Data Donations and Political Blind Spots: Examining Bias in Combined Survey and Social Media Trace Data

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Abstract

Combined survey responses and social media digital trace data are quickly becoming the gold standard in studying the influence of social media on political outcomes. This process of "data donation" asks survey respondents to provide researchers with their digital footprint on relevant platforms for tracking how survey responses may be associated with online behaviors and consumption. Yet population-level inferences may be biased if the decision to donate is associated with characteristics related to the outcome being studied. Thus, testing for the representativeness of both easily observed demographic characteristics and harder-to-observe attitudes is a prerequisite to population-level inference and interpretations. On surveys we fielded through YouGov in 2022 and 2024 we asked respondents to donate Facebook data, YouTube histories, TikTok data and install a browser plug-in to evaluate how politically salient characteristics correlate with data donation behavior. We show that ideological conservatives under-donate, as do individuals who self-report exposure to sensitive or polarizing content online. We find that using our sample of respondents who donated digital trace data, unadjusted, would underestimate key political quantities of interest, such as affective polarization, or the level of conservatism in one's social media diet. We then recommended researchers collecting richer measures of political attitudes to inform reweighting strategies.

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1 Introduction

In recent years, access to social media platform data has become increasingly constrained (Ward, 2023; Gotfredsen, 2023). Platforms have heavily restricted public API access, effectively halting academic research through those pathways.[1] This has led to the rise of using data donations—a class of user-level platform data which individuals can request for themselves and then send to researchers— as a promising source of insight during the present era of diminishing access. Individuals request their own data from platforms, and then "donate" their data to researchers, offering a novel, user-centric pathway for studying online experiences and content exposure Ohme et al. (2024). Researchers have used data donations to study social media platforms themselves (Zannettou et al., 2023), as well as the impact these platforms have on users (Zannettou et al., 2024; Breuer et al., 2023).

While data donations present a rich and fine-grained source of platform-related data, questions remain about their representativeness. Several layers of selection effects can distort the population of individuals who donate their data relative to the general population of platform users. Prior work has shown that the likelihood of donation differs based on several demographic characteristics including age, ethnicity, and education (Keusch et al., 2024; Strycharz et al., 2024; Kmetty et al., 2024). However, less attention has been devoted to the role of politically relevant parameters such as ideology or partisanship in shaping participation in data donation efforts. Further, research utilizing data donations typically involves just one platform, making it difficult to interpret how the platform in question may impact the donation decision.

Our research objective is to assess the relationship between politically-relevant characteristics and whether an individual will agree to donate their data to researchers. Over the past 9 years, we have asked our panel of approximately 4,000 YouGov participants if they would

[1] In 2018, Meta reduced access to its API. Twitter and Reddit both ended free API access in 2023. Most new social media platforms do not have free APIs. There have been some recent improvements though. For example, regulatory frameworks such as the Digital Services Act (DSA) and the General Data Protection Regulation (GDPR) require platforms which operate within the EU to allow users access to their own data. However, unforced access to social media data has declined overall.

be willing – in return for additional monetary compensation – to provide a variety of data donations across most of the leading social media platforms, including Facebook, YouTube, and TikTok, as well as browsing history data.[2] Consistent with prior research, we find that conventional measures such as age and income play significant roles in shaping participation. However, moving beyond the extant literature, we also demonstrate that political attitudes, most notably ideological position, is strongly correlated with donation behavior. Specifically, we find that conservatives are significantly less likely to donate their data compared to liberals, and in particular very conservative respondents are less likely to donate.[3] Given the central role of political ideology in so many studies of political behavior and opinion, our finding has crucial implications for using donated data to make inferences in political science research. We also find evidence that those who self-report seeing extremist or sensitive content online, as well as those who hold less racially progressive attitudes (score high on the FIRE racism measurement scale)[4], are less likely to donate their data. Conservatives with these attitudes and content exposure are particularly prone to this selection effect. This means that we can miss subgroups that may be audiences for topics of research such as hate speech and online extremism (Siegel and Badaan, 2020; Siegel, 2020; Mitts, 2022).

In the following sections, we review existing literature on data donation and its limitations. We then outline our methodological approach, detailing the YouGov panel recruitment strategy and the social media platforms from which we collect data. We present our empirical results, highlighting in particular the ideological gap in participation in data donation, as well showing that selection bias goes beyond this to other political attitudinal measures uncovered through supervised machine learning approach. We then discuss the implications of these findings for the future of social media research with an application to the study of affective polarization. Our findings suggest that researchers hoping to use digital trace data to supplement public opinion studies should collect a richer set of political and psychological

[2]We focus on panel waves in 2022 and 2024 for most relevant donation efforts.

[3]Because this behavior is concentrated among the most conservative respondents, weighting to a coarse measure of conservatism is unlikely to be adequate for robust inferences.

[4]See Appendix Table A1.

measures, going beyond standard ideology and partisanship, if they want to make generalizable claims from donor-based samples. We end with a exercise showing how researchers can reweight their samples based on this richer set of survey measures.

2 Donation Predictors: Traits, Attitudes, and the Digital Trace

There are several types of documented bias in participation rates for survey research, which presents a challenge for population-level inference. The request for data donations has the potential to introduce another complex layer of bias. In this section, we review the extant research documenting these biases and, where our data lets us move beyond established findings, develop the hypotheses we test in the empirical sections below. These potential biases can be grouped into three dimensions: the traits of the user, the user's attitudes, and the characteristics of the digital trace data itself (what is being donated). Traits are the best-established of the three in prior work, so we state directional expectations for them rather than formal hypotheses; attitudes and digital-trace content are where our data extends beyond existing research, and we formalize those expectations as Hypotheses 1 through 3.

2.1 Traits

The traits below are well established in prior literature and we report them as directional expectations we anticipate replicating, rather than as formal hypotheses, since they are not the focus of our theoretical contribution. Several demographic characteristics are known to be correlated with participation rates in data donation. Younger, more educated individuals are generally more likely to donate data (Strycharz et al., 2024; Silber et al., 2022), but this relationship is inverted in certain settings (Kmetty et al., 2024). Most researchers hypothesize that this pattern can be explained largely by digital literacy, which also predicts donation (Silber et al., 2022; Ohme and Araujo, 2022; Breuer et al., 2023). Women are also more likely to donate (Kmetty et al., 2024; Hase and Haim, 2024). Within multi-ethnic contexts, there is some evidence that non-white individuals are less likely to donate data (Hopkins and Gorton, 2024). Those with higher digital literacy and technical skills are also more likely to donate (Hase and Haim, 2024; Kmetty et al., 2024; Strycharz et al., 2024). Accordingly, making the donation process simpler for participants can greatly increase donation rates (Silber et al., 2022; Ohme and Araujo, 2022; Breuer et al., 2023).

Further, many scholars focus on the role of digital literacy (Strycharz et al., 2024), arguing that it can be more important than attitudinal measures such as trust. However, as Guess and Munger (2023) argue, digital literacy itself is complicated to measure. We expect digital literacy to be linked to donation behavior consistent with previous research; however, we also expect there will be politically relevant covariates linked to donation.

We are unaware of any prior research which directly examines the correlation between partisanship and data donation rates in the US. However, data from survey panels in general show that online platforms tend to have a higher amount of Democrat respondents, relative to Republicans (Hopkins and Gorton, 2024).[5] We expect that the donation behavior of our panel will line up with prior research. In particular, we expect that donation propensity will be decreasing with age and income (Strycharz et al., 2024; Kmetty et al., 2024), will be higher for women (Kmetty et al., 2024), and higher for white individuals (Hopkins and Gorton, 2024). We also anticipate that partisanship will be correlated with data donation rates, with Democrats over-donating (data) relative to Republicans. However, as will be discussed below, our prior is that ideology is doing the work and not partisanship. Thus, our primary analyses focus on ideology.

2.2 Attitudes

Trust is one of the attitudes which has been most-examined in relation to data donations. Social media trace data contains very personal information, and it requires a level of trust in

[5] "Professional survey takers" also raise validity concerns for online survey panels, although Von Hohenberg et al. (2025) show that these professionals have a minimal impact on inferences from these samples.

the requester, as well as the platform on which the data is collected. Prior research has shown that higher levels of general trust can increase the rate of donation, but the relationship is tenuous (Welbers et al., 2024; Keusch et al., 2024). Efforts to increase specific trust in the requesting researchers have had mixed impacts on eliciting donations. Transparency, for example, should ostensibly engender trust, however donation behavior can actually drop as an individual's understanding of what is being donated increases (Kreuter et al., 2020).[6] Several other approaches, such as personalized appeals and increased technical support, have also failed to significantly motivate those who opt out (Hase and Haim, 2024). One notable exception is face-to-face requests, which do significantly increase the rate of donation (Welbers et al., 2024). However, it is not clear whether this approach works because it increases trust, makes the process easier, or affects some other mechanism.

An individual's valuation of their data also impacts their willingness to share it with researchers, and at what price. While researchers often refer to this type of data as a "donation," this is typically a misnomer, as participants are almost always offered some form of compensation for this data.[7] The type and amount of compensation, as one would expect, greatly affects the rate of data provision (Kmetty et al., 2024; Silber et al., 2022). However, it appears that this relationship is not linear; some individuals are unlikely to give their data at any price, and abnormally high prices can actually raise suspicion and decrease donation rates (Silber et al., 2022).

Political interest and left-leaning ideology have been shown to predict higher rates of donation in Germany (Hase and Haim, 2024). Self-reported privacy concerns have been shown to weakly predict lower donation rates (Strycharz et al., 2024; Hase and Haim, 2024). Specifically in the U.S. context (our area of interest because of our data), conservatives have

[6] This can create an ethical dilemma for researchers, as there is a trade-off between transparency and recruitment. There have been attempts to characterize the proper amount of disclosure to participants (Kreuter et al., 2020; Ohme and Araujo, 2022). However, the diversity in platform-level affordances makes it difficult to prescribe a standard disclosure level. For our participants, we explain that the data that will be transferred to and stored on secure servers, that we de-identify the collected data, and that we minimize the personally-identifiable fields which are transferred.

[7] Note, in this paper we use data donation and data export interchangeably.

also responded to a variety of research contact efforts (polls, surveys, and study participation) at lower rates (Clinton, Lapinski and Trussler, 2022). While this may be a partisan bias (Lee, 2021), it is also likely that individuals opt out for ideological reasons. Conservatives may opt out not because of partisan cues, but because they value privacy and are generally suspicious of scientists or social media platforms (Gligorić, van Kleef and Rutjens, 2025). While conservative ideology is correlated with lower levels of trust in science and scientists (Alvarez, Debnath and Ebanks, 2023) and a preference for limited institutional intrusion into private lives (Gross, Medvetz and Russell, 2011), we hold that ideology is not simply a proxy for trust in this context. Similarly, we expect that ideology will have an effect distinct from partisanship because it represents these broader belief-based cues about privacy. Thus, we expect left-leaning ideology to predict donation, even after controlling for trust and partisanship. We expect that decreased trust and conservative ideology are both associated with lower rates of data donation outlined in hypothesis one and two.[8]

Hypothesis 1 *Individuals who are less trusting are less likely to donate their data.*

Hypothesis 2 *Individuals who are ideologically conservative are less likely to donate their data.*

2.3 Digital Trace Data

The actual content of a user's digital trace data can also have an impact on donation rates. We expect that most individuals, when deciding whether they would like to download and hand over their data to a third party, will likely consider what that data would reveal about them. Similar to how social desirability bias leads respondents to consciously or subconsciously adjust how they respond to survey questions, individuals may opt out of a

[8]We have data on both partisanship and ideology. We feature both in our models, but focus primarily on ideology. While they are highly correlated in certain outcomes, we do not expect them to inherently explain the same thing in the context of data donations. We propose that the underlying conservative values about privacy and limited institutional intervention are more relevant to data donation behavior rather than contemporary partisan cues. We seek to focus on political concepts rather than just demographics in order to fully understand the implications of selection bias in question-driven applications of this data.

data donation if they fear the data might reflect poorly on them. In the context of a survey response, it has been shown that individuals adjust their replies in many cases towards what they believe is the socially desirable response (Kuklinski, Cobb and Gilens, 1997; Grimm, 2010). With data donations, individuals are not able to easily manipulate the data. Thus, the same mechanisms driving social desirability bias could also lead to a bias in willingness to donate. We are not aware of any existing research which has tested this dynamic with willingness to donate data. However, it has been shown to occur on other settings where some form of data provision is made optional. For example, a case study of making SAT scores optional in college admissions optional showed that those who omitted their SAT scores tended to have "under-performed" on the test (Robinson and Monks, 2005).

