 Wave 2 participants, 936 (84%) opted in to the experiment (probability of assignment to treatment: 50%). Those in the news binging treatment ($N = 442$) were instructed to consume more news for two weeks; the control ($N = 494$) received no instructions.[2] We do not observe any concerning attrition bias when comparing the samples that completed the preceding waves, those who opted in to the experiments, and those who completed the post-test (SI B.3, B.4). In addition, SI B shows that randomization was successful. In both experiments, the control and the treated groups do not differ significantly from each other, both when opting in and at the post-test.

Across both studies, we recorded compliance using both self-reported and behavioral data. First, every two days, participants completed short surveys about news media use. Second, we rely on participants' browsing data to assess their online news consumption during the duration of the experiments. As the visualizations of the compliance tests in Fig. 1 show, in the US, the experimental group decreased their news intake more than the control, while in Poland the experimental group increased their news intake more than the control. Both groups were asked to complete the post-test after seven days in the US (treatment $N = 378$; control $N = 288$) and after 12 days in Poland (treatment $N = 397$, control $N = 402$).

Results

News exposure in perspective. Do our respondents consume news? We first describe the roughly 30 million visits in the US trace data and the 17 million visits in the Polish trace data. We find that only 3.54% of these visits across both countries were to news domains (US 2.24%, Poland 5.75%). That is, the average participant encountered only one news domain for every 28 sites they visited. Centrist sites were most popular (53%), and visits to like-minded domains accounted for 28% of news visits with ideological classification (or mere 0.80% of all browsing!). These descriptives offer one crucial insight: News is only a small drop in an ocean of online content, and so it is questionable whether changing this small part of people's information diet will make any difference. We return to this finding in the discussion.

News exposure effects. We examine a range of outcomes, each measured using multiple indicators: political knowledge (both self-reported and actual, assessed with questions about current events), attitude and affective polarization, perceptions of the political system (i.e., attribution of malevolence to the out-party, support for compromise, and perceived polarization), and general well-being (both psychological, such as feeling anxious or depressed, and physical, such as drinking alcohol or the desire to hit someone). SI Tab.A.3 lists all items used in this study, as well as key statistics and reliability measures. SI Tab. B.7 reports the summary statistics of the variables as they appear in the analyses, while SI Tab. B.8 summarizes the untransformed variables. SI Fig. B.2 and SI Fig. B.3 visualize the over-time variability; and SI Fig. B.4 and SI Fig. B.5 visualizes the variable distributions. Fig. 2 shows the results for the 'No News' experiment in yellow and those for the 'More News' experiment in grey. [3]. SI C disaggregates the results for the individual items of the composite outcome variables. The dataset and the replication code are available on Harvard Dataverse and Github.

We first address the beneficial outcomes: political knowledge and participation (we do not have pre-measurements for these variables). Unlike hypothesized, participants who consumed *more news* were not any more knowledgeable (Facet *ii*) - or felt they were (Facet *i*) - than the control. In addition, those in the No News condition were not any less knowledgeable than those in the control, nor did they feel as such. Similar null effects from 'news vacation' and 'news binging' emerge for participants' engagement in a range of civic and political activities, from signing a petition to protesting (Facet *iii*).

We turn to negative outcomes, testing if news exposure increases attitude polarization (i.e., attitude importance and strength on five salient issues per country) and affective polarization (i.e., hostility toward out-ideologues, out-partisans, and citizens with opposite policy beliefs, each measured in three ways), see SI A.3. Using multiple measures ensures that the detected patterns are not due to any specific measurement alone. Again, the over-time treatment - whether decreasing or increasing news use - had no significant effects on attitude (Facets *iv* for importance and *v* for strength) and affective (Facets *vi* to *viii*) polarization. Treatment effects do not surpass the 2% mark independently of which indicator and which political out-group we examine.

Adding to this null pattern, news exposure had near-zero effects on three negative system perceptions: whether people think the out-party wants to harm the country (*Attribution of malevolence*, Facet *ix*)), oppose politicians crossing the aisle and reaching compromise (*No support for compromise*, (Facet *x*), and perceive the political climate as polarized (*Perceived polarization*, Facet *xi*), even though - theoretically - media's focus on negativity (16), conflict, horse-race, and in-your face debates (17–19) was expected to worsen these outcomes.

Lastly, we predicted that news exposure would reduce individual well-being. Studies find links between news consumption and stress, anxiety, fatigue, or sleep loss (Jan 31, 2018, click here), especially when news is personally relevant (30), and negative effects of hard news exposure on one's mental well-being (31). These emotional responses may trigger unhealthy behaviors to alleviate the stress. Yet, our causal tests find no significant news effects on emotional well-being (e.g., anxiety, anger, among other emotions) and physical well-being (e.g., consuming alcohol, getting into arguments, wanting to hit someone) during the treatment period (Facets *xii* and *xi*).

Robustness checks. To ascertain that these (near-zero) effects are robust, we test whether our treatment has different effects depending on one's prior news diet. For instance, some partic-

[2] In SI B.2, we show that the samples well represent the general populations (but overrepresent those 25–54 and those with graduate degrees, as often the case in online samples. Importantly, comparison between the top visited news websites reported by Alexa and our data suggests that our participants' browsing behavior corresponds to that of the populations (see SI B.1). Power analyses show that the sample sizes suffice to observe small effects;See SI Figure B.1.

[3] To help readability, we rescaled all variables to range between 0 and 100. Coefficients denote the percentual increase in the outcome for a one percent increase in the predictor. Unless stated otherwise, all models control for respondents' pre-measurement on the outcome. Items marked by an asterisk (*) were reversed to construct the scales

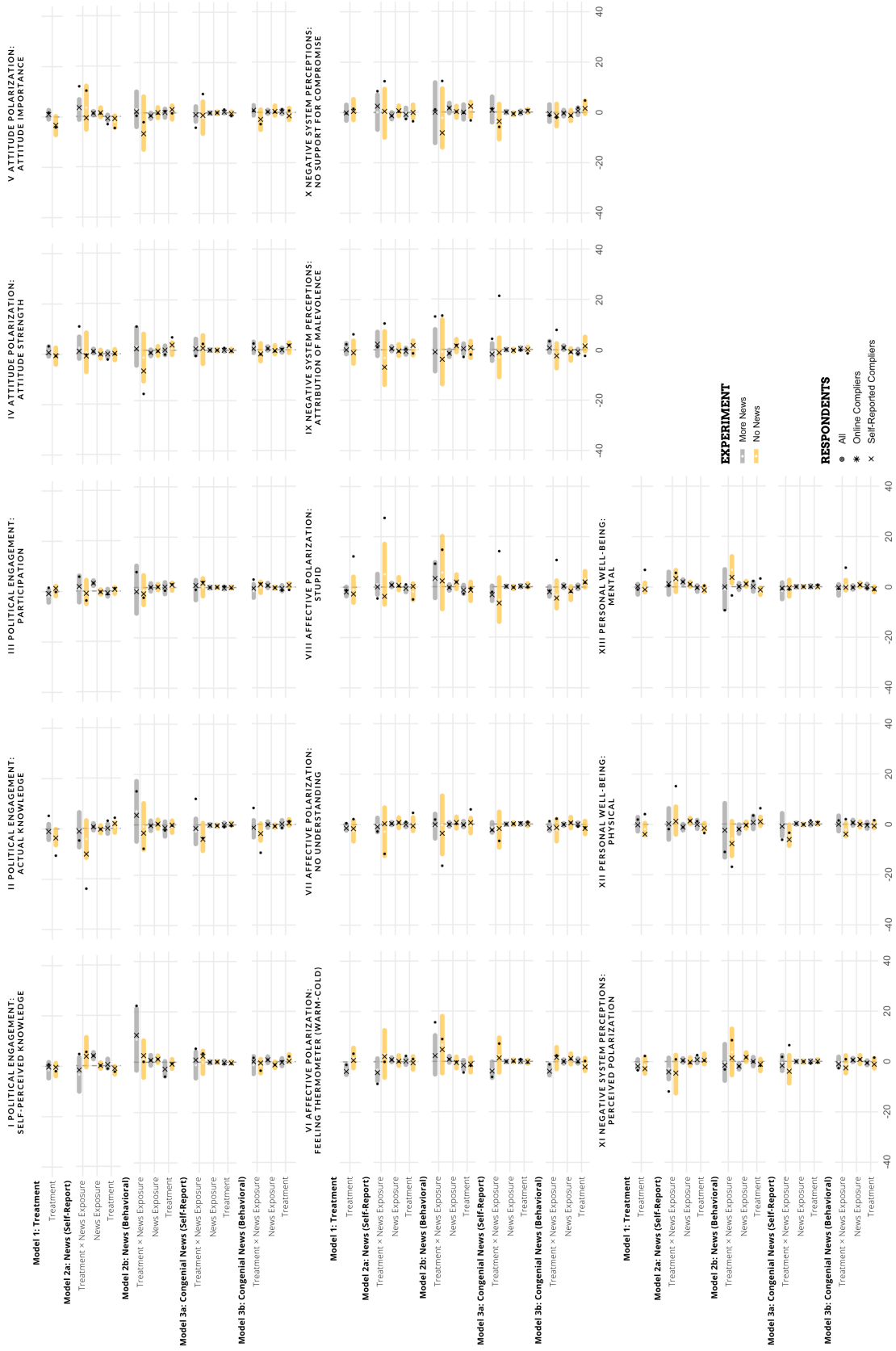

Fig. 2. Results

ipants in the No News experiment may consume no news in general, and thus unable to reduce their intake. Also, heavy news consumers in the More News experiment may already have reached a saturation point before the experiment. Four models tested heterogeneous treatment effects by levels of prior news exposure (Models 2a, 2b) and of prior congenial news exposure (Models 3a, 3b). Models *a* use a self-reported measure of how often participants consume news via nine different channels (e.g., TV, newspapers, etc.). Models *b* rely on behavioral measures, whereby we averaged the number of visits to news websites per day in our online trace data in general and to ideologically like-minded sites, using validated machine learning models (see SI A.2). The null-effects do not hold any heterogeneity. We do not observe different effects for heavy or light news consumers, nor for those whose media diet is primarily like-minded.

Furthermore, in maximizing ecological validity by embedding treatments in a larger project and testing news effects in naturalistic settings, we lose some control over treatment. To account for the extent to which participants in the experimental conditions complied with the treatment, we calculate two pre-registered compliance measures. The self-reported measure (indicated by a cross) asked participants every second day whether they consumed less or more news than usual. The behavioral measure (indicated by a star) compares the amount of news exposure in online trace data before and after the start of the experiment. As Fig. 2 shows, the null estimates are nearly identical to those already presented.

In short, the null findings do not depend on the extent of prior (congenial) news diet and hold when looking at those assigned to the treatment (i.e., ITT estimates) as well as the participants who more clearly complied with the treatment in both experiments (i.e., CACE).

Discussion

This project systematically evaluated the democratic role of news media and also addressed potential side-effects of news exposure. Across two unique experimental designs combining participants' survey self-reports and behavioral browsing data in two distinct countries, prolonged decreases (in the US) and increases (in Poland) in individual news consumption had absolutely no effects on any of the outcomes tested, whether positive (political knowledge and participation) or negative (polarization, worsened perceptions of the political system, or decreased well-being). Furthermore, although we used both self-reported and behavioral indicators of prior levels of news consumption and its congeniality, news effects did not depend on individual typical news diet. That is, the decrease in news use was not less impactful for the avid news consumers or the increase in news use did not affect those rarely exposed to news. Similarly, changes in one's news diet did not depend for the respondents who more clearly complied with the treatments. Testing our hypotheses in two distinct contexts further assures that the results are not due to idiosyncrasies of any particular media or party system alone.

Although ours is among the most comprehensive causal examinations of various effects of news exposure, these null effects are not precise estimates of population average treatment effects because our samples are not a perfect cross-section of the populations. This limitation is common to most work relying on data from online samples willing to share their behavioral traces, in that no such work can claim representativeness. [4] Also, it is possible that people selectively shape what content they opt out of in a way that preserve their existing attitudes. In other words, participants may have complied in volume but adjusted sources or content in ways that buffers any potential change. In a similar vein, our findings cannot speak to the content seen by the participants. We attributed the potential negative effects to various biases in journalistic routines, yet the news our participants typically see may not be about negativity, conflict, or polarization. News content aside, the robust null pattern is noteworthy.

These results counter the popular narrative that news media contribute to healthy citizenry and our expectations that they should have a range of adverse effects. Nevertheless, we argue that these effects portray the reality of (very limited) effects of news exposure in the real world more accurately. Past work cannot speak to actual exposure in naturalistic settings, where people can select from unlimited content and where politics accounts for a small fraction of citizens' online activities. In our data, spanning six months of individual web browsing, visits to news websites comprised 3.54% of the overall browsing. This is normatively problematic, as citizens should stay informed about politics. At the same time, this finding puts into perspective news media effects altogether. Because news content is nearly unnoticeable in the context of overall information and communication ecology of most individuals, as we show, its effects are also very limited. This evidence aligns with the vast literature on minimal media impact.

Naturally, news media *are* important. They keep other powers in check by investigating and publicizing the truth, offer information, and bind citizens together around shared events or concerns. Furthermore, news media may still play a paramount role in the development of political attitudes during political socialization (33) and have cumulative effects on people's perceptions of (political) reality (34), long-term effects that we cannot capture. This project, however, the first to rely on incentivized over-time designs using both self-reported and online behavioral indicators in naturalistic settings and across countries, suggests that the contributions of news media may be more limited than typically hoped or assumed.

Materials and Methods

See SI Appendix for a detailed description of all materials and methods used within this study as well as additional robustness checks, extended discussion of the used classifiers as well as alternative classifications. The data and the code will be made available upon publication on GitHub and on Harvard Dataverse.

ACKNOWLEDGMENTS. This project was funded by the European Research Council (ERC Starting Grant EXPO- 756301; Principal Investigator, Magdalena Wojcieszak).

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[4] We re-estimated our models using weights (even though using weights in experiments may be problematic ((32)). SI **??** presents the results

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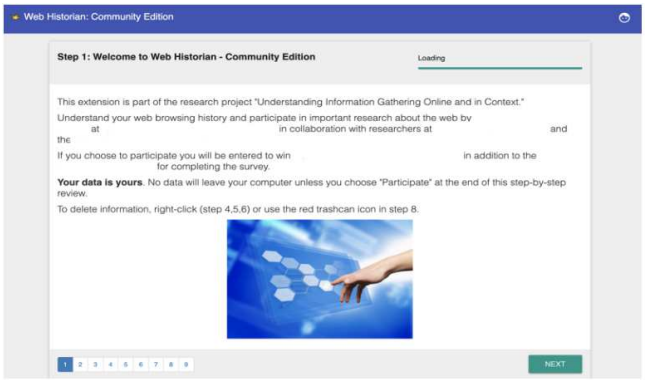
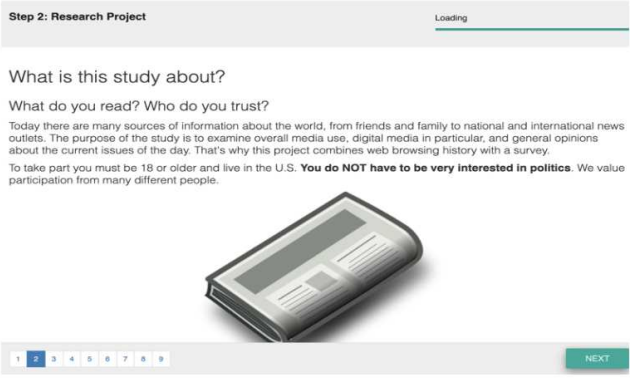
A. Study Material

A.1. Web Historian. Screenshots are provided of the interactive informed consent process for this study created by the Web Historian tool on the participants' local computers. Participants went through the nine steps process pictured below but the data visualized was their own web browsing data and differed for each participant. The web browsing data pictured are example data that are not from a participant.

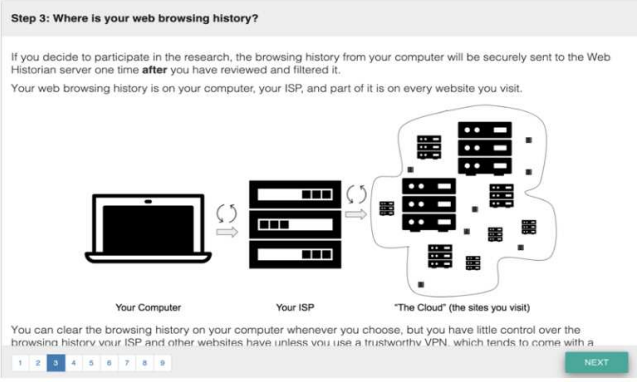
Fig. A.1. Web Historian interface



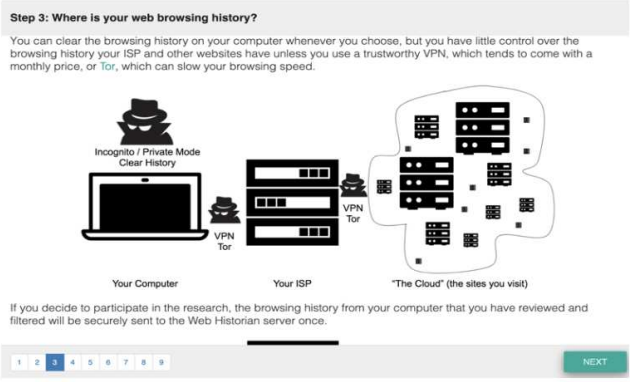
(a) Welcome screen



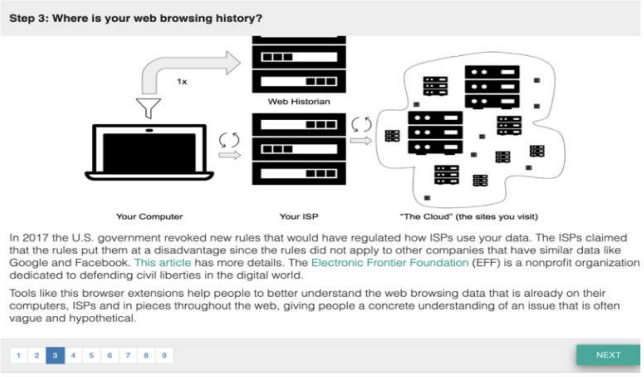
(b) Introduction



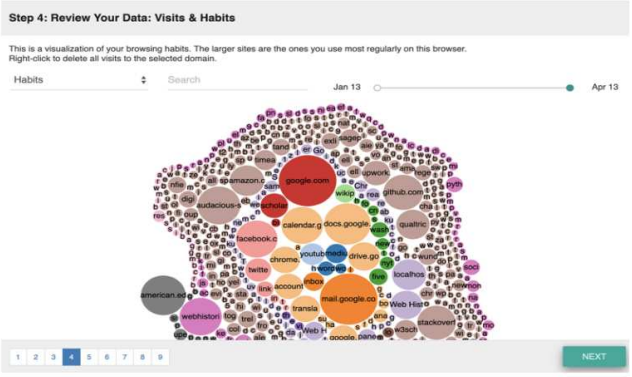
(c) Explanation of web browsing history data I



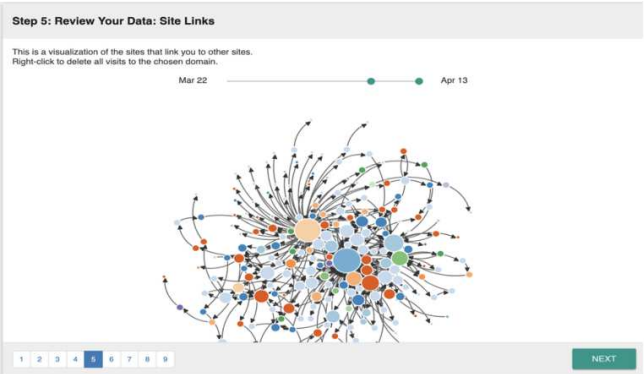
(d) Explanation of web browsing history data II



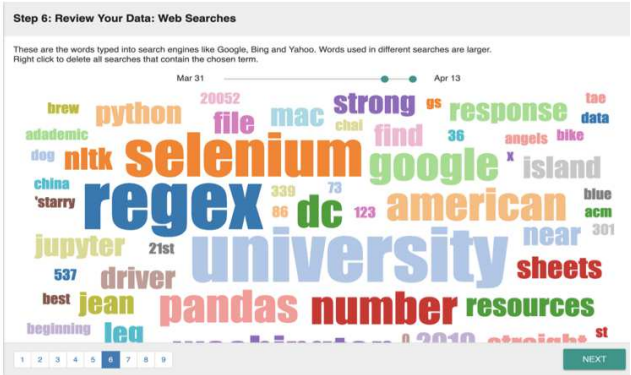
(e) Explanation of web browsing history data III