Researchers have several tools to prevent and detect social desirability bias in survey responses, including list questions, self-administered surveys, and social desirability scales (Nederhof, 1985; Larson, 2019). Unfortunately, social desirability bias in data donation consent cannot be directly measured or corrected as the needed data is ultimately missing.[9] While mainstream social media platforms typically remove content that is egregiously problematic, sensitive content remains and can be found on even heavily monitored, mainstream platforms. Sensitive content can include hate speech or racist content (Siegel, 2020), extremist content (Mitts, 2025), or adult content. If an individual recalls that they have engaged with a notable amount of sensitive content, they may be less likely to agree to donate their data for that platform. Exposure to harmful content online has been shown to be correlated with adverse outcomes offline, including increased prejudice, victimization, negative moods, and desensitization (Oksanen et al., 2014; Soral, Bilewicz and Winiewski, 2018; Ramasubramanian, 2013). It may be the case that individuals who hold intolerant attitudes are also more frequently exposed to problematic content on social media, and therefore opt out of data donation at higher rates. If this is true, studies that seek to understand sensitive or objectionable content or the audiences that engage with it will systematically underestimate

[9]Self-reports of content exposure provide a workable proxy, but face the same limitations as survey responses.

both its prevalence and its effects.

We know from Kreuter et al. (2020) that individuals are less likely to donate when the contents of the data that will be transferred is made salient. For example, if an individual learns that a researcher will have access to a type of data that they hadn't previously considered, such as their watch history, we would expect that the heightened perception of what is being given will decrease willingness to donate. We propose that, compounding this general sensitivity for privacy, individuals will be less likely to donate if they feel they have more to hide. For example, an individual who routinely watches hateful or extremist content would likely be less willing to donate their YouTube data than someone who only uses it for football highlights.

Unfortunately, we cannot directly observe what content is seen by individuals who opt out of data donation. Thus, we utilize two proxies to infer what might be present in an individual's data. First, we simply ask them how often they see sensitive, extreme, or polarizing content on social media. Second, we use a measure of racial attitudes to infer whether an individual likely consumes content which may be construed as racist (and thus could trigger caution in sharing that data (Tourangeau, Groves and Redline, 2010)). We expect that these measures will be correlated with lower donation rates as shown in hypothesis three.

Hypothesis 3 *Individuals who have sensitive content on their social media feeds (polarizing, graphic, racist) are less likely to donate their data.*

3 Data and Methods

For this project, we rely on a YouGov Panel Survey conducted between 2016 and 2024, with waves during presidential election years and the 2018 and 2022 midterms. Our team contracted with YouGov to obtain a politically representative sample of respondents, based on age, gender, race/ethnicity, education, region, and home ownership. As with many large-scale online panels used in political science research, YouGov draws respondents from an opt-in panel who are then matched to a representative sampling frame derived from the American Community Survey, voter file records, and national election benchmarks using propensity score methods, rather than through probability-based recruitment. Our findings should therefore be interpreted as characterizing the population of individuals willing to participate in this type of online panel survey rather than the U.S. adult population as a whole. Respondents were asked a multitude of questions about American politics and social media use. We focus here on the 2022 and 2024 survey waves which included requests for respondents to donate YouTube, Facebook, and TikTok data, and to install a Chrome browser extension (URL Historian) which tracks URLs visited.[10]

In 2022, we asked panelists if they would be willing to download their YouTube and/or Facebook data and send it to us for compensation. In 2024, we requested YouTube and TikTok data. In this wave, we also offered compensation for their downloading and using an app which logs the root URL for all websites visited for a period of time. In all waves, all participants were given the opportunity to consent to all types of trace data for that wave.[11]

We monitor two outcomes for each platform: whether the user consented to donate

[10]These waves and platforms were chosen because they feature similar wordings and export processes. We include our request for participants to download URL Historian because, while it is not a social media data request, it also represents a data takeout request that shows a person's digital footprint.

[11]Through several of our survey waves, we also asked for participants to provide Twitter/X data. However, the nature of this request is distinct from the requests on other platforms. For all but one of these requests, we asked for the user's Twitter handle, which they were informed would be used to collect their activity on Twitter, but it is not a multi-step data download like the other tasks. This distinction is substantively important for the paper's argument. The platforms we analyze here all require respondents to actively navigate platform settings, initiate a data export, receive and download a file, and then upload it to our servers—a multi-step process that demands deliberate, repeated choices to donate data. The Twitter request, by contrast, asked only for a single text field entry (a handle), with researchers then collecting whatever the API permitted. The behavioral burden and the respondent's sense of what they are handing over differ fundamentally: a takeout file is a concrete artifact the respondent personally produces and transfers, whereas a handle grants passive permission for researchers to extract data the respondent never directly sees or controls. This difference in cognitive and behavioral demand is the mechanism through which we theorize that political identity is related to data donation. It is most likely to operate when respondents must actively work through a process they perceive as invasive. Consistent with the request being structurally different, Twitter donations in our sample produced a distinct ideological pattern from the takeout-based platforms, suggesting it selected a different type of respondent. The URL Historian browser extension, while also involving researcher-side data collection, is more comparable to the takeout platforms because it requires respondents to actively install software and grant ongoing tracking consent—a behaviorally demanding step analogous to the export process. Thus, we focus in this paper on the four platforms whose donation requests share the same multi-step takeout structure. We use the Twitter data as a check in the final section on what the media diet looks like of someone less primed by the selection bias issues of data donation.

their data[12] and whether we successfully received data from them.[13] Our main analyses focus on actual donation behavior. The results for the consent phase are reported in the Appendix, and are substantively similar. In each wave, we ask participants whether they have an account and actively use each platform. We use this response to define whether the participant was "eligible" to donate. For the browser extension download, we classify all respondents as eligible because we do not have a measure of active Chrome users. Chrome penetration in the year this sample was collected is roughly 65%, so the population of individuals in our sample who have Chrome and are thus eligible is likely about 2,275 in 2022 and 2,600 in 2024. Results for URL Historian should be interpreted with the caveat that we don't have a true measure of the eligible sample. At the same time, this limitation is not a non-starter for interpretation: respondents could download Chrome specifically in order to participate, so baseline Chrome non-use does not map perfectly onto true ineligibility. For that reason, we view the URL Historian analyses as substantively informative, while recognizing that they are measured with more eligibility uncertainty than the platform-based takeout outcomes. Table 1 reports donation rates across our data.

Year	Total N	Platform	Eligible N	Consented	Consented %	Donated	Donated %
2022	3,500	Facebook	1,805	817	46%	619	34%
		YouTube	1,363	773	57%	405	30%
		URL Historian	3,500	1,457	42%	306	9%
2024	4,000	YouTube	2,779	1,911	69%	526	19%
		TikTok	1,277	769	60%	190	15%
		URL Historian	4,000	1,466	37%	416	10%

Table 1: Platform-Specific Eligibility, Consent, and Donation by Year

Note: Consented and donated columns are only out of eligible population. Eligibility for the URL Historian measure is defined differently from platform-based measures. Because Chrome usage is not directly observed, all respondents are treated as eligible. As a result, eligibility for this measure should be interpreted with caution, as the true eligible population is likely smaller.

[12] In most requests, participants were able to select "yes," "no," or "I do not use [platform]." In our coding, all "yes" responses are coded as 1, and if they were eligible (had an account) and said "no", they are coded as 0. For Chrome, 1 and 0 are consent and did not consent. We are not able to identify the eligible sample for Chrome use in the same way, and we document that limitation in the main text.

[13] The process for each platform differs, but in all cases we classify receipt as receiving a valid data file linked to their YouGov ID.

In our primary analyses, we model the relationship between consent to data donation and seven respondent attributes which have been shown by other authors to be correlated with donation behavior: ideology, party identification, race/ethnicity, income, education, gender, and age. Ideology is measured as a 5-point Likert scale, from very liberal (1) to very conservative (5). Next, party identification is measured on the typical PID 7 Likert scale with (1) being Strong Democrat and (7) Strong Republican. We also measure race/ethnicity as a categorical variable, income quintiles, a binary classification for whether the respondent has at least a bachelor's degree, a binary classification for gender where woman is 1, and age as a continuous variable. In addition to these variables, we also leverage several questions asked elsewhere in our survey to evaluate other potential predictors of willingness to donate. To measure trust, we use two survey questions asking about general trust (how often can you trust others) and trust in the government (how often can you trust the government to do what is right) that ranged from 1-4 where higher values indicate more trust.

To understand how features of a participant's digital trace data may affect willingness to donate, we ask participants how often they see content which is graphic or extremist, and separately content which might not be suitable for children. Higher values correspond to higher frequency of seeing this content. For racial attitudes, we use the FIRE (Fear, Institutionalized Racism, and Empathy) index where higher values on the index correspond to higher levels of racial resentment (DeSante and Smith, 2020).[14] The FIRE racial attitude measure featured in the plot is the full 4-item aggregate index.

[14]This index is an updated racial attitudes measure, designed to supplement or replace existing racial resentment measures. Additional information about the FIRE battery is also featured in the Appendix.

4 Results

4.1 Respondent Characteristics

We begin with respondent characteristics to benchmark our donation patterns against the existing data donation literature and to show that our sample reproduces many of the conventional correlates of participation before turning to the paper's main focus on political determinants of donation. For each donation request—across platforms and years—we also estimate the relationship between donation behavior and education, age, income, gender, and ethnicity as standard demographics other data donation papers use as controls. Results are featured in the Appendix in Tables A6, A20, A24, and A40.[15] We find that data donation likelihood is decreasing with age with older individuals donating data less. Education and income are not consistently statistically significant, but for most platforms and years we observe that having at least a bachelor's degree predicts slightly lower donation probability, though this relationship varies in direction across years and platforms, and higher income generally predicts a lower probability of donation.

We find that women tend to be less likely to donate relative to men, but again, this is not consistently significant. For ethnicity, Hispanic individuals are slightly less likely to donate for most platforms, relative to white participants. Our point estimates for Black individuals suggest that they may be more likely to donate, relative to white participants, but the estimate is noisy. We also examine partisan identity and find that party ID does have a significant relationship alone, but this effect disappears when ideology is included, which we discuss further in the following section.