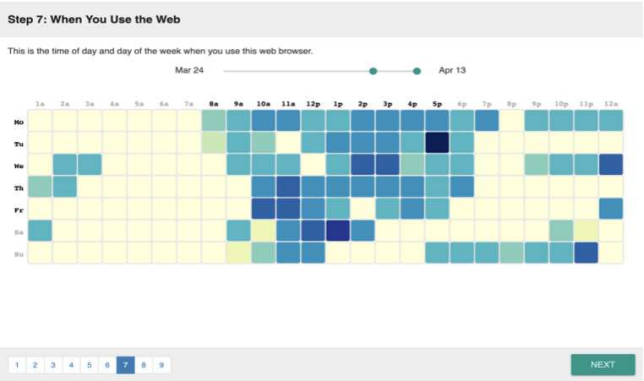
(f) Interactive visualizations IV



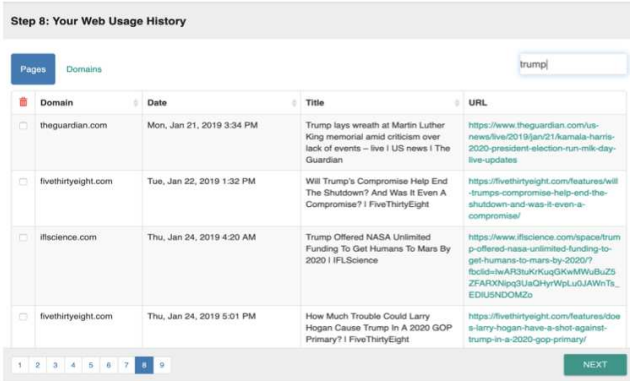
(g) Interactive visualizations V



(h) Interactive visualizations VI

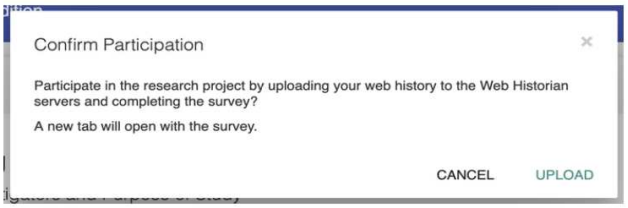


(i) Interactive visualizations VII

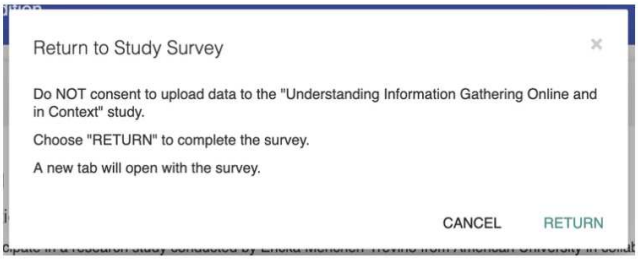


(j) Interactive visualizations IIX

(k) Informed consent I



(l) Informed consent II



(m) Confirmation screen

A.2. Ideology Classifier.

A.2.1. United States. To classify the ideological leaning of the news domains, we use scores based on the Twitter linking patterns of partisans from Robertson et al. (2019). These scores were cross validated with self-reported data and other methods of measuring a domain's political leaning (see Robertson et al., 2018 for details and robustness checks) and highly correlate with classifications from other work (r = .98; Eady et al., 2019). Lower scores indicate the outlet has a more liberal audience and higher scores indicate a more conservative audience. Using these scores, we categorized the domains as either liberal, centrist, or conservative, such that liberal news sites were those with an ideological score of −.20 or lower, conservative sites included those with scores of .09 or higher, and news sites with scores between −.19 and .08 were categorized as centrist.

These categorizations were based on natural cut points in the data that made intuitive sense and had face validity. Because our dataset is public, these categories can be reassigned. Appendix Figure A.2 visualizes the ideology ranking of all sites that were visited at least 5 times by our participants and had ideology scores.

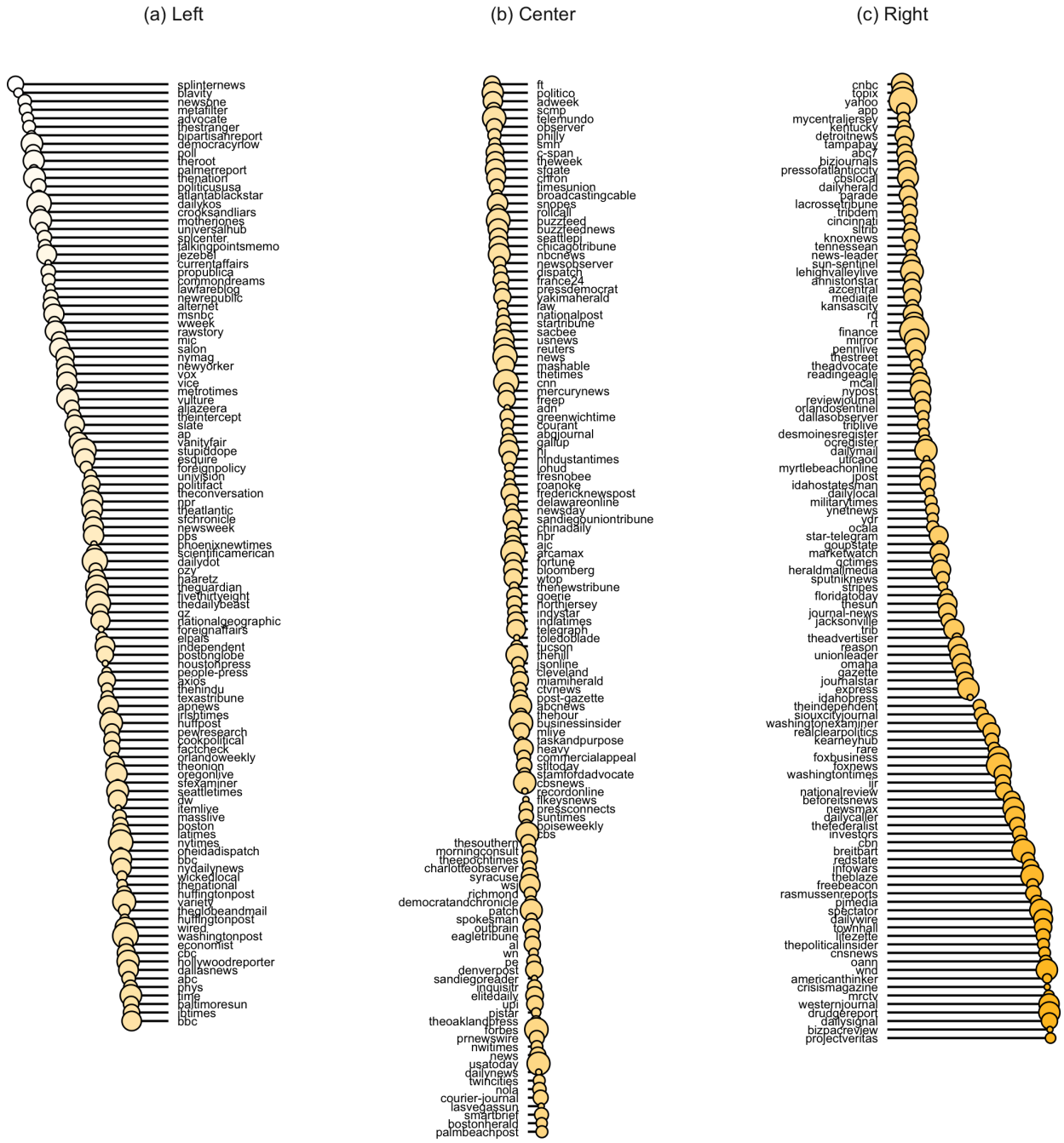
A.2.2. Poland. In the absence of parallel scores for Poland, we rely on a technique that uses follower patterns of news media accounts on Twitter. We start with the list of news organizations compiled earlier, but only consider those (1) that have a visit frequency in our data of above the median, or are national outlets even though less visited (2) and that have a Twitter account. This leaves us with 153 domains in Poland.

Our scaling approach builds on the "mediascores" model by Eady and Linder (click here), which is based on the assumption of homophily: users on social media, conceived as a one-dimensional ideological space, are more likely to share news from news media accounts close to them. Instead of using sharing behavior, we use following behavior, thus assuming that users are more likely to follow news organizations close to them.

To build the bipartite graph that indicates whether any user follows any media account, we obtain the list of Twitter followers of all media organizations. To avoid an overly sparse graph, we exclude organizations with less than 250 followers. To better estimate ideology scores for small media accounts, we first look at accounts with less than 30,000 followers, and get all followers who follow at least 10 of them. We take all of these users into account. Then, for the media accounts with more than 30,000 followers, we only pull a random sample of 300 followers. For validation purposes, we also add parliament members as followers to the graph, again excluding those with less than 250 followers.

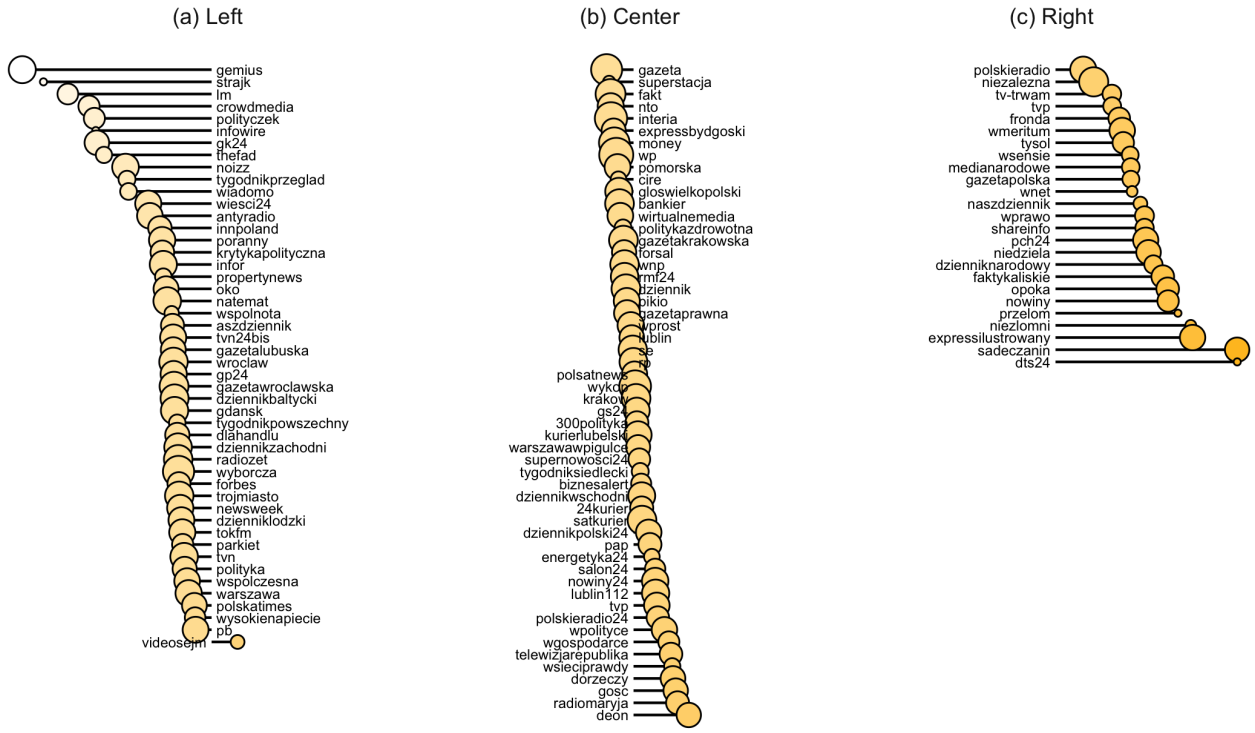
Running the model on this graph results in ideology scores, which according to several political experts in both countries have good face validity. Repeating the analyses with members of parliament provides further validation: Most opposition politicians are on one end, most government politicians one the other end. Finally, we compare the ideology score of a news domain with the average user ideology visiting that domain, as found in our browsing data. Appendix Figure A.3 visualizes the ideology ranking of all sites that were visited at least 5 times by our participants and had ideology scores.

Fig. A.2. Ideology classification American domains



Notes. The horizontal axis signals the ideology estimates. Lower and negative scores indicate a more liberal and higher scores more conservative share of audience responding to the outlet. The size of the points represents the logged number of visits in our data. The news domains list was compiled by manually coding the domains listed in Alexa's Top 1000, the 1000 most browsed domains in our own data and the 1000 most shared domains by politicians on Twitter. Only sites that were visited five times or more are displayed in this figure. The full table containing the raw scores is available in the data folder in the replication repository as 'Figure A.2[A.3] - Data.csv'.

Fig. A.3. Ideology classification Polish domains



Notes. The horizontal axis signals our own ideology estimates based on Twitter linking patterns. Lower and negative scores indicate a more liberal and higher scores more conservative share of audience responding to the outlet. The size of the points represents the logged number of visits in our data. The news domains list was compiled by manually coding the domains listed in Alexa's Top 1000, the 1000 most browsed domains in our own data and the 1000 most shared domains by politicians on Twitter. Only sites that were visited ten times or more are displayed in this figure. The full table containing the raw scores is available in the data folder in the replication repository as 'Figure A.2[A.3] - Data.csv'.

A.3. Survey Material.

Table A.1. Question wording and scaling statistics

	United States			Poland		
	Mean	SD	α	Mean	SD	α
Partisanship Please select the option that best describes your political affiliation. United States: 1 ‘strong Democrat’ to 7 ‘strong Republican’ Poland: 1 ‘opponent’ to 10 ‘proponent’ of the government	3.59	2.11		3.70	3.25	
Self-reported news exposure Thinking about a typical week, how many days do you get information about politics and current events from the following sources? • Television. • Newspapers or magazines (paper and online). • Radio (including podcasts and online). • Online websites and blogs. • Social media (e.g., Facebook, Twitter). • Messaging applications (e.g., Whatsup, messenger). • Talking to people face-to-face. • News app or news alerts on a mobile phone. • Search engine e.g. Google, Bing. 0 days to 7 days	3.42	1.61		3.25	1.63	
Self-reported like-minded news exposure Generally speaking, when you get information about politics and current affairs from the news media, most of the sources you use are in your opinion: 1 ‘completely left-leaning’ to 7 ‘completely right-leaning’	0.71	3.20		0.74	2.40	
Self-perceived knowledge How much do you agree with the following statements? • I know pretty much about politics. • I do not feel very knowledgeable about politics. • Among my circle of friends, I’m one of the experts. • Compared to most other people, I know less. • When it comes to politics, I really don’t know a lot. 1 ‘strongly disagree’ to 7 ‘strongly agree’	4.09	1.43	0.87	3.65	1.39	0.87
Participation In the list below, select all political activities in which you were involved in. • Signed a petition • Donated or collected money for a political cause. • Among my circle of friends, I’m one of the experts. • Shared my thoughts on politics in social media. • Attended a political meeting. • Participated in a protest. • Contacted a politician. • Volunteered for a campaign. • Wrote a letter to the media. 0 ‘no’ or 1 ‘yes’	1.97	1.78		1.06	1.43	

	United States			Poland		
	Mean	SD	α	Mean	SD	α
Attitude importance How important is each of the following issues to you personally?	5.68	1.49	0.63	5.26	1.04	0.68
Attitude strength How strong are your views on each of the following issues? United States: • Gun control. • Immigration. • Climate change. • The economy. Poland: • Women's rights. • Religion and the Church in public life. • Poland's relations with the EU. • The economy. 1 'not at all strong' to 7 'very strong'	5.15	1.14	0.66	5.27	1.07	0.79
Feeling thermometer We'd like you to rate several different groups using something called a 'feeling thermometer'. The higher the number, the warmer or more favorable you feel toward the group, the lower the number, the colder or less favorable. . . 0 'cold' to 100 'warm'	47.6	17.42	0.71	71.56	18.36	0.90
Negative trait rating To what extent do you agree or disagree with the statement that members of the following groups are stupid. 1 'strongly disagree' to 7 'strongly agree'	3.12	1.33	0.93	4.08	1.4	0.90
Understanding How much do you understand the perspectives and values of the following groups ("I understand" does not necessarily mean that you agree with them). 1 'not at all' to 7 'very much' • [out-partisans*] • [out-ideologues] • [citizens with opposite policy beliefs**] * in Poland out-partisans were defined as (a) people who hold opposite stances on the government (b) people who support the largest party on the opposite side of the spectrum, and (c) people who support the party respondents feel farthest from. ** a separate item for each of the four issues listed above.	2.79	1.12	0.89	1.76	0.75	0.89
Attribution of malevolence To what extent do you agree with the following statements? • I worry that [out-partisans] are deliberately trying to hurt [country]. • [out-partisans] are knowingly sabotaging the country. • [out-partisans] don't care about [country]. • I believe [out-partisans] genuinely want what is best for [country]. • I trust [out-partisans] to do what they think is best for [country]. 1 'strongly disagree' to 7 'strongly agree'	4.22	1.64	0.90	4.73	1.31	0.84

	United States			Poland		
	Mean	SD	α	Mean	SD	α
Support for compromise Which position most closely reflects your views? • Politicians must be faithful to their values, no matter what – Politicians must cooperate with each other to be effective first of all, sometimes at the expense of values • Politicians should never compromise their values – Sometimes compromise is necessary when solving important problems • I want politicians who stick to their opinions and principles – I want politicians who cooperate with each other. • Values should never be violated – Principles should never block progress. 1 'left position' to 7 'right position'	2.04	1.53	0.90	2.35	1.65	0.92
Perceived polarization How much do you agree or disagree with the following statements: • [partisans] hate each other. • The differences between [partisans] are too great to be reconciled. • [citizens] are greatly divided when it comes to the most important values. • Polarization in [country] is greater than ever before. 1 'strongly disagree' to 7 'strongly agree'	4.79	1.16	0.72	5.20	1.11	0.85
Mental well-being Over the past week, how much have you felt each of the following? • Depressed. • Anxious. • Happy. • Satisfied with life. • Optimistic about the future. • Calm and peaceful. 1 'Not at all' 7 'To a great extent'	2.42	1.34	0.88	2.85	1.22	0.90
Physical well-being Over the past week, how much have you felt each of the following? • Had one or more alcoholic beverage. • Ordered pizza or other fast food. • Felt like hitting someone. • Satisfied with life. • Gotten into an argument. • Exercised. 0 days to 7 days	2.5	0.97	0.41	3.00	1.05	0.40

B. Descriptives

Table B.1. Correspondence news ranks between our and Alexa browsing data

United States			Poland		
Domain	Alexa	Own Ranking	Domain	Alexa	Own Ranking
cnn	1	1	onet	1	2
nytimes	2	5	wp	2	1
foxnews	3	4	interia	3	3
breitbart	4	29	gazeta	4	6
bbc	5	16	o2	5	5
washingtonpost	6	2	wykop	6	4
patch	7	30	tvn24	7	11
buzzfeed	8	3	wyborcza	8	7
vice	9	32	money	9	10
forbes	10	7	tvp	10	93
usatoday	11	10	businessinsider.com	11	94
businessinsider	12	9	fakt	12	8
theguardian	13	18	naszemiasto	13	9
theepochtimes	14	75	gemius	14	21
dailymail.co.uk	15	17	krakow	15	15
huffpost	16	12	se	16	12
cnbc	17	25	wpolityce	17	42
westernjournal	18	55	natemat	18	32
npr.org	19	20	niezalezna	19	38
drudgereport	20	24	infor	20	29

Notes. We find a correspondence between the rank of the news sites included in our study and the rank of the news sites using site rankings from Alexa (we note that Alexa has no visit statistics for Google News and Yahoo News). As this table shows, the top browsed news sites reported by Alexa are also among the top browsed sites in our samples.

Table B.2. Survey vs. population statistics

	Population		Experiment	
	United States	Poland	United States	Poland
Age: 0–17	18.73	14.80		
18–24	13.27	10.34	12.35	11.84
25–54	39.45	43.44	59.43	56.68
55+	28.54	31.42	28.21	31.47
Education: Less than high school	9.92		1.57	1.67
High school or vocational degree	28.11		35.99	19.69
Some college	27.34		9.30	30.89
Bachelor degree	22.55		10.87	32.18
Graduate school	12.07		42.27	15.57
Sex: Male	48.90	48.50	49.76	47.37
Female	51.10	51.50	50.24	52.63

Table B.3. Attrition by condition across waves (Poland)

	Wave 1	Wave 2	Accepting participation	Post-wave	Wave 3	Sign.
Age: 18–24	11.65	9.73	9.94	8.99	7.78	
25–54	69.76	70.08	70.09	70.60	66.27	0.97
55+	18.58	20.18	19.98	20.41	25.94	
Education: Less than high school	1.65	1.74	1.50	1.58	1.65	
High school or vocational degree	36.46	34.94	34.19	35.72	31.60	
Some college	11.93	10.25	10.47	9.36	11.79	0.99
Bachelor degree	10.71	11.37	11.75	10.81	9.91	
Graduate school	39.25	41.70	42.09	42.53	45.05	
Sex: Male	56.08	51.02	50.64	49.82	45.28	0.87
Female	43.92	48.98	49.36	50.18	54.72	

Notes. Table shows key demographic statistics per wave for the Poland. The final column shows significance tests (p-value of a chi-squared test) for differences between the sample in Wave 2, the sample accepting participation and the sample in the post-survey

Table B.4. Attrition by condition across waves (US)

	Wave 1	Wave 2	Wave 3	Accepting participation	Post-experiment wave	Sign.
Age: 18–24	10.79	8.89	8.98	8.75	9.32	
25–54	65.87	66.21	67.66	68.38	67.82	0.99
55+	23.35	24.90	23.36	22.88	22.86	
Education: Less than high school	1.44	1.08	1.15	1.13	1.36	
High school or vocational degree	16.34	13.89	14.07	14.54	14.93	
Some college	30.01	31.70	31.60	31.58	30.77	1.00
Bachelor degree	31.83	33.37	34.49	34.34	33.94	
Graduate school	17.01	16.63	15.69	15.54	15.99	
Sex: Male	44.72	43.19	43.69	43.46	43.54	0.99
Female	51.67	56.42	55.96	56.16	56.31	