We additionally test whether digital literacy is influential in predicting data donation as in previous studies. We do find that digital literacy is an influential predictor of donation; however political determinants of data donation matter even after digital literacy is accounted

[15] Consent-stage models for each platform and year are also reported in the Appendix: YouTube 2022 (Table A5), YouTube 2024 (Table A8), Facebook 2022 (Table A19), and URL Historian 2022 (Table A34). Results at the consent stage are broadly consistent with the donation-stage findings reported in the main text.

for (as shown in Table A7 and Table A21).[16]

4.2 Trust and Ideology

We first test H1, which predicts that individuals who are less trusting are less likely to donate their data. We next investigate the relationship between trust (both in others and in the government) and donation behavior. We report results here on how trust relates to donation behavior in 2024 at both the consent and actual donation follow through since results vary by stage.[17] General trust in others is not linked to donation behavior in our 2024 sample for YouTube, TikTok, or URL Historian (Tables A14, A13, A25, A29, A41, and A45). Across the government-trust specifications, trust appears more related to initial consent than to completed donation. While there does not appear to be a relationship between trust and YouTube consent (Table A16), or between trust and TikTok consent (Table A26), the relationship between trust and URL Historian consent is positive and statistically significant (Table A42). Follow-through estimates are inconsistent, with a null estimate for trust and TikTok (Table A28) and negative estimates for trust and YouTube and URL Historian donation/follow-through (Tables A17, A15, and A44). These results suggest that trust does not provide a consistent explanation for completed data donation, especially once respondents move from agreeing in principle to actually transferring their data.

H2 predicts that conservative individuals may opt out of data donation for ideological reasons. In our analysis, we evaluate measures for both ideology and partisan identity. Between the two, we find that ideology is a stronger predictor for willingness to donate even

[16]We find that digital literacy is inconsistently related to donation behavior based on how the sample is defined. In the case of YouTube, digital literacy predicts donation and ideology stays significant in the same direction. However, in the case of Facebook, when one defines the sample as donated data and described themselves as an active user, digital literacy did not predict donation. This suggests that being an active user on the platform may explain some previous findings that digital literacy predicts donation. Tables in the Appendix are Table A7 and A21. While many of the traits we measure may influence whether an individual will participate in our panel, they are not significantly predictive for whether an individual will donate data.

[17]Trust questions were not asked in 2022 so no comparison to 2022 digital trace samples are possible.

controlling for trust.[18] Therefore, for the remainder of the paper we focus on ideology and testing hypothesis two.

For our main analyses we report predicted probabilities of donation using marginal means.[19] In the predicted probability plots, we feature a horizontal dotted black line which denotes the 50% mark, meaning those above 50% are more likely to donate than not, and below it more likely to opt out.

We first focus on the influence political ideology has on donating, then move to other areas of substantive interest such as extremist/sensitive content, and racist content. Figure 1 reports the predicted probability of data donations across ideology for the platforms YouTube, Facebook, URL Historian and TikTok.[20] We find that, within our sample, individuals who self-identify as liberal are much more likely to donate data, relative to conservatives (conditioning on demographic characteristics included in the model). Ideologically moderate people are also more likely to donate compared to conservatives. This holds for all platforms. The difference in donation rate between the strongest liberal and strongest conservative ranges from 0.16 to 0.23 across platforms, showing that the donation gap is fairly consistent across social media platforms as well as URL Historian. While the overall donation rates on URL Historian are much lower because their eligible sample is drastically larger, the rate of difference between conservative and liberal donor stays consistent with

[18] We additionally test for the interaction between ideology and government trust in consent stages where government trust did matter, and find null results (Tables A27 and A43).

[19] Marginal means were calculated with the *emmeans* package in R. For transparency, Appendix Tables A4 (YouTube), A18 (Facebook), A22 (TikTok), and A33 (URL Historian) report the corresponding bivariate donation rates by ideology for each platform. The regression specifications used to generate the Figure 1 marginal predictions are reported in Appendix Tables A9 (YouTube), A20 (Facebook), A24 (TikTok), and A40 (URL Historian). These tables show both the raw ideology-by-donation relationship in the observed data and the adjusted model estimates on which the predicted probabilities are based in Figure 1. Specifically, for each level of ideology, we compute the predicted probability of consent while marginalizing over the empirical distribution of all other covariates in the model. We calculate the predicted probability for each observation in the dataset as if they held a given level of ideology, then average those predicted probabilities across all observations. This approach yields the average expected probability of donation at each ideology level, while fully accounting for the observed distribution of the other covariates in the sample. Unlike predictions based on fixed or modal values, this approach averages over the observed distribution of covariates in the sample.

[20] The model used for these predicted probabilities controls for party identification, race/ethnicity, income quintiles, a binary classification for whether the respondent has at least a bachelor's degree, gender, and age.

the other platforms.[21]

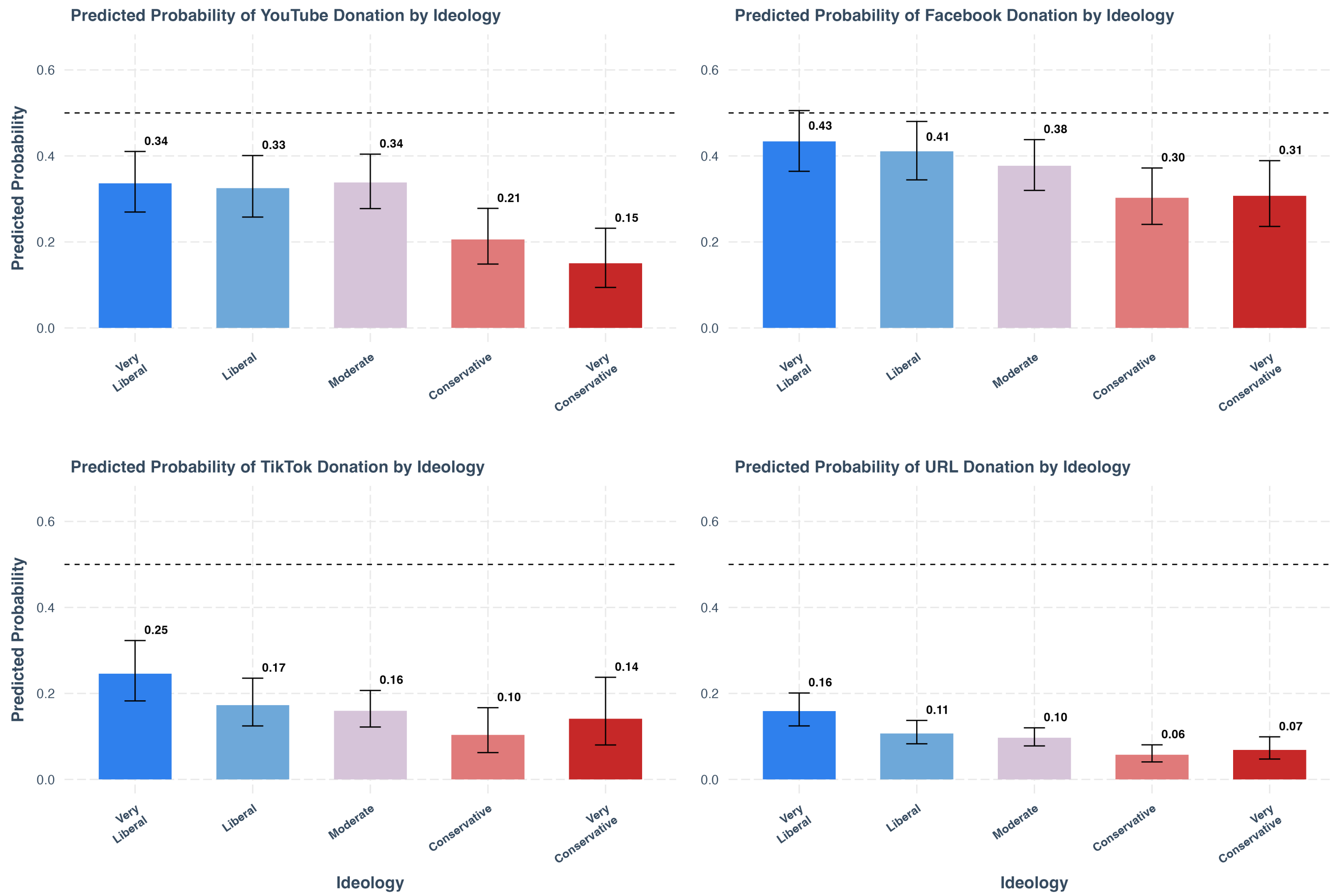

Figure 1: Predicted Probabilities for Data Donation Across Four Platforms

In all cases, ideology is significantly predictive of data donation. As alluded to earlier in the paper, we think conservative values such as a preference for minimal institutional intrusion onto private life may plausibly be associated with lower willingness to participate in data donations which are admittedly intrusive. This association between ideology and data donation consistently holds in logistic regressions predicting donation behavior (for YouTube, Facebook) while conditioning on the other relevant demographic and digital literacy variables. These can be seen in Appendix Tables A6 and A20 showing that conservative

[21] We replicate the findings here for any donation that was asked twice (from YouTube and URL Historian) and the results are featured in the Appendix. In the following section on sensitive content and racial attitudes, we show a clear association between ideology and donation behavior to YouTube even controlling for other relevant factors.

ideology (higher values of the ideology five-point scale) is negatively associated with both consenting and participating in data exports.

Taken together, ideology is the strongest and most consistent correlate of donation probability among the predictors we examine, producing predicted probability gaps of 0.16 to 0.23 between the most liberal and most conservative respondents across platforms. We note that overall model fit is modest (Tjur D ranging from 0.014 to 0.091 across specifications), reflecting the considerable unexplained variance in individual donation decisions similar to other papers on the topic, but the ideology gradient is substantively meaningful and replicates consistently across platforms and years.

To illustrate how this affects our sample composition, Figure 2 visualizes how the sample shifts at every phase of the data donation process for one of our requests: YouTube in 2022. Figure 2 begins from the full panel of 2,212 survey respondents with a valid ideology score (the most representative baseline available) rather than the YouTube-active subsample (N = 1,363; see Table 1), which is why these counts differ.[22] Of the full panel, 777 YouTube-active respondents consented to a data donation, and 404 actually completed the data submission process. At each stage of the process, we lose conservative and very conservative individuals. While the full panel was comprised of 12.4% "very conservative" respondents, by the time we winnow down to the completed digital trace donation category we are down to 4.7%. At each stage of the export process, the sample becomes more moderate and liberal.

[22]The consented and completed stages are restricted to YouTube-active respondents by construction: consent and follow-through outcomes are coded as missing for non-YouTube users, so only YouTube users appear in those bars. The small difference between the 777 shown here and the 773 in Table 1 reflects four respondents with ambiguous party identification who are retained in the figure but excluded from regression analyses.

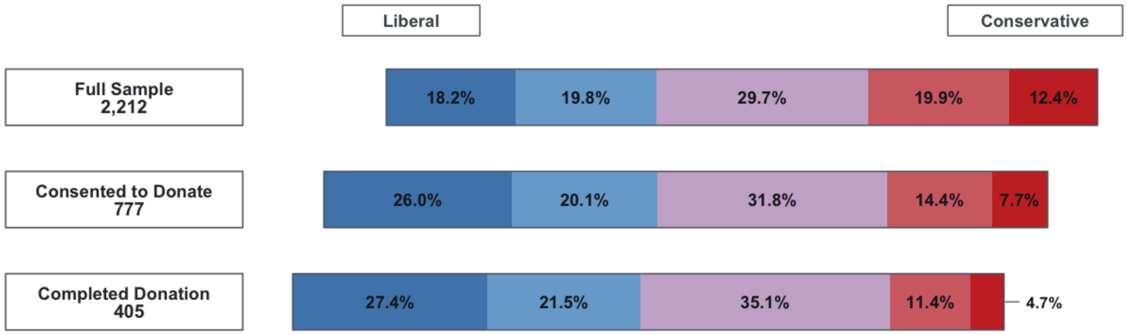

Figure 2: Ideology responses through the donation funnel (YouTube 2022)

4.3 Social Desirability and Sensitive Feeds

Next, we test H3, which predicts that those with sensitive content in their digital trace data will be less likely to share it. We focus the main-text visualizations for this section on YouTube because it provides the clearest substantive example, while the corresponding TikTok and URL Historian specifications are reported in the Appendix (Tables A30, A31, A32, A46, A47, and A48). For our 2024 data requests, we asked participants how often they view content which they would classify as graphic, or which is not suitable for children.[23] Figure 3 shows that there is, indeed, a small negative relationship between seeing content not suitable for children more frequently and willingness to donate. This means that a researcher will have a sample of digital trace data that could understate particularly toxic parts of internet consumption: people who consume the most toxic content are those least likely to donate that content.