Notes. Table shows key demographic statistics per wave for the United States. The final column shows significance tests (p-value of a chi-squared test) for differences between the sample in Wave 2, the sample accepting participation and the sample in the post-survey

Table B.5. Balance and differential attrition (Poland)

	Accepting participation			Post-experiment wave			Accepting vs. post-wave	
	Control	Treatment	Sign.	Control	Treatment	Sign.	Sign. (control)	Sign. (treatment)
Age: 18–24	9.31	10.63		8.96	9.32			
25–54	70.24	69.91	0.77	70.40	70.78	0.96	0.98	0.82
55+	20.45	19.46		20.65	19.90			
Education: Less than high school	2.02	0.90		1.99	1.01			
High school or vocational degree	31.58	37.10		33.83	36.78			
Some college	10.32	10.63	0.1	9.45	9.82	0.42	0.95	0.99
Bachelor degree	13.77	9.50		12.69	9.32			
Graduate school	42.31	41.86		42.04	43.07			
Sex: Male	53.24	47.74	0.11	51.74	46.85	0.19	0.7	0.85
Female	46.76	52.26		48.26	53.15			

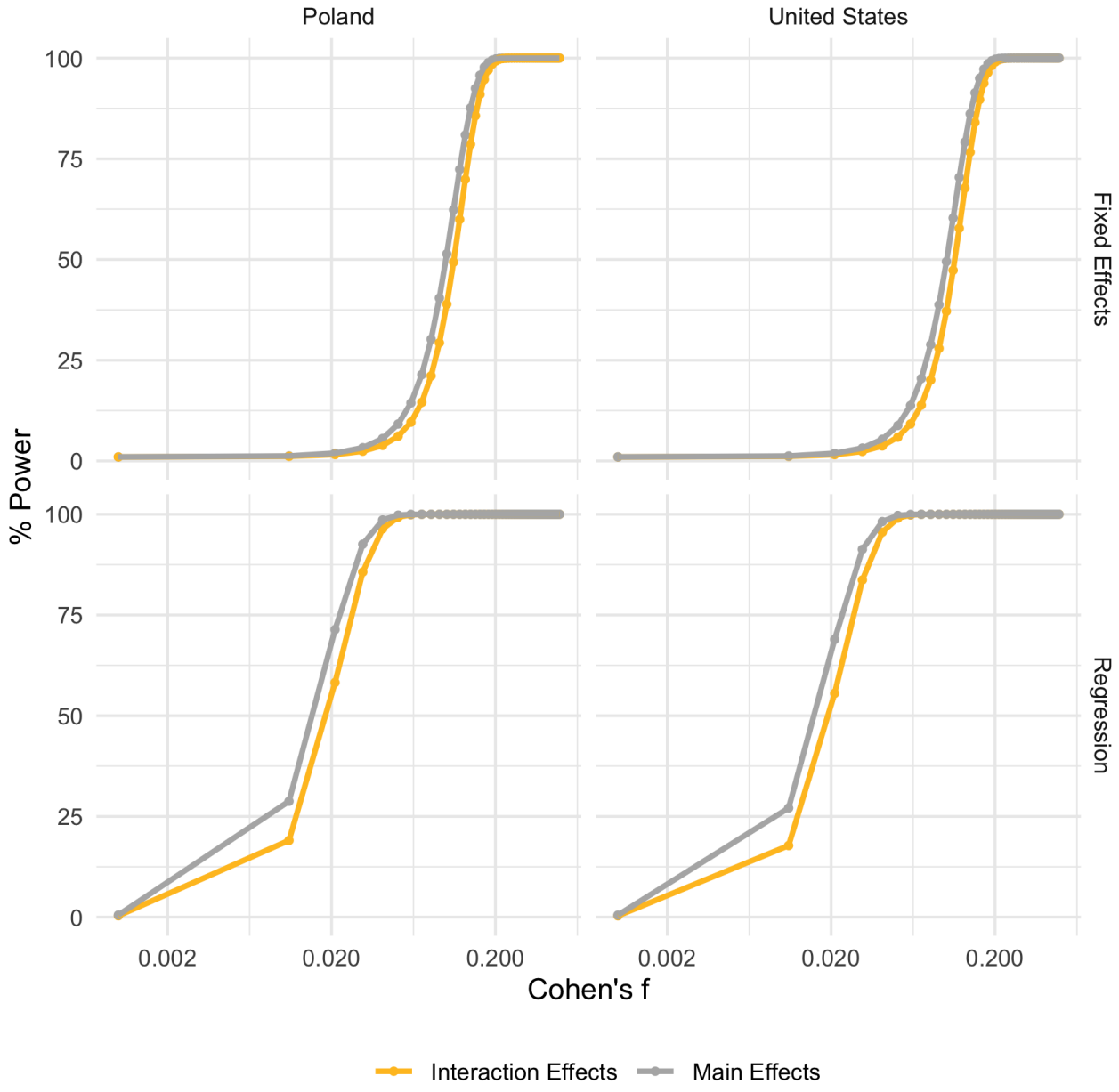
Notes. Table shows balance statistics between treatment and control for those accepting participation, and separately for those responding to the post-experiment survey. Columns labelled "Sign." show significance tests (p-value of a chi-squared test) for differences between treatment and control, or differences between those accepting and responding to post-survey within a condition.

Table B.6. Balance and differential attrition (United States)

	Accepting participation			Post-experiment wave			Accepting vs. post-wave	
	Control	Treatment	Sign.	Control	Treatment	Sign.	Sign. (control)	Sign. (treatment)
Age: 18–24	7.83	9.45		7.99	10.34			
25–54	66.96	69.45	0.33	67.36	68.17	0.43	0.89	0.9
55+	25.22	21.10		24.65	21.49			
Education: Less than high school	0.58	1.54		0.70	1.86			
High school or vocational degree	15.41	13.88		14.98	14.89			
Some college	29.94	32.82	0.52	29.97	31.38	0.48	0.99	0.99
Bachelor degree	34.30	34.36		33.10	34.57			
Graduate school	15.99	15.20		17.07	15.16			
Sex: Male	44.51	42.67	0.67	45.49	42.06	0.44	0.9	0.27
Female	55.20	56.89		54.51	57.67			

Notes. Table shows balance statistics between treatment and control for those accepting participation, and separately for those responding to the post-experiment survey. Columns labelled "Sign." show significance tests (p-value of a chi-squared test) for differences between treatment and control, or differences between those accepting and responding to post-survey within a condition.

Fig. B.1. Power



Notes. Figure is based on G*Power analyses for linear fixed effects analysis (F test-family) with 2 as the denominator of the degrees of freedom for the main effect models and 3 for the moderation effect models. Effect sizes below 0.2 are considered very small effect sizes, effect sizes between 0.2 and 0.5 small, and between 0.5 and 0.8 medium.

Table B.7. Summary statistics

	United States						Poland							
	Pre-Survey			Post-Survey			Pre-Survey			Post-Survey				
	Mean	Median	Std.Dev	Mean	Median	Std.Dev	Mean	Median	Std.Dev	Mean	Median	Std.Dev	Min.	Max.
Political Engagement: Self-perceived Knowledge				61.56	63.33	23.82				54.09	50.00	23.22	0.00	100.00
Political Engagement: Actual Knowledge				43.53	50.00	31.72				63.62	75.00	22.63	0.00	100.00
Political Engagement: Participation				21.89	11.11	19.79				13.25	0.00	17.84	0.00	100.00
Attitude Polarization: Attitude Strength	70.95	70.83	18.07	67.10	66.67	19.89	72.53	75.00	17.29	69.86	70.83	18.25	0.00	100.00
Attitude Polarization: Attitude Importance	54.37	56.25	13.26	63.33	62.50	22.34	72.07	70.83	16.84	69.91	70.83	17.81	0.00	100.00
Affective Polarization: Feeling Thermometer	68.12	69.92	21.14	57.36	54.67	24.19	72.06	73.12	17.95	71.05	71.71	18.76	0.00	100.00
Affective Polarization: Lack of Understanding	41.28	40.28	24.94	38.05	37.50	24.94	46.90	41.22	20.43	45.32	37.82	20.30	0.00	100.00
Affective Polarization: Stupid	51.19	50.00	27.92	42.46	43.06	30.81	52.15	50.00	23.69	50.57	50.00	22.88	0.00	100.00
Negative System Perceptions: Attribution of Malevolence	60.77	56.67	27.42	59.80	60.00	27.40	69.33	66.67	21.12	68.33	63.33	22.53	0.00	100.00
Negative System Perceptions: No Support for Compromise	34.86	33.33	25.90	33.18	29.17	25.04	40.54	37.50	27.76	37.90	37.50	27.05	0.00	100.00
Negative System Perceptions: Perceived Polarization	62.29	62.50	18.69	64.34	62.50	20.02	69.75	70.83	18.44	70.28	70.83	18.72	0.00	100.00
Well-being: Mental				34.82	33.33	22.26				41.94	44.44	20.34	0.00	100.00
Well-being: Physical				30.27	28.57	17.36				31.46	28.57	14.94	0.00	100.00
News Exposure: Total	8.61	7.44	6.37				6.20	4.93	5.38				0.44	72.00
News Exposure: Congenial	0.71	0.08	3.20				0.74	0.16	2.40				0.00	63.76

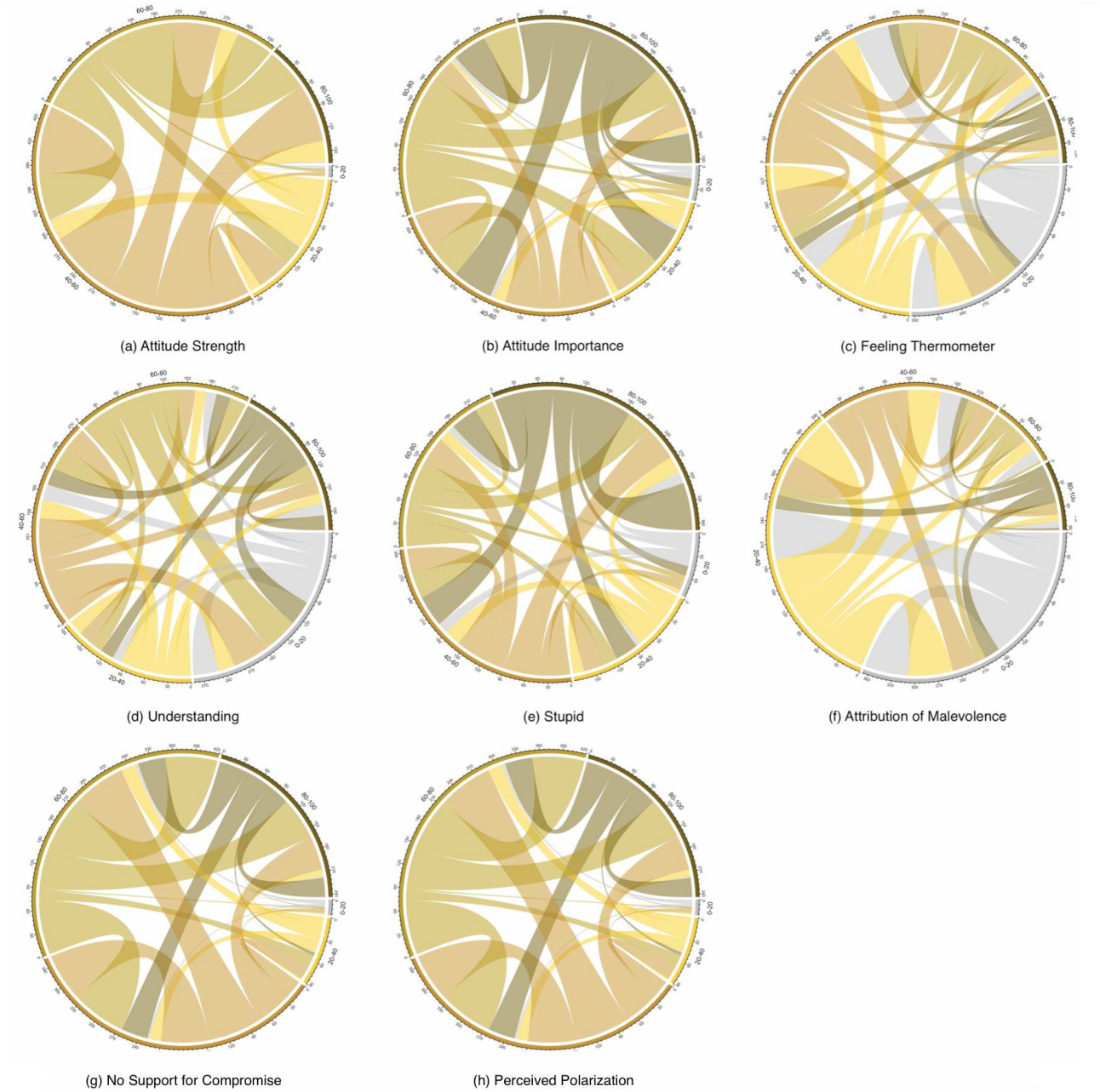
Notes. Table displays the summary statistics of the variables the way they appear in the analyses. The dependent variables in the analyses were rescaled to range between 0 and 100. The exposure variables were constructed by dividing the number of visits by the number of days an individual logged onto the computer (active days). These variables were log-transformed and subsequently rescaled to range between 0 and 100.

Table B.8. Untransformed measures

	United States						Poland							
	Pre-Survey			Post-Survey			Pre-Survey			Post-Survey				
	Mean	Median	Std.Dev	Mean	Median	Std.Dev	Mean	Median	Std.Dev	Mean	Median	Std.Dev	Min.	Max.
Political Engagement: Self-perceived Knowledge				4.09	4.20	1.43				3.65	3.40	1.39	0.40	6.40
Political Engagement: Actual Knowledge				1.74	2.00	1.27				2.54	3.00	0.91	0.00	4.00
Political Engagement: Participation				1.97	1.00	1.78				1.06	0.00	1.43	0.00	9.00
Attitude Polarization: Attitude Strength	5.26	5.25	1.08	5.03	5.00	1.19	5.35	5.50	1.04	5.19	5.25	1.09	1.00	7.00
Attitude Polarization: Attitude Importance	5.35	5.50	1.06	6.07	6.00	1.79	5.32	5.25	1.01	5.19	5.25	1.07	1.00	9.00
Affective Polarization: Feeling Thermometer	51.34	52.69	15.85	43.27	41.25	18.14	72.06	73.12	17.95	71.05	71.71	18.76	0.00	100.00
Affective Polarization: Lack of Understanding	2.86	2.81	1.12	2.71	2.69	1.12	25.53	22.54	10.76	24.70	20.75	10.69	0.83	53.50
Affective Polarization: Stupid	3.30	3.25	1.26	2.91	2.94	1.39	4.13	4.00	1.42	4.03	4.00	1.37	1.00	7.00
Negative System Perceptions: Attribution of Malevolence	4.25	4.00	1.65	4.19	4.20	1.64	4.76	4.60	1.27	4.70	4.40	1.35	0.60	6.60
Negative System Perceptions: No Support for Compromise	2.09	2.00	1.55	1.99	1.75	1.50	2.43	2.25	1.67	2.27	2.25	1.62	0.00	6.00
Negative System Perceptions: Perceived Polarization	4.74	4.75	1.12	4.86	4.75	1.20	5.18	5.25	1.11	5.22	5.25	1.12	1.00	7.00
Well-being: Mental				2.42	2.33	1.34				2.85	3.00	1.22	0.33	6.33
Well-being: Physical				2.50	2.40	0.97				3.00	2.80	1.05	0.80	7.80
News Exposure: Total	8.61	7.44	6.37				6.20	4.93	5.38				0.44	72.00
News Exposure: Congenial	0.71	0.08	3.20				0.74	0.16	2.40				0.00	63.76

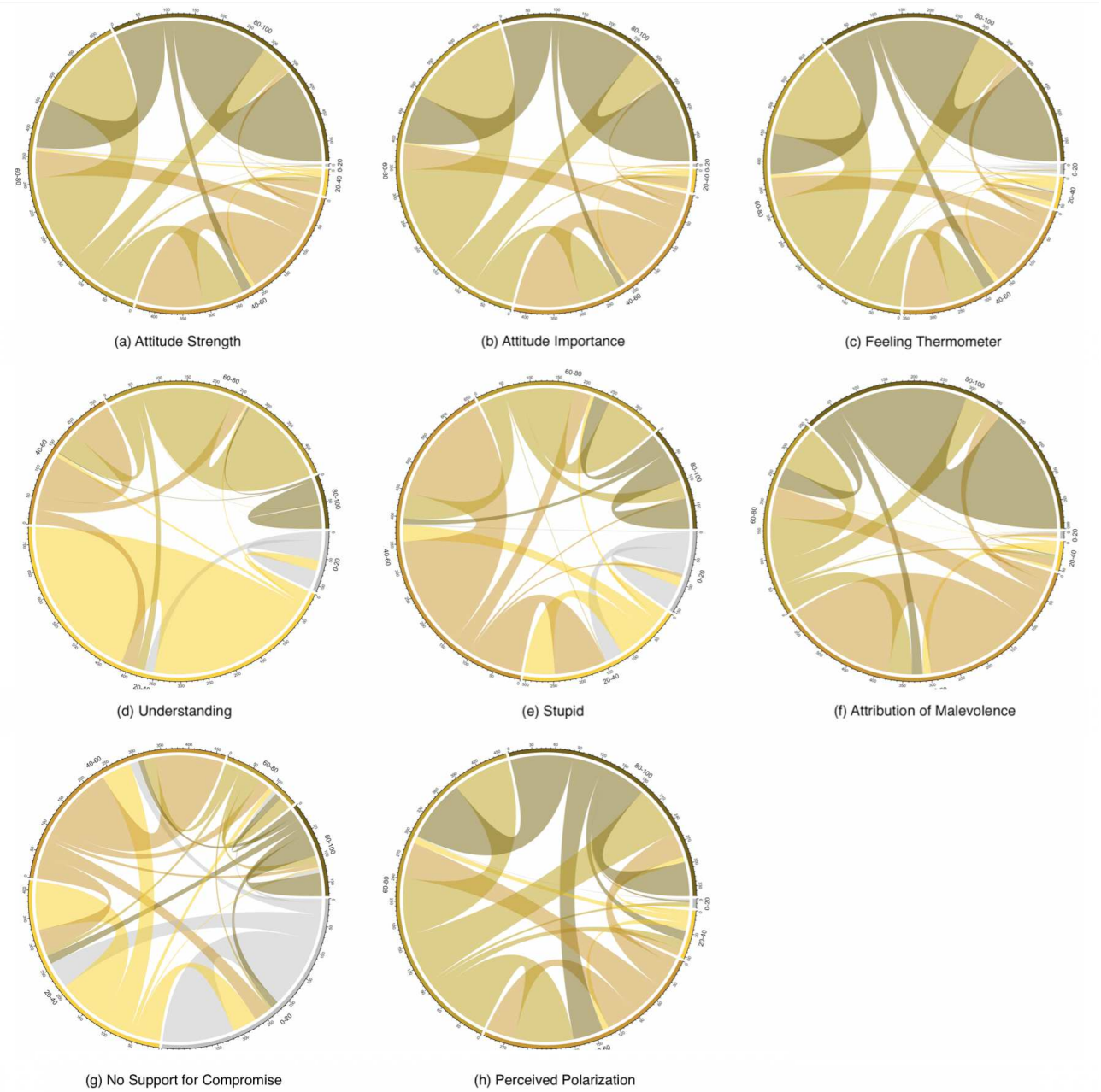
Notes. Table displays the summary statistics of the untransformed exposure measures. The exposure measures were calculated as the number of news visits per active day. This table shows the summary statistics of these measures, e.g., the mean number of news visits per active day across all respondents. Columns display the statistics for all respondents who submitted their browsing data, irrespective of whether they participated in the next wave of the survey or not. The final column reports whether any significant changes across these categories could be detected.