Racially charged content is another type of sensitive content which may affect willingness to donate. Figure 4 shows that for our sample, individuals who score higher on the FIRE

[23]We split our sample and asked two different versions of this question. For half of the sample, we asked about content which is not suitable for children (sensitive in general), and for the other half we asked about graphic content (either violent, sexual, or political extremism). We analyze them separately, then combine them for the final result in the table since the results for both were the same.

index (i.e., hold less racially progressive attitudes) are less likely to donate data, even after conditioning on other relevant covariates such as ideology and demographics. [24] It should be noted that for this measure we do not directly ask individuals about exposure to racist or racially-charged content. It is not necessarily the case that individuals who score higher on the FIRE index are exposed to more racist content online. However, if a researcher wanted to try to study identity-inflected issues online, say attitudes towards Black Lives Matter or support for elite messaging along racial lines, a sample of donated data would likely miss those who have the least racially progressive attitudes.

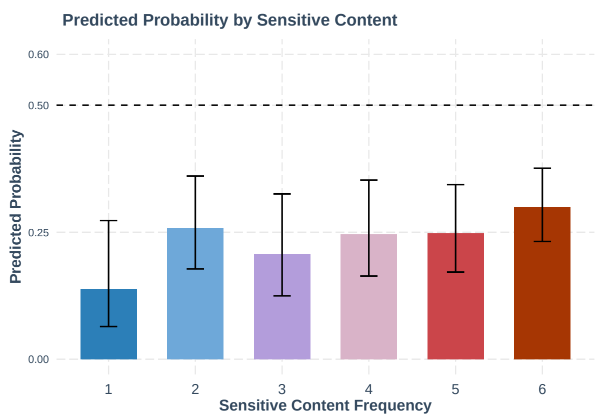

Figure 3: Sensitive Content and YouTube Donation

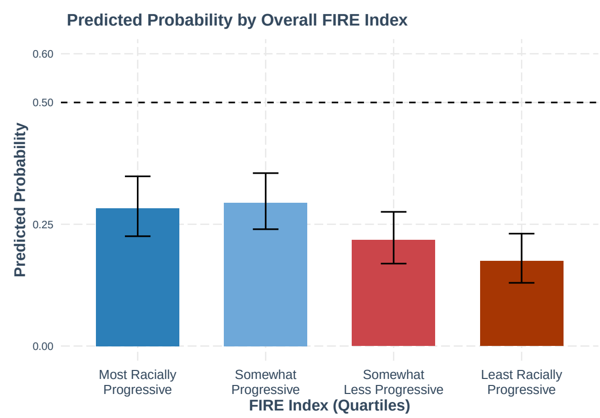

Figure 4: Racial Attitudes and YouTube Donation

Overall, we do find that individuals who self-report having more sensitive or graphic content in their feeds donate less in Figure 3. Individuals who are less racially progressive also under-donate in Figure 4. These patterns imply compositional bias in contributed trace data, where respondents who consume sensitive/graphic or hold less racially progressive attitudes are under-represented among donors.[25] We will return to how racial attitudes

[24]We take the continuous FIRE index and turn it into quartiles (Q1: 1.0–1.5, Q2: 1.5–2.25, Q3: 2.25–3.0, Q4: 3.0–4.75) rather than rounding it to whole points.

[25]We test to see if there is an interactive effect between ideology and either exposure to sensitive content or racial attitudes to confirm it is not just conservatives in these groups driving these findings. We find no relationship between ideology and sensitive feeds, conservatives and liberals report this exposure at the same rate. However, we note that conservatives are higher in their reporting of less racially progressive attitudes, and both less racially progressive attitudes and conservative ideology independently predict not completing data donation while controlling for the other.

relate to other measures such as group feeling thermometers as the potential source of non-donation.

5 Application: Using Data Donations to Study Polarization

To illustrate the implications, we present an application with a substantive example many political scientists are interested in—affective polarization—to exemplify a use case of the risk of using social media trace data for public opinion modeling without a sound reweighting strategy (Iyengar, Sood and Lelkes, 2012). Consider a scenario where a researcher has both survey and digital trace data and wishes to study affective polarization based on a social media "exposure" variable derived from the digital trace data. For instance, suppose the researcher defines exposure as the frequency with which a respondent encounters partisan content on YouTube. In practice, this variable might be measured through indicators such as whether the respondent follows official partisan channels (e.g., party-linked media outlets or politicians), the prevalence of affectively charged partisan discourse in their recommended videos, or the amount of time spent watching ideologically distinctive channels (for example, a right-leaning channel such as Daily Wire or a left-leaning channel such as The Young Turks). The researcher might then model affective polarization using this exposure measure as the key independent variable, with the difference between out-party thermometer ratings from the survey data as the dependent variable. The substantive research question is straightforward: *Is higher exposure to partisan YouTube content correlated with higher levels of affective polarization?*

If donation is systematically patterned as we have found, the resulting trace sample will not simply overrepresent liberals and moderates, a problem that can be addressed through reweighting on observed characteristics such as ideology. Rather, the concern is selection on unobserved features, specifically the type of content individuals consume within ideological groups. Among conservatives, those who choose to donate may differ systematically from those who do not in their media environments, for example in the extremity, tone, or sources of the content to which they are exposed. As a result, even after adjusting for the overall ideological distribution of respondents, the trace sample may misrepresent the composition of online discourse within ideology. This induces bias in the kinds of political content, discussions, and narratives that are captured, leading the data to understate or distort the presence and influence of certain forms of content, particularly more extreme or affectively charged material. We demonstrate how this bias manifests when looking at the dependent variable (affective polarization) and the independent variable of interest (social media exposure).

5.1 Difference in Attitudes – Risk of Selection Bias Example on Dependent Variables

We use partisan feeling thermometer questions to build measures of affective polarization (Iyengar, Sood and Lelkes, 2012; Druckman and Levendusky, 2019; Tyler and Iyengar, 2024). Affective polarization measures the degree to which Democrats and Republicans dislike each other, and is measured by the absolute value of the difference between the feeling thermometer towards Democrats and the feeling thermometer towards Republicans.

Among respondents who do not donate digital trace data, individuals with the lowest feeling thermometer scores toward Democrats are disproportionately represented.[26] As a result, these individuals are underrepresented in the subset of respondents who donate digital trace data and thus comprise our trace sample. If a researcher were to measure affective polarization using only this donor sample without correction, they would likely underestimate affective polarization among conservatives. We observe this pattern when modeling affective polarization by partisanship in Figure 5. In this analysis, we estimate a regression model that assumes a curvilinear relationship between partisanship and affective polarization, consistent with prior work (Janssen and Turkenburg, 2024), and control for ideology and other relevant

[26] See Appendix Figure A1.

covariates.[27] We present predicted values using marginal means for affective polarization in Figure 5.

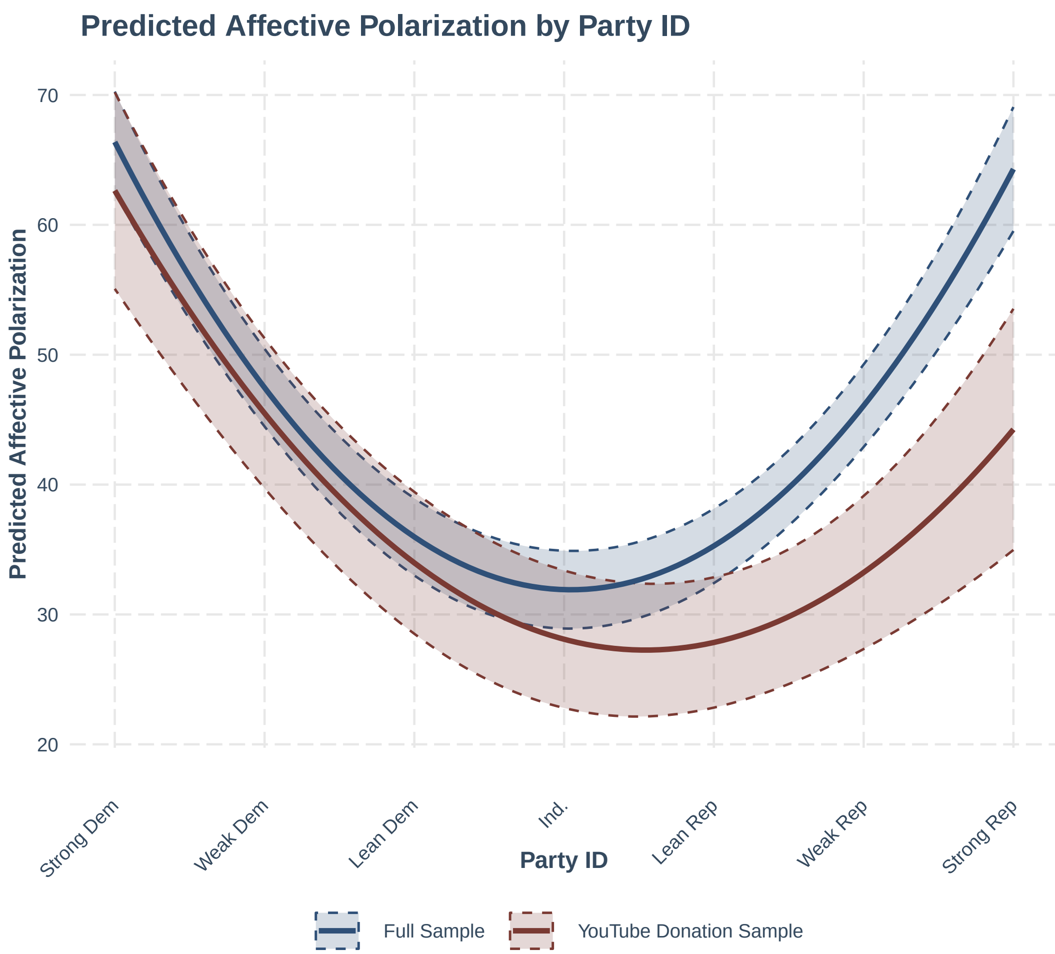

Figure 5: Difference in Predicted Probabilities for Affective Polarization by Sample

We see that for Strong Democrats, there is little difference in the amount of predicted affective polarization between samples. However, for Strong Republicans and Republicans (those who rank 6 and 7 on the PID7 scale), we considerably understate their affective polarization scores if we were using an unadjusted data donor sample. This means that we are missing Republicans who have the strongest difference between out-party and in-party animus in our trace despite controlling for partisanship and ideology. Substantively, these individuals are among the most interesting to study in the context of social media, as they

[27]See Table A57.

could be immersed in the most extreme echo (curation) chambers or exposed to the most polarizing content.