Fig. B.2. Overtime variability dependent variables United States



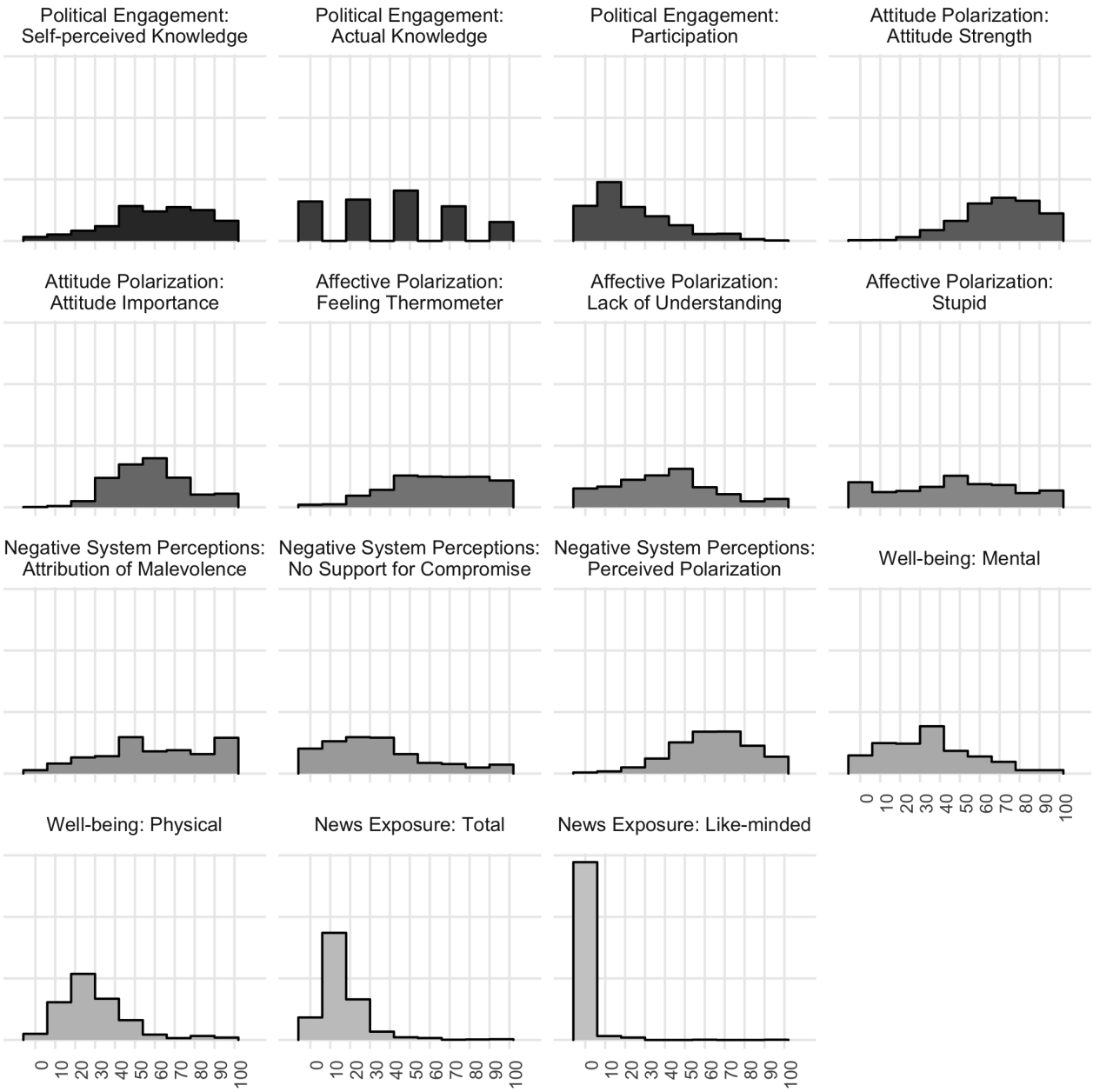
Notes. The chord diagrams visualize the overtime change in the values in the dependent variables. Arcs within the same category or colors (for example from grey '0-20' to grey '0-20) indicate the percentage of respondents who reported no change between the pre- and post-measurement. Arcs between categories (for example from grey '0-20' to dark blue '20-40') denote the percentage of respondents who reported a change from one category to the other between the two timepoints. The 'messier' the diagram is, the larger the overtime variability.

Fig. B.3. Overtime variability dependent variables Poland



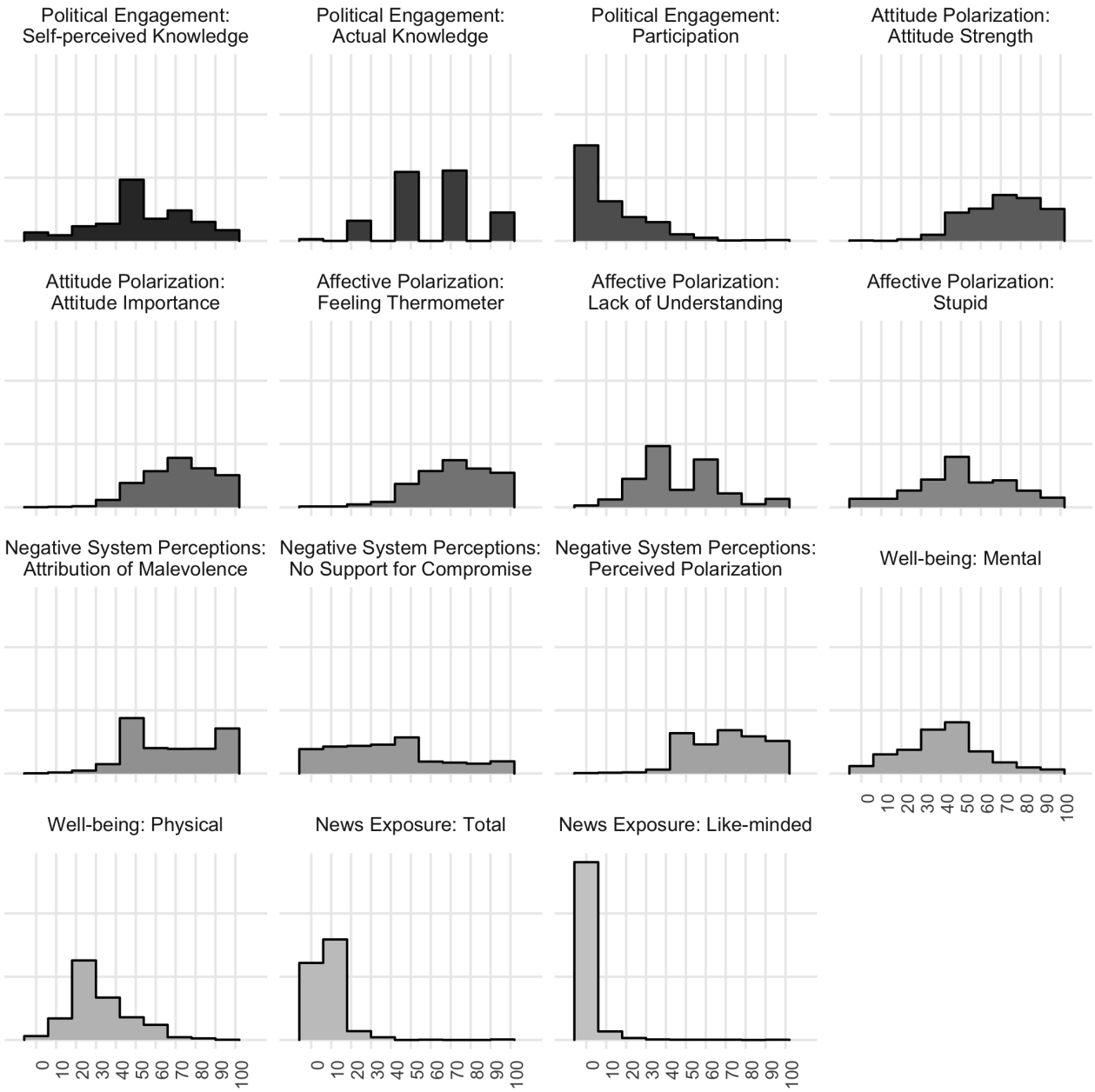
Notes. The chord diagrams visualize the overtime change in the values in the dependent variables. Arcs within the same category or colors (for example from grey '0-20' to grey '0-20) indicate the percentage of respondents who reported no change between the pre- and post-measurement. Arcs between categories (for example from grey '0-20' to dark blue '20-40') denote the percentage of respondents who reported a change from one category to the other between the two timepoints. The 'messier' the diagram is, the larger the overtime variability.

Fig. B.4. Variable distributions United States



Notes. All variables were rescaled to range between 0 and 100, as is the case in the analyses, to make the distributions easier to read.

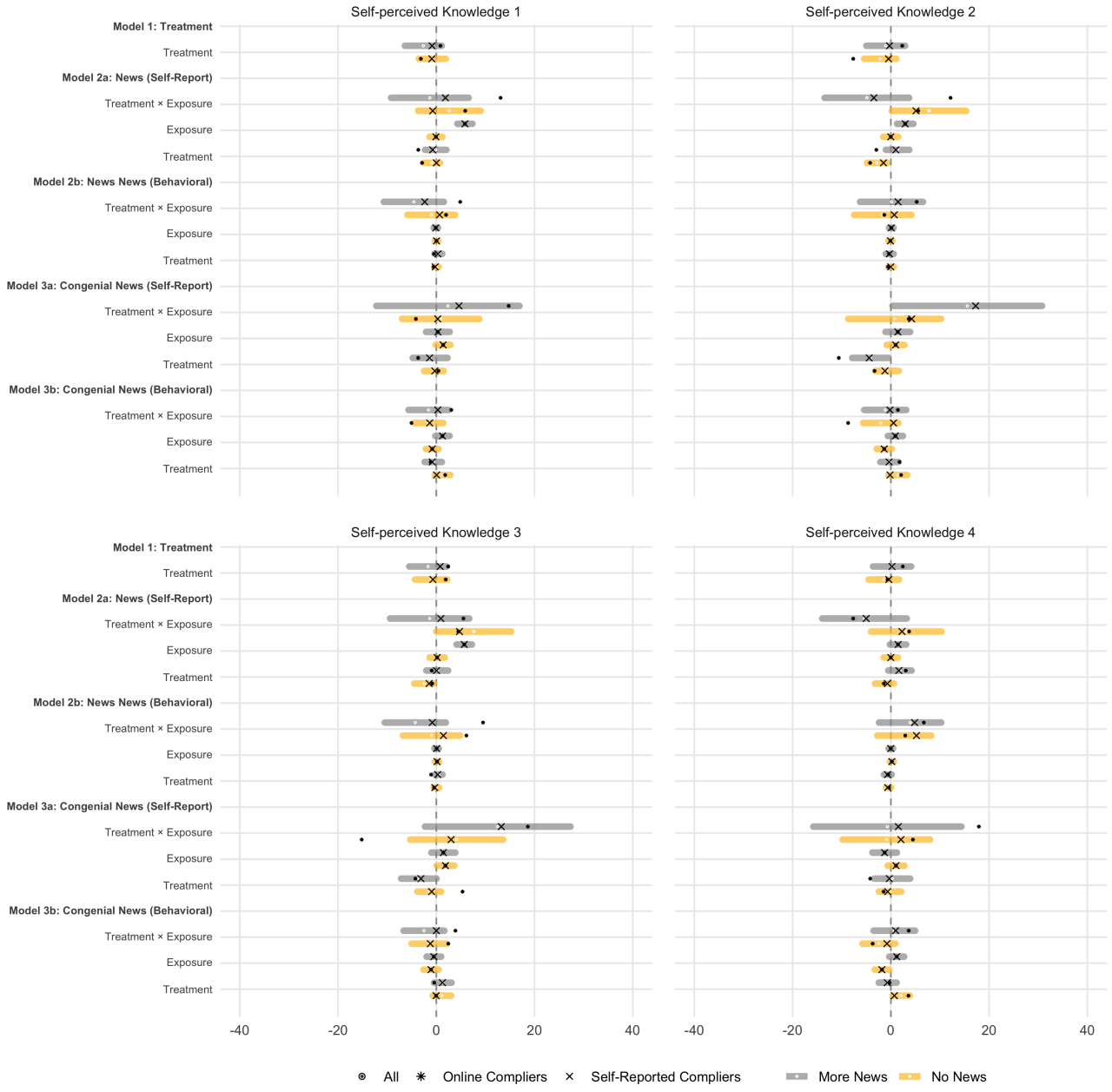
Fig. B.5. Variable distributions Poland



Notes. All variables were rescaled to range between 0 and 100, as is the case in the analyses, to make the distributions easier to read.

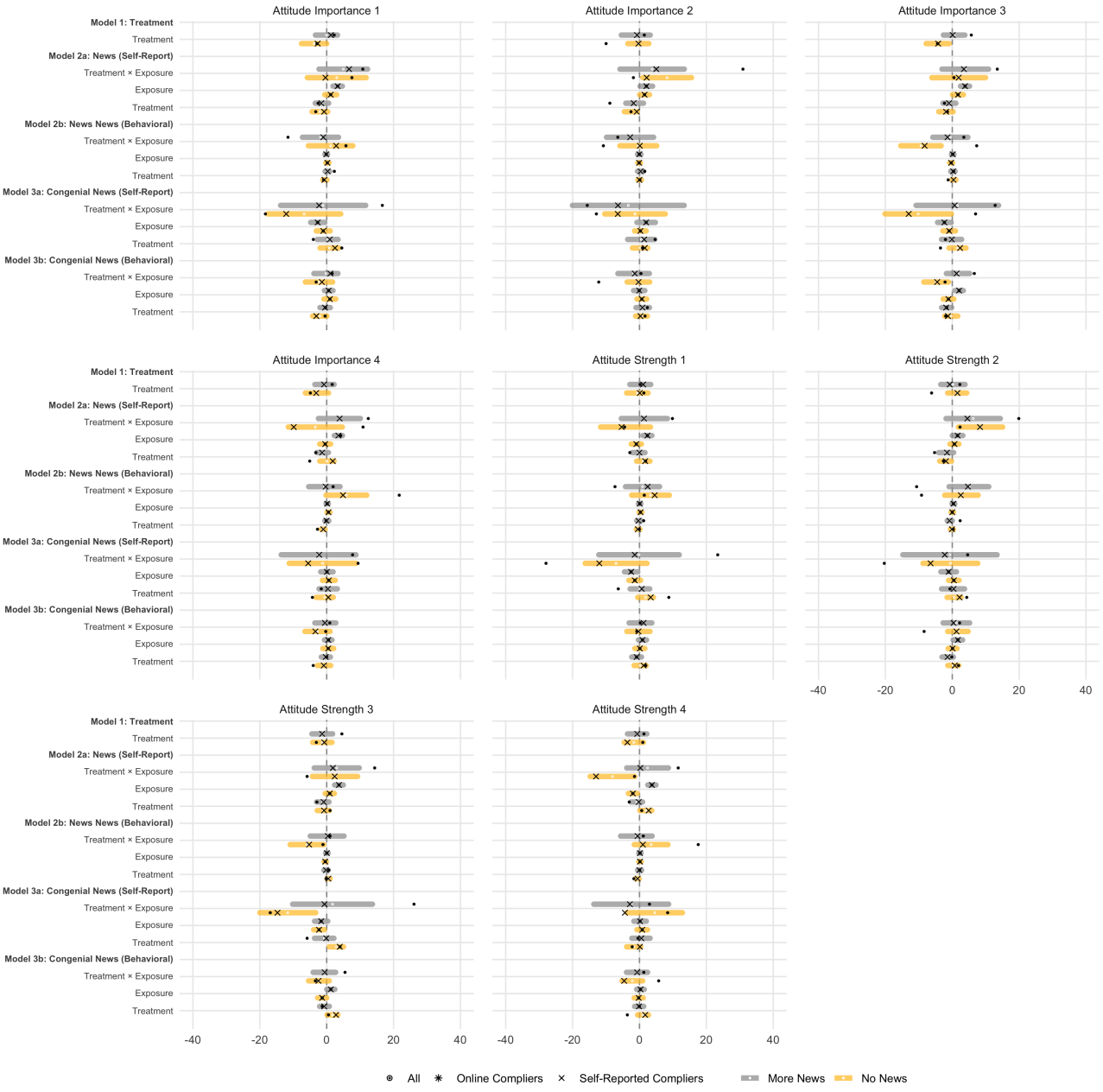
C. Additional Analyses

Fig. C.1. Disaggregated analyses political engagement



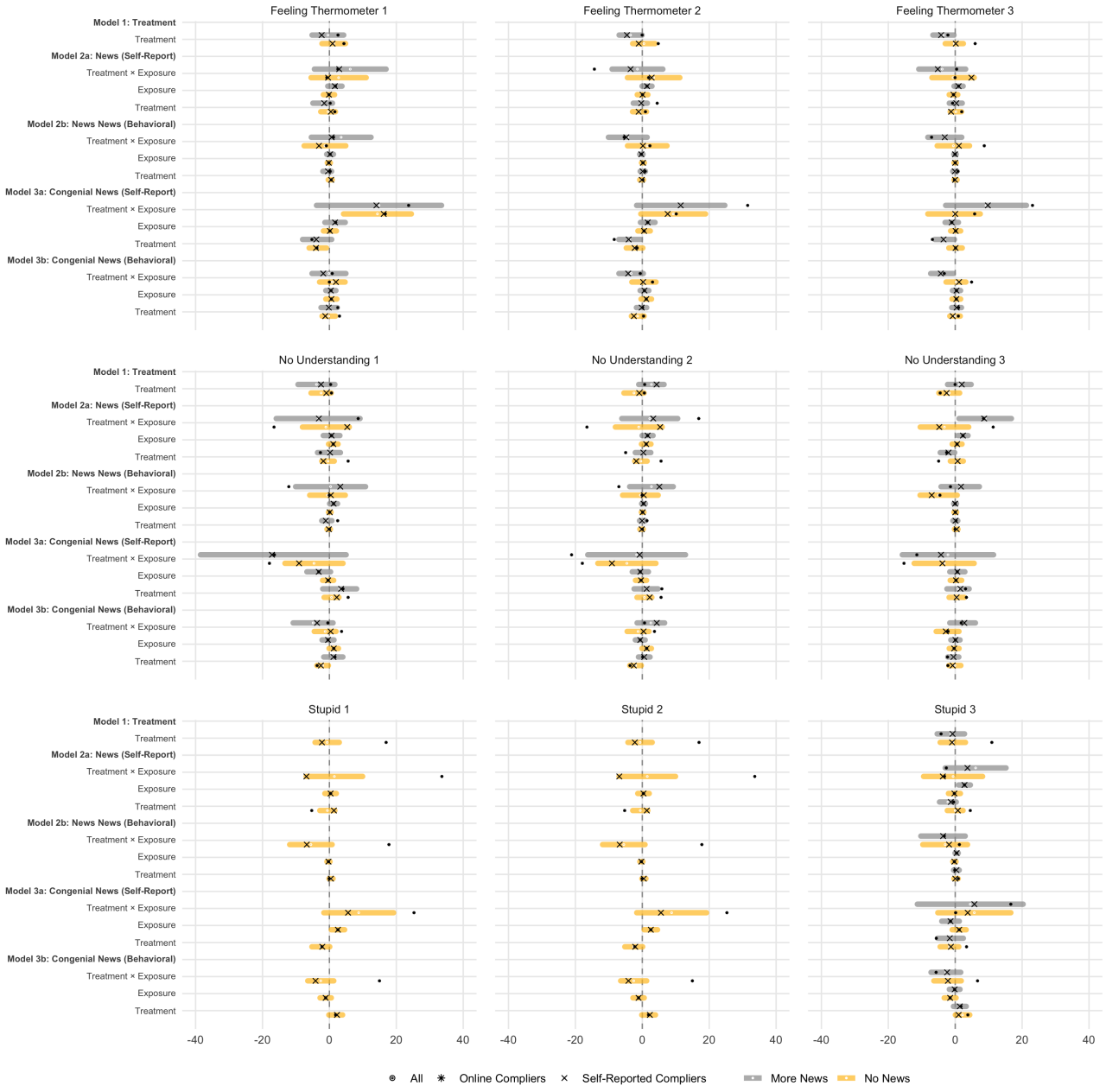
Notes. The horizontal bars indicate a 95% confidence interval surrounding the point estimate. Model 1 is based on a fixed effects model. Models 2 and 3 are based on a random effects model with a cross-level interaction between the news exposure variables and the experimental manipulation. All exposure measures were log-transformed to account for the skewed distribution. The dependent variables were rescaled between 0 and 100 so that the coefficients denote the percentual change in the dependent variable as the result of one unit increase in the independent variable. The table containing the raw scores is available in the output/tables folder in the replication repository as 'Figure C.1[C.10] - Data.xlsx'.

Fig. C.2. Disaggregated analyses attitude polarization



Notes. The horizontal bars indicate a 95% confidence interval surrounding the point estimate. Model 1 is based on a fixed effects model. Models 2 and 3 are based on a random effects model with a cross-level interaction between the news exposure variables and the experimental manipulation. All exposure measures were log-transformed to account for the skewed distribution. The dependent variables were rescaled between 0 and 100 so that the coefficients denote the percentual change in the dependent variable as the result of one unit increase in the independent variable. The table containing the raw scores is available in the output/tables folder in the replication repository as 'Figure C.1[C.10] - Data.xlsx'.

Fig. C.3. Disaggregated analyses affective polarization



Notes. The horizontal bars indicate a 95% confidence interval surrounding the point estimate. Model 1 is based on a fixed effects model. Models 2 and 3 are based on a random effects model with a cross-level interaction between the news exposure variables and the experimental manipulation. All exposure measures were log-transformed to account for the skewed distribution. The dependent variables were rescaled between 0 and 100 so that the coefficients denote the percentual change in the dependent variable as the result of one unit increase in the independent variable. The table containing the raw scores is available in the output/tables folder in the replication repository as 'Figure C.1[C.10] - Data.xlsx'.

Fig. C.4. Disaggregated analyses negative system perceptions

Notes. The horizontal bars indicate a 95% confidence interval surrounding the point estimate. Model 1 is based on a fixed effects model. Models 2 and 3 are based on a random effects model with a cross-level interaction between the news exposure variables and the experimental manipulation. All exposure measures were log-transformed to account for the skewed distribution. The dependent variables were rescaled between 0 and 100 so that the coefficients denote the percentual change in the dependent variable as the result of one unit increase in the independent variable. The table containing the raw scores is available in the output/tables folder in the replication repository as 'Figure C.1[C.10] - Data.xlsx'.

Fig. C.5. Disaggregated analyses general well-being

Notes. The horizontal bars indicate a 95% confidence interval surrounding the point estimate. Model 1 is based on a fixed effects model. Models 2 and 3 are based on a random effects model with a cross-level interaction between the news exposure variables and the experimental manipulation. All exposure measures were log-transformed to account for the skewed distribution. The dependent variables were rescaled between 0 and 100 so that the coefficients denote the percentual change in the dependent variable as the result of one unit increase in the independent variable. The table containing the raw scores is available in the output/tables folder in the replication repository as 'Figure C.1[C.10] - Data.xlsx'.