If the bias in willingness to donate is correlated with ideology, a natural response would be to reweight the sample by ideology. However, there may be important heterogeneity within the subsets of the population that under-donate. If a specific type of conservative is missing, for example those who are most affectively polarized or least racially progressive, then upweighting the conservatives who do appear in the sample risks exacerbating rather than correcting the bias. In the following sections we use our survey data on non-donors to characterize if there is a media diet gap, and where it comes from. We focus on attitudinal and policy based dimensions to see what most strongly differentiate conservative donors from non-donors.

5.2 Differences in Media Diets - Risk of Selection Bias Example with Social Media Data Independent Variables

The attitudinal differences documented above suggest that estimates from models including attitudes as a dependent variable and media diets as an independent variable will be biased. Section 5 showed that donors report higher affective polarization than the full panel. Here we examine whether they also differ in the ideological character of their social media networks which is a difference that would compound selection concerns for research using donated trace data to study content exposure or echo chambers.

We are unable to directly observe social media data for participants who opt out of donation, since by definition they did not complete the download and upload process. However, across several survey waves we also asked participants to provide their Twitter (X) username as part of our standard data collection. For those who consented, we retrieved who they followed and activity directly by scraping their profile, a process that requires nothing more than providing a handle with no data export or file upload on the respondent's part. Because sharing a Twitter handle imposes far less burden than the YouTube donation workflow, participation was less affected by the same barriers that drive donation refusal. This presents an opportunity to observe media environments for respondents who declined to donate their YouTube data but were nonetheless willing to share a Twitter handle. For those who provided a handle, we applied the network-based method of Barberá (2015) to estimate the ideological orientation of each respondent's Twitter network from the accounts they follow. This provides a measure of their social media "diet," which we use to compare the ideological content encountered by YouTube donors and non-donors. We use these scores as a close proxy for the kinds of content a respondent is "exposed" to on Twitter to understand if a respondent is going to see content that is more ideologically slanted one way or another.

Some limitations of this measure warrant acknowledgment. The Twitter (X) ideology score is an imperfect measure of political exposure on Twitter, as it captures the ideological composition of who someone follows rather than the content algorithmically surfaced to them. Furthermore, because Twitter and YouTube operate through distinct recommendation architectures the Twitter network score functions as an imperfect proxy for YouTube media diet rather than a direct measure of the YouTube content environment of non-donors. Lastly, giving a Twitter handle is still a form of data provision (that we do believe is distinct from data donation patterns), but still respondents willing to share their handle may differ systematically from those who were not.

In Figure 6 we plot respondents' social media ideology scores (as estimated from the Twitter data in the density curves) by YouTube donation status (blue and red colors) and the respondent's self-identified ideology reported in the survey (each facet). Results featured here are from 2022 YouTube data donation and 2022 Twitter digital trace data scraping. The scale runs from -2 to 2, with 2 being the most liberal and -2 being the most conservative. We see that in Figure 6 the donor and non-donor group's media diets look very similar for self-reported liberal and moderate respondents. However, when we look at the media diets of the self-reported conservatives, the sample of YouTube donors looks more moderate, and is less concentrated at the most extreme conservative end of the scale than non-donors are. This indicates that within the conservative self-report category, the media diets of donors and non-donors vary significantly.

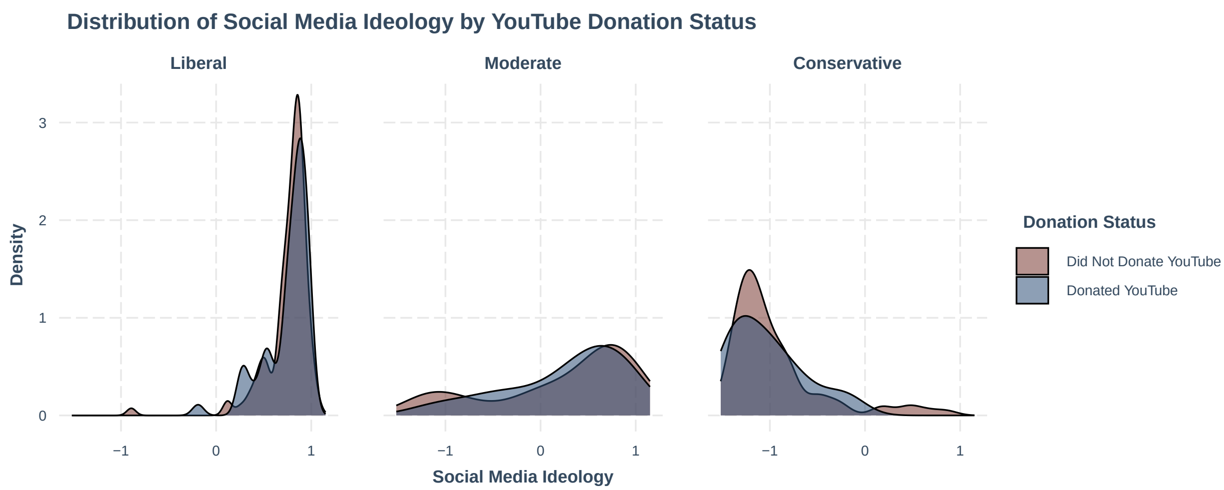

Figure 6: Ideological composition of Twitter networks by donation status and self-reported ideology

Note: Facets indicate respondents' self-identified ideology based on survey responses. The two curves distinguish respondents who donated YouTube data from those who did not in 2022 survey wave. Curves show the distribution of respondents' media diets, measured using the ideology of accounts followed on Twitter in 2022 following Barberá (2015).

This gap is concentrated within the conservative category, and because conservative donors cluster toward the moderate end of the Twitter ideology spectrum even among self-identified conservatives, standard post-stratification by ideology or party would likely increase the prevalence of more moderate conservative media diets rather than accurately reflecting the full spectrum of conservative media diets.

More concretely, up-weighting the self-identified conservative donors we already have does not add the missing extremity back into the sample, but it merely gives more weight to conservatives who we have established have digital trace data that are likely unrepresentative of conservatives as a whole. For a correction to work, it would need to upweight the donors whose media diets most resemble the *missing* non-donors and downweight the others, which requires knowing what distinguishes them beyond ideology. To explore this we use a method that can search across the full set of covariates at once and let the data reveal which ones matter.

6 Identifying the Source of Donation Bias

Our goal is to identify the other measures alongside ideology which account for why some conservatives donate their data and others do not, so that reweighting the conservative donors we do have by these covariates yields an unbiased estimate of outcomes. Supervised machine learning allows us to incorporate all available covariates from that survey wave simultaneously, identifying which dimensions of respondents' attitudes and behaviors most strongly differentiate conservative donors from non-donors beyond ideology alone. We apply gradient boosting (GBM) among self-identified conservatives in all platform and wave iterations. In all cases we rank predictors by gradient boosting feature importance and identify the top 25 variables predicting data donation.

In Appendix Tables A55 and A56 we detail results for conservative respondents across YouTube and Facebook 2022, and YouTube and TikTok 2024 donation requests. The variables most predictive of within-conservative donation behavior fall into three interpretable clusters. The largest comprises measures of *partisan and policy preferences*: issue positions and salience spanning attitudes on healthcare, size of government, and Trump's positions, jointly accounting for roughly 55% of the model's predictive gain across platforms. A second cluster of *affective group attitudes* which are feeling thermometers toward racial groups, parties, and activist organizations, contributes a further 29%. Within this cluster, the thermometers toward undocumented immigrants and thermometers towards the Republican party are the strongest consistent predictors. In this cluster in both years, immigration attitudes were a clear differentiating factor alongside both a FIRE measure in 2024 and multiple thermometers for racial groups in 2022 (where a FIRE measure is not present). We interpret this as racial attitudes being an important cleavage in differentiating data donors and non-donors. A third cluster captures *social network and media use*—the extent to which respondents inhabit ideologically homogeneous environments both online and offline, and the sorts of content they consume. This includes perceived ideological congruence of Facebook and Twitter feeds, the perception of political content on social feeds, and the kinds of media they consume including traditional news media, together accounting for approximately 17% of gain.

Overall, our findings suggest that researchers designing joint survey and data donation studies can draw largely on standard political science batteries to correct for donation bias, with a few targeted additions. The variables most predictive of within-conservative donation behavior are ones that political scientists are likely already collecting, including issue positions across social, economic, and fiscal domains, as well as feeling thermometers towards groups, and racial attitudes. While social media network batteries are less common in the discipline, they emerged as important in the machine learning approach. Items asking respondents whether they perceive their social media feeds as ideologically similar to their own views, what sorts of media they consume, and how much politics they see online also add meaningful signal. We recommend that researchers anticipating the need to reweight a donated sample include a short set of questions covering the nature of the respondent's online environment alongside more standard political attitude questions.

We now apply the top variables from the GBM results in 2022 to our affective polarization example to show how one may reweight. For the reweighting process we recommend using age (a demographic consistently linked in the literature and our sample) plus an abbreviated political battery with entropy weighting which reweights donors so that their means (for identified covariates like our GBM top 8 and age) exactly match those of non-donors without requiring a parametric model of donation propensity Hainmueller (2012). We reweight only the right aligned component of our sample from Figure 5 as these are the respondents where donors substantively differ from non-donors in a way that will bias results uncorrected.[28]

[28] We use party identification rather than ideology because affective polarization and Figure 5 are both organized by PID7 (substantively this is also how most researchers would approach working with affective po-

In this we calibrate conservative donors to conservative non-donors on the GBM-selected covariates that appear in both 2022 platform top-25 lists, plus age.

Nine variables meet that cross-platform criterion. We drop the Republican Party feeling thermometer from the calibration set because affective polarization is constructed from the partisan feeling thermometers, and balancing on a component of the outcome would build the result we are testing into the weights. That leaves eight covariates plus age.[29] Out of the 8 variables we use, two variables come from the group and racial attitudes cluster which are GOP immigration stance and the feeling thermometer toward undocumented immigrants. The remaining six come from the policy, partisan, and candidate attitudes cluster. These include one's own stance on size of government, GOP size-of-government stance, Trump's size-of-government stance, Trump's tax-the-wealthy stance, Biden's single-payer stance, and retrospective personal-finance evaluation. No variable from the network homophily and media use cluster met the cross-platform criterion in this case, but may be applicable if a researcher uses other reweighting strategies. Figure 7 applies this approach to our affective polarization example below.[30]

larization); results are substantively similar when the reweighting group is defined by self-identified ideology (ideology 4-5).

[29]If respondents had missing values for their top 8 we used MICE imputation where $M = 5$.

[30]We report the regression models underlying Figure5 and 7 in Table A57.

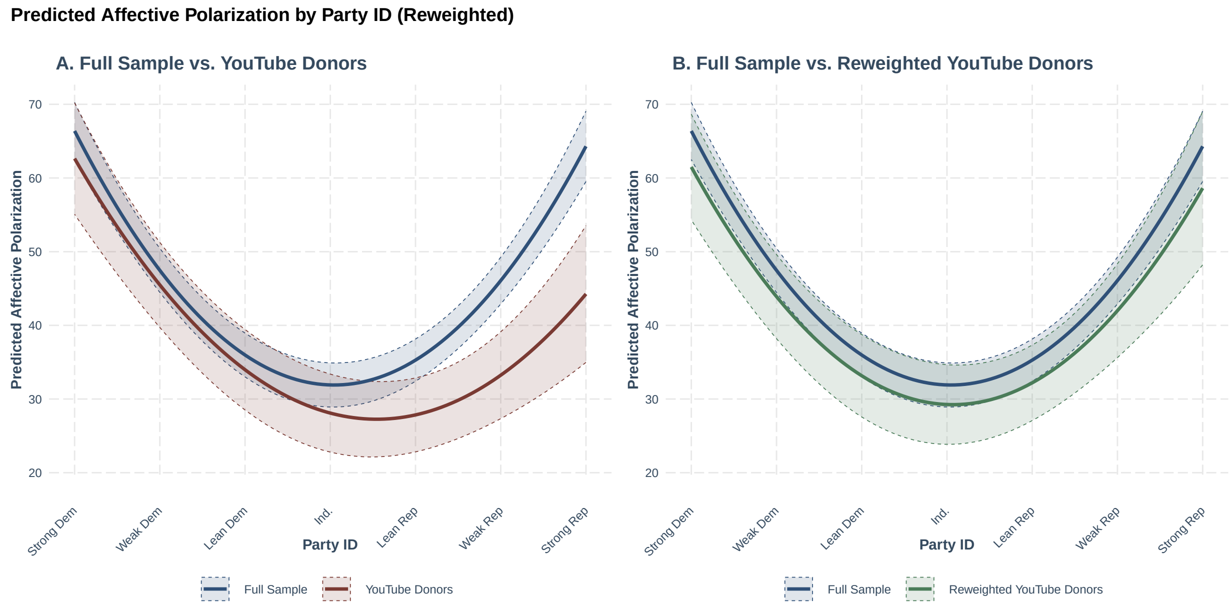

Figure 7: Predicted Affective Polarization by Party ID, Conservatives-Only Entropy-Balanced Reweighting

Panel A reproduces Figure 5's original comparison. Panel B shows the same full-sample benchmark against the reweighted donor sample. The reweighted donor sample in Panel B's affective polarization curve better follows the full-sample benchmark than the raw donor sample in Panel A, particularly among strong Republicans. This supports our recommendation that researchers should include other measures of political attitudes, as they can meaningfully close the gap introduced by data donation selection bias. Researchers working with data-donation samples and comparable survey measures can apply entropy balancing, inverse probability weighting, or other appropriate reweighting methods to correct for this kind of selection bias depending on their sample size constraints and goals. We find that entropy balancing with an informed subset of covariates that impact data donation should be an appropriate starting place for many researchers.

7 Conclusion

There are a multitude of reasons why a researcher may be interested in leveraging digital trace data from data donations. As with all sources of data, it is crucial to understand and account for any biases and asymmetries in the data collection process. In this piece we show that ideology is correlated with lack of data donation, and this has implications on the downstream analyses that can be undertaken without corrections. Across multiple platforms and years, we show that YouGov panelists who self-identify as conservative are less likely to agree to donate data. We also find evidence for under-representation of people who see extreme content or who hold less racially progressive views, even when controlling for ideology. These patterns are observed among YouGov panelists, and we expect ideological selection pressures of this kind to operate in other opt-in online panels commonly used to collect data donations, though the degree to which these findings generalize to probability-based samples remains an open question.

For some research questions, this asymmetry is not detrimental. A researcher may be interested in using donated data to understand a platform's recommendation behavior, or general engagement patterns (Zannettou et al., 2024). A biased sample of usage data may suffice for this task, so long as the dimensions of interest are orthogonal to politics. However, if researchers intend to leverage data donations for political questions, the underlying biases in data donation frequency can significantly compromise the validity of inferences.

A clear example concerns research on whether partisans experience echo chambers on social media. A common design would collect donated trace data, label the ideological leaning of content in users' browsing histories, and estimate the extent of counter-attitudinal exposure. The key concern is not that such a sample may contain too few conservatives, which can be addressed through reweighting on ideology, but that it may contain a non-representative subset of conservatives. If, within ideological groups, individuals who donate their data differ systematically from those who do not in their patterns of content consumption, then the observed trace data will misrepresent the distribution of exposure within ideological groups.

For instance, if conservative donors are less likely than conservative non-donors to inhabit tightly bounded or homogeneous information environments, estimates of echo chamber exposure will be biased downward. More generally, when selection into donation is correlated with unobserved features of media consumption within ideology, analyses of trace data may understate or distort the prevalence of echo chambers.

Our findings point to the importance of carefully diagnosing and correcting for biases in donation samples before making inferences about the political landscape. As social science continues to rely more heavily on digital trace data, strategies like the one we propose may help ensure that insights drawn from these sources reflect the full range of political behaviors and attitudes, rather than a systematically skewed slice of them.

Data Availability Statement

Research documentation that supports the findings of this study will be made available on the Political Analysis Dataverse.

Artificial Intelligence Use Statement

Additionally, the authors disclose the use of Claude Code (Anthropic) and Codex (OpenAI) at various points during the life cycle of the paper, for the following purposes: copyediting and improving the logical flow of the prose; implementing figures and tables to author-specified designs and improving their readability; and reviewing code for the statistical analyses for debugging and ensuring reproducibility. In each case, the human was in control of the work and all of the concepts, analytical decisions, figure and table designs, interpretation of results was done by the authors, with AI tools used to assist. The paper was produced through human effort and judgment, and the authors take full responsibility for any and all errors in the text.

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A Abbreviated Question List

A.1 FIRE Battery & Sensitive Content

Statement	Response Options
I am fearful of people of other races.	1. Strongly Disagree 2. Somewhat Disagree 3. Neither Agree nor Disagree 4. Somewhat Agree 5. Strongly Agree
White people in the US have certain advantages because of the color of their skin.	1. Strongly Disagree 2. Somewhat Disagree 3. Neither Agree nor Disagree 4. Somewhat Agree 5. Strongly Agree
Racial problems in the US are rare, isolated situations.	1. Strongly Disagree 2. Somewhat Disagree 3. Neither Agree nor Disagree 4. Somewhat Agree 5. Strongly Agree
I am angry that racism exists.	1. Strongly Disagree 2. Somewhat Disagree 3. Neither Agree nor Disagree 4. Somewhat Agree 5. Strongly Agree

Table A1: Survey items and associated response options.

Question	Response Options
We know people come across many different kinds of content on social media. How often do you come across any of the following types of content on social media: graphic violent content, graphic sexual content, or extreme political content?	1. Everyday 2. 3–5 days a week 3. 1–2 days a week 4. Every few weeks 5. Less often 6. Never

Table A2: Sensitive content exposure item (asked only of respondents assigned to Split_X).

Question	Response Options
We know people come across many different kinds of content on social media. How often do you see content on social media that is not suitable for children?	1. Everyday 2. 3–5 days a week 3. 1–2 days a week 4. Every few weeks 5. Less often 6. Never

Table A3: Adult content exposure item (asked only of respondents assigned to Split_Y).

A.2 Questions Text for Key GBM Variables

While most of the important variables that could be used for reweighting are standard American National Election Studies questions, we recognize the social media echo chamber questions are not standardized. We feature our main one below:

Question prompt	**Response Options**
How often do you see content on Social Media:	1. All the time
	2. Frequently
	3. Sometimes
	4. Hardly ever
	5. Never

Variable Code	**Item**
1035A	you do not find interesting or appealing
1035B	that is ideologically similar to you
1035C	that is ideologically more conservative than you
1035D	that is ideologically more liberal than you
1035E	that you would consider right wing extremism
1035F	that you would consider left wing extremism
1035G	that contains conspiracy theories

B Tables for Supplemental Analysis

B.1 YouTube

B.1.1 Descriptive Table

Table A4: YouTube Donation by Ideology in 2022

Ideology category	Eligible N	Number donated	Donation rate
Very Liberal	299	111	37.1%
Liberal	272	87	32.0%
Moderate	392	142	36.2%
Conservative	230	46	20.0%
Very Conservative	135	19	14.1%
Total	**1,328**	**405**	**30.5%**

Notes: Donation rate is the percent of eligible respondents within each ideology category who donated.

B.1.2 2022 Base Models

Table A5: YouTube 2022 Base Model: Consent

YouTube 2022 Base Model: Consent			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	2.74	2.07 – 3.41	**<0.001**
Ideology (5-Point Scale)	-0.23	-0.38 – -0.08	**0.003**
Party ID (7-Point Scale)	0.02	-0.07 – 0.10	0.719
Race: Black	0.35	-0.10 – 0.81	0.126
Race: Hispanic	0.16	-0.33 – 0.66	0.520
Income Quintile	-0.03	-0.13 – 0.06	0.506
Has BA Degree	-0.45	-0.72 – -0.18	**<0.001**
Gender	-0.19	-0.44 – 0.05	0.124
Age	-0.03	-0.03 – -0.02	**<0.001**
Observations	1180		
Tjur D	0.061		

Note: Tjur D is a coefficient of discrimination for binary logistic regression, computed as the difference in mean predicted probabilities between observed positives (donors) and observed negatives (non-donors). It ranges from 0 (no discriminatory power) to 1 (perfect separation), and is reported throughout the appendix tables as a measure of overall model fit. We caveat all models showing that Tjur D is low, indicating that these measures don't capture all of the features relevant to donation. However, the size of Tjur D or other comparable measures if fit linearly (R^2) are not sizably different from other social science models with relatively low explanatory power.

Table A6: YouTube 2022 Base Model: Donation

YouTube 2022 Base Model: Donation			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	1.74	1.07 – 2.40	**<0.001**
Ideology (5-Point Scale)	-0.17	-0.33 – -0.02	**0.030**
Party ID (7-Point Scale)	-0.03	-0.13 – 0.06	0.500
Race: Black	0.09	-0.36 – 0.53	0.702
Race: Hispanic	-0.18	-0.69 – 0.34	0.501
Income Quintile	0.02	-0.08 – 0.12	0.718
Has BA Degree	-0.17	-0.46 – 0.11	0.229
Gender	-0.20	-0.47 – 0.06	0.130
Age	-0.03	-0.04 – -0.03	**<0.001**
Observations	1180		
Tjur D	0.068		

B.1.3 2022 Digital Literacy Models

Table A7: YouTube 2022 Digital Literacy Model

YouTube 2022 Digital Literacy Model			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	-0.21	-1.97 – 1.56	0.817
Ideology (5-Point Scale)	-0.22	-0.43 – -0.01	**0.042**
Race: Black	-0.24	-1.09 – 0.61	0.580
Race: Hispanic	-0.57	-1.71 – 0.58	0.332
Income Quintile	-0.05	-0.25 – 0.15	0.644
Has BA Degree	-0.48	-1.04 – 0.08	0.094
Gender	-0.42	-0.94 – 0.10	0.116
Age	-0.02	-0.05 – -0.00	**0.015**
Digital Literacy Index	0.46	0.17 – 0.74	**0.002**
Observations	352		
Tjur D	0.091		

B.1.4 2024 Base Models

Table A8: YouTube 2024 Base Model: Consent

YouTube 2024 Base Model: Consent			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	-0.15	-0.54 – 0.25	0.465
Ideology (5-Point Scale)	-0.11	-0.21 – -0.01	**0.035**
Party ID (7-Point Scale)	-0.03	-0.09 – 0.03	0.295
Race: Black	0.13	-0.13 – 0.38	0.326
Race: Hispanic	-0.06	-0.38 – 0.26	0.722
Income Quintile	-0.13	-0.20 – -0.06	**<0.001**
Has BA Degree	0.10	-0.09 – 0.29	0.321
Gender	-0.15	-0.33 – 0.03	0.094
Age	0.00	-0.00 – 0.01	0.126
Observations	2376		
Tjur D	0.014		

Table A9: YouTube 2024 Base Model: Donation

YouTube 2024 Base Model: Donation			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	-0.73	-1.20 – -0.25	**0.003**
Ideology (5-Point Scale)	-0.23	-0.36 – -0.11	**<0.001**
Party ID (7-Point Scale)	-0.03	-0.10 – 0.04	0.470
Race: Black	-0.01	-0.32 – 0.30	0.958
Race: Hispanic	-0.55	-1.01 – -0.10	**0.018**
Income Quintile	-0.08	-0.17 – 0.00	0.052
Has BA Degree	0.24	0.01 – 0.47	**0.041**
Gender	-0.18	-0.40 – 0.04	0.101
Age	0.00	-0.00 – 0.01	0.283
Observations	2376		
Tjur D	0.022		

B.1.5 2024 Sensitive Content Models

Table A10: YouTube 2024 Sensitive Content Models: Graphic violence / sexual / extreme political content

Predictors	*Log-Odds*	*CI*	*p*
Intercept	0.67	-0.12 – 1.46	0.097
Ideology (5-Point Scale)	-0.37	-0.51 – -0.22	**<0.001**
Sensitive content: graphic violence/sexual/extreme political	-0.11	-0.21 – -0.01	**0.037**
Has BA Degree	0.14	-0.23 – 0.50	0.463
Income Quintile	-0.12	-0.26 – 0.01	0.066
Age	0.00	-0.01 – 0.01	0.502
Gender	-0.32	-0.66 – 0.03	0.074
Race: Black	0.08	-0.40 – 0.55	0.748
Race: Hispanic	-0.26	-0.91 – 0.38	0.422
Observations	723		
Tjur D	0.051		

Table A11: YouTube 2024 Sensitive Content Models: Content not suitable for children

Predictors	*Log-Odds*	*CI*	*p*
Intercept	0.47	-0.41 – 1.36	0.338
Ideology (5-Point Scale)	-0.29	-0.43 – -0.14	**<0.001**
Sensitive content: not suitable for children	0.07	-0.04 – 0.18	0.234
Has BA Degree	0.41	0.04 – 0.78	**0.028**
Income Quintile	-0.07	-0.20 – 0.07	0.328
Age	-0.02	-0.03 – -0.01	**0.004**
Gender	-0.12	-0.47 – 0.23	0.503
Race: Black	0.03	-0.48 – 0.53	0.915
Race: Hispanic	-0.98	-1.72 – -0.23	**0.010**
Observations	722		
Tjur D	0.057		

B.1.6 2024 FIRE Models

Table A12: YouTube 2024 FIRE Model

YouTube 2024 FIRE Model			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	0.77	0.17 – 1.37	**0.014**
Ideology (5-Point Scale)	-0.24	-0.36 – -0.12	**<0.001**
FIRE index	-0.18	-0.36 – -0.00	**0.049**
Has BA Degree	0.26	0.01 – 0.52	**0.045**
Income Quintile	-0.10	-0.19 – -0.00	**0.041**
Age	-0.01	-0.02 – 0.00	0.050
Gender	-0.23	-0.48 – 0.01	0.061
Race: Black	0.01	-0.34 – 0.35	0.972
Race: Hispanic	-0.60	-1.08 – -0.12	**0.014**
Observations	1445		
Tjur D	0.047		

B.1.7 2024 Trust Models

Table A13: YouTube 2024 Trust Model: General Trust

YouTube 2024 Trust Model: General Trust			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	0.40	-0.15 – 0.96	0.178
Ideology (5-Point Scale)	-0.31	-0.41 – -0.21	**<0.001**
General Trust	0.17	-0.08 – 0.42	0.189
Has BA Degree	0.30	0.04 – 0.55	**0.024**
Income Quintile	-0.10	-0.20 – -0.01	**0.031**
Age	-0.01	-0.01 – 0.00	0.082
Gender	-0.19	-0.43 – 0.05	0.123
Race: Black	0.07	-0.28 – 0.41	0.704
Race: Hispanic	-0.58	-1.06 – -0.10	**0.019**
Observations	1445		
Tjur D	0.045		

Table A14: YouTube 2024 General Trust Model: Consent

YouTube 2024 General Trust Model: Consent			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	1.60	1.09 – 2.12	**<0.001**
Ideology (5-Point Scale)	-0.21	-0.30 – -0.12	**<0.001**
General Trust	0.02	-0.21 – 0.24	0.891
Race: Black	0.27	-0.05 – 0.58	0.096
Race: Hispanic	-0.08	-0.46 – 0.30	0.696
Income Quintile	-0.18	-0.26 – -0.10	**<0.001**
Has BA Degree	0.11	-0.12 – 0.34	0.342
Gender	-0.19	-0.40 – 0.03	0.090
Age	-0.01	-0.02 – -0.00	**0.011**
Observations	1445		
Tjur D	0.038		

Table A15: YouTube 2024 Trust Model: Government Trust

YouTube 2024 Trust Model: Government Trust			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	0.66	0.11 – 1.21	**0.022**
Ideology (5-Point Scale)	-0.32	-0.42 – -0.22	**<0.001**
Government Trust	-0.44	-0.75 – -0.13	**0.006**
Has BA Degree	0.29	0.04 – 0.55	**0.025**
Income Quintile	-0.09	-0.18 – 0.01	0.065
Age	-0.01	-0.02 – -0.00	**0.041**
Gender	-0.23	-0.47 – 0.02	0.068
Race: Black	0.09	-0.25 – 0.44	0.603
Race: Hispanic	-0.60	-1.08 – -0.12	**0.015**
Observations	1445		
Tjur D	0.049		

Table A16: YouTube 2024 Trust Model: Consent

YouTube 2024 Trust Model: Consent			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	1.68	1.17 – 2.19	**<0.001**
Ideology (5-Point Scale)	-0.21	-0.30 – -0.12	**<0.001**
Government Trust	-0.18	-0.44 – 0.09	0.193
Race: Black	0.29	-0.03 – 0.60	0.077
Race: Hispanic	-0.07	-0.45 – 0.31	0.701
Income Quintile	-0.18	-0.26 – -0.09	**<0.001**
Has BA Degree	0.11	-0.12 – 0.34	0.347
Gender	-0.20	-0.42 – 0.02	0.072
Age	-0.01	-0.02 – -0.00	**0.007**
Observations	1445		
Tjur D	0.039		

Table A17: YouTube 2024 Trust Model: Donation

YouTube 2024 Trust Model: Donation			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	0.66	0.11 – 1.21	**0.022**
Ideology (5-Point Scale)	-0.32	-0.42 – -0.22	**<0.001**
Government Trust	-0.44	-0.75 – -0.13	**0.006**
Race: Black	0.09	-0.25 – 0.44	0.603
Race: Hispanic	-0.60	-1.08 – -0.12	**0.015**
Income Quintile	-0.09	-0.18 – 0.01	0.065
Has BA Degree	0.29	0.04 – 0.55	**0.025**
Gender	-0.23	-0.47 – 0.02	0.068
Age	-0.01	-0.02 – -0.00	**0.041**
Observations	1445		
Tjur D	0.049		

B.2 Facebook

Facebook was only collected in 2022, no 2024 takeouts are available for analyses.

B.2.1 Descriptive Table

Table A18: Facebook Donation by Ideology in 2022

Ideology category	Eligible N	Number donated	Donation rate
Very Liberal	337	144	42.7%
Liberal	357	136	38.1%
Moderate	517	189	36.6%
Conservative	339	90	26.5%
Very Conservative	209	60	28.7%
Total	**1,759**	**619**	**35.2%**

Notes: Donation rate is the percent of eligible respondents within each ideology category who donated.

B.2.2 2022 Base Models

Table A19: Facebook 2022 Base Model: Consent

Facebook 2022 Base Model: Consent			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	2.41	1.81 – 3.00	**<0.001**
Ideology (5-Point Scale)	-0.20	-0.32 – -0.07	**0.003**
Party ID (7-Point Scale)	0.02	-0.05 – 0.09	0.635
Race: Black	0.32	-0.09 – 0.72	0.123
Race: Hispanic	0.26	-0.21 – 0.72	0.280
Income Quintile	-0.07	-0.15 – 0.01	0.106
Has BA Degree	-0.29	-0.52 – -0.07	**0.011**
Gender	-0.29	-0.50 – -0.08	**0.006**
Age	-0.03	-0.04 – -0.02	**<0.001**
Observations	1596		
Tjur D	0.058		

Table A20: Facebook 2022 Base Model: Donation

Facebook 2022 Base Model: Donation			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	1.43	0.84 – 2.02	**<0.001**
Ideology (5-Point Scale)	-0.19	-0.32 – -0.06	**0.005**
Party ID (7-Point Scale)	0.02	-0.05 – 0.10	0.564
Race: Black	0.18	-0.22 – 0.59	0.372
Race: Hispanic	0.15	-0.31 – 0.61	0.529
Income Quintile	-0.03	-0.11 – 0.05	0.465
Has BA Degree	-0.22	-0.45 – 0.01	0.061
Gender	-0.38	-0.59 – -0.16	**<0.001**
Age	-0.02	-0.03 – -0.01	**<0.001**
Observations	1596		
Tjur D	0.038		

B.2.3 2022 Digital Literacy Models

Table A21: Facebook 2022 Digital Literacy Model

Facebook 2022 Digital Literacy Model			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	-0.52	-1.93 – 0.89	0.468
Ideology (5-Point Scale)	-0.03	-0.20 – 0.13	0.691
Race: Black	0.62	-0.15 – 1.38	0.113
Race: Hispanic	-0.06	-0.94 – 0.83	0.899
Income Quintile	-0.07	-0.23 – 0.09	0.412
Has BA Degree	-0.16	-0.60 – 0.29	0.493
Gender	-0.47	-0.88 – -0.07	**0.023**
Age	-0.00	-0.02 – 0.01	0.662
Digital Literacy Index	0.19	-0.00 – 0.39	0.053
Observations	455		
Tjur D	0.030		

B.3 TikTok

TikTok takeouts were only requested in 2024, no 2022 takeouts are available for analyses.

B.3.1 Descriptive Table

Table A22: TikTok Donation by Ideology

Ideology category	Eligible N	Number donated	Donation rate
Very Liberal	240	51	21.2%
Liberal	246	36	14.6%
Moderate	449	68	15.1%
Conservative	195	18	9.2%
Very Conservative	94	12	12.8%
Total	**1,224**	**185**	**15.1%**

Notes: Donation rate is the percent of eligible respondents within each ideology category who donated.

B.3.2 2024 Base Models

Table A23: TikTok 2024 Base Model: Consent

TikTok 2024 Base Model: Consent			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	0.24	-0.33 – 0.82	0.366
Ideology (5-Point Scale)	-0.05	-0.19 – 0.08	0.436
Party ID (7-Point Scale)	-0.03	-0.10 – 0.05	0.471
Race: Black	0.37	0.05 – 0.68	**0.024**
Race: Hispanic	-0.05	-0.47 – 0.38	0.835
Income Quintile	-0.20	-0.30 – -0.11	**<0.001**
Has BA Degree	0.03	-0.24 – 0.30	0.813
Gender	-0.33	-0.58 – -0.08	**0.009**
Age	0.01	0.00 – 0.02	**0.038**
Observations	1086		
Tjur D	0.033		

Table A24: TikTok 2024 Base Model: Follow-Through

TikTok 2024 Base Model: Follow-Through			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	-0.43	-1.20 – 0.34	0.250
Ideology (5-Point Scale)	-0.25	-0.43 – -0.07	**0.007**
Party ID (7-Point Scale)	0.02	-0.08 – 0.11	0.758
Race: Black	0.50	0.10 – 0.90	**0.013**
Race: Hispanic	0.15	-0.42 – 0.72	0.600
Income Quintile	-0.16	-0.29 – -0.03	**0.017**
Has BA Degree	0.18	-0.19 – 0.54	0.341
Gender	-0.10	-0.44 – 0.24	0.569
Age	-0.01	-0.02 – 0.00	0.159
Observations	1086		
Tjur D	0.023		

B.3.3 2024 Trust Models

Table A25: TikTok 2024 General Trust Model: Consent

TikTok 2024 General Trust Model: Consent			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	0.73	-0.10 – 1.56	0.078
Ideology (5-Point Scale)	-0.14	-0.28 – 0.00	0.052
General Trust	0.02	-0.33 – 0.36	0.927
Race: Black	0.69	0.26 – 1.12	**0.002**
Race: Hispanic	0.39	-0.18 – 0.96	0.180
Income Quintile	-0.23	-0.36 – -0.10	**<0.001**
Has BA Degree	0.15	-0.21 – 0.50	0.425
Gender	-0.19	-0.53 – 0.15	0.283
Age	0.01	-0.00 – 0.02	0.161
Observations	604		
Tjur D	0.045		

Table A26: TikTok 2024 Trust Model: Consent

TikTok 2024 Trust Model: Consent			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	0.74	-0.08 – 1.55	0.068
Ideology (5-Point Scale)	-0.14	-0.28 – 0.00	0.051
Government Trust	0.00	-0.39 – 0.39	0.991
Race: Black	0.69	0.25 – 1.12	**0.002**
Race: Hispanic	0.39	-0.18 – 0.96	0.181
Income Quintile	-0.23	-0.36 – -0.10	**<0.001**
Has BA Degree	0.15	-0.21 – 0.50	0.424
Gender	-0.19	-0.53 – 0.15	0.280
Age	0.01	-0.00 – 0.02	0.165
Observations	604		
Tjur D	0.045		

Interaction check: We also estimated a TikTok consent model interacting ideology with government trust. The interaction term was not statistically distinguishable from zero, indicating that the association between government trust and consent does not appear to vary meaningfully by ideology in this specification.

Table A27: TikTok 2024 Trust Model - Consent with Ideology x Government Trust

TikTok 2024 Trust Model - Consent with Ideology x Government Trust			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	0.82	-0.01 – 1.66	**0.048**
Ideology (5-Point Scale)	-0.18	-0.34 – -0.02	**0.031**
Government Trust	-0.44	-1.42 – 0.55	0.387
Race: Black	0.68	0.25 – 1.12	**0.002**
Race: Hispanic	0.38	-0.19 – 0.95	0.188
Income Quintile	-0.23	-0.36 – -0.10	**<0.001**
Has BA Degree	0.15	-0.21 – 0.50	0.425
Gender	-0.19	-0.53 – 0.15	0.277
Age	0.01	-0.00 – 0.02	0.139
Ideology (5-Point Scale):Government Trust	0.16	-0.17 – 0.49	0.345
Observations	604		
Tjur D	0.047		

Table A28: TikTok 2024 Trust Model: Follow-Through

TikTok 2024 Trust Model: Follow-Through			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	-0.04	-1.00 – 0.93	0.910
Ideology (5-Point Scale)	-0.31	-0.48 – -0.13	**<0.001**
Government Trust	-0.23	-0.72 – 0.26	0.350
Race: Black	0.62	0.15 – 1.10	**0.011**
Race: Hispanic	0.24	-0.44 – 0.92	0.491
Income Quintile	-0.13	-0.29 – 0.03	0.100
Has BA Degree	0.19	-0.24 – 0.63	0.389
Gender	-0.00	-0.42 – 0.42	0.991
Age	-0.01	-0.02 – 0.01	0.337
Observations	604		
Tjur D	0.039		

Table A29: TikTok 2024 General Trust Model: Follow-Through

TikTok 2024 General Trust Model: Follow-Through			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	-0.25	-1.25 – 0.75	0.598
Ideology (5-Point Scale)	-0.30	-0.48 – -0.12	**<0.001**
General Trust	0.21	-0.22 – 0.63	0.337
Race: Black	0.61	0.14 – 1.09	**0.012**
Race: Hispanic	0.28	-0.41 – 0.96	0.430
Income Quintile	-0.15	-0.31 – 0.01	0.067
Has BA Degree	0.20	-0.24 – 0.63	0.377
Gender	0.04	-0.38 – 0.46	0.844
Age	-0.01	-0.02 – 0.01	0.406
Observations	604		
Tjur D	0.039		

B.3.4 2024 FIRE Models

Table A30: TikTok 2024 FIRE Model

TikTok 2024 FIRE Model			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	-0.19	-1.05 – 0.66	0.655
Ideology (5-Point Scale)	-0.25	-0.46 – -0.05	**0.014**
FIRE index	-0.15	-0.44 – 0.15	0.330
Race: Black	0.61	0.13 – 1.08	**0.012**
Race: Hispanic	0.26	-0.42 – 0.94	0.452
Income Quintile	-0.14	-0.30 – 0.02	0.087
Has BA Degree	0.18	-0.26 – 0.62	0.418
Gender	-0.04	-0.46 – 0.37	0.847
Observations	604		
Tjur D	0.038		

B.3.5 2024 Sensitive Content Models

Table A31: TikTok 2024 Sensitive Content Models: Graphic violence / sexual / extreme political content

Predictors	*Log-Odds*	*CI*	*p*
Intercept	-0.05	-1.18 – 1.08	0.931
Ideology (5-Point Scale)	-0.44	-0.69 – -0.19	**<0.001**
Sensitive content: graphic violence/sexual/extreme political	0.02	-0.15 – 0.19	0.797
Race: Black	0.31	-0.41 – 1.02	0.400
Race: Hispanic	0.47	-0.45 – 1.39	0.315
Income Quintile	-0.16	-0.38 – 0.07	0.164
Has BA Degree	0.32	-0.30 – 0.93	0.311
Gender	0.01	-0.56 – 0.59	0.960
Observations	310		
Tjur D	0.055		

Table A32: TikTok 2024 Sensitive Content Models: Content not suitable for children

Predictors	*Log-Odds*	*CI*	*p*
Intercept	-1.22	-2.55 – 0.11	0.072
Ideology (5-Point Scale)	-0.16	-0.41 – 0.10	0.233
Sensitive content: not suitable for children	0.09	-0.09 – 0.27	0.339
Race: Black	0.95	0.30 – 1.60	**0.004**
Race: Hispanic	-0.02	-1.06 – 1.03	0.976
Income Quintile	-0.08	-0.30 – 0.15	0.512
Has BA Degree	-0.01	-0.64 – 0.63	0.984
Gender	-0.08	-0.69 – 0.52	0.786
Observations	294		
Tjur D	0.044		

Table A33: URL Donation by Ideology

Ideology category	Eligible N	Number donated	Donation rate
Very Liberal	555	100	18.0%
Liberal	699	83	11.9%
Moderate	1,296	140	10.8%
Conservative	743	43	5.8%
Very Conservative	495	33	6.7%
Total	**3,788**	**399**	**10.5%**

Notes: Donation rate is the percent of eligible respondents within each ideology category who donated.

B.4 URL Historian

B.4.1 Descriptive Table

B.4.2 2022 Base Models

Notes: For URL Historian 2022, we report both PID-adjusted and no-PID specifications. In this platform-wave combination, ideology and party identification are closely correlated; with both included, ideology weakens, while in the no-PID donation model the ideology gradient is more apparent.

Table A34: URL Historian 2022 Base Model: Consent

URL Historian 2022 Base Model: Consent			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	1.59	1.08 – 2.11	**<0.001**
Ideology (5-Point Scale)	-0.11	-0.22 – 0.00	0.057
Party ID (7-Point Scale)	-0.04	-0.10 – 0.03	0.242
Race: Black	0.27	-0.07 – 0.61	0.125
Race: Hispanic	0.27	-0.14 – 0.68	0.198
Income Quintile	-0.12	-0.19 – -0.04	**0.002**
Has BA Degree	-0.07	-0.27 – 0.13	0.507
Gender	0.10	-0.09 – 0.28	0.310
Age	-0.02	-0.03 – -0.01	**<0.001**
Observations	1993		
Tjur D	0.046		

Table A35: URL Historian 2022 Base Model: Consent (No PID)

URL Historian 2022 Base Model: Consent (No PID)			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	1.58	1.06 – 2.09	**<0.001**
Ideology (5-Point Scale)	-0.16	-0.24 – -0.09	**<0.001**
Race: Black	0.31	-0.02 – 0.65	0.070
Race: Hispanic	0.27	-0.13 – 0.68	0.188
Income Quintile	-0.11	-0.19 – -0.04	**0.002**
Has BA Degree	-0.07	-0.27 – 0.13	0.512
Gender	0.10	-0.09 – 0.29	0.297
Age	-0.02	-0.03 – -0.01	**<0.001**
Observations	1993		
Tjur D	0.045		

Table A36: URL Historian 2022 Base Model: Donation

URL Historian 2022 Base Model: Donation			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	-0.49	-1.55 – 0.58	0.370
Ideology (5-Point Scale)	-0.06	-0.32 – 0.19	0.621
Party ID (7-Point Scale)	-0.09	-0.24 – 0.06	0.236
Race: Black	-0.09	-0.79 – 0.61	0.800
Race: Hispanic	0.64	-0.06 – 1.34	0.071
Income Quintile	0.04	-0.13 – 0.20	0.667
Has BA Degree	-0.12	-0.59 – 0.34	0.596
Gender	-0.30	-0.72 – 0.12	0.158
Age	-0.02	-0.03 – -0.00	**0.033**
Observations	819		
Tjur D	0.021		

Table A37: URL Historian 2022 Base Model: Donation (No PID)

URL Historian 2022 Base Model: Donation (No PID)			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	-0.53	-1.58 – 0.52	0.325
Ideology (5-Point Scale)	-0.18	-0.35 – -0.01	**0.036**
Race: Black	-0.01	-0.70 – 0.68	0.969
Race: Hispanic	0.65	-0.05 – 1.35	0.067
Income Quintile	0.04	-0.13 – 0.21	0.635
Has BA Degree	-0.13	-0.59 – 0.33	0.588
Gender	-0.29	-0.71 – 0.12	0.165
Age	-0.02	-0.03 – -0.00	**0.044**
Observations	819		
Tjur D	0.020		

B.4.3 2024 Base Models

Table A38: URL Historian 2024 Base Model: Consent

URL Historian 2024 Base Model: Consent			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	1.24	0.90 – 1.57	**<0.001**
Ideology (5-Point Scale)	-0.01	-0.09 – 0.07	0.818
Party ID (7-Point Scale)	-0.04	-0.09 – 0.01	0.093
Race: Black	0.42	0.20 – 0.64	**<0.001**
Race: Hispanic	-0.16	-0.44 – 0.12	0.251
Income Quintile	-0.19	-0.25 – -0.14	**<0.001**
Has BA Degree	-0.17	-0.33 – -0.01	**0.039**
Gender	-0.14	-0.29 – 0.01	0.066
Age	-0.02	-0.02 – -0.02	**<0.001**
Observations	3377		
Tjur D	0.056		

Table A39: URL Historian 2024 Base Model: Follow-Through

URL Historian 2024 Base Model: Follow-Through			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	-0.10	-0.67 – 0.47	0.732
Ideology (5-Point Scale)	-0.31	-0.45 – -0.17	**<0.001**
Party ID (7-Point Scale)	0.02	-0.06 – 0.09	0.684
Race: Black	-0.32	-0.68 – 0.04	0.082
Race: Hispanic	-0.16	-0.67 – 0.34	0.530
Income Quintile	-0.03	-0.12 – 0.07	0.614
Has BA Degree	0.47	0.19 – 0.75	**0.001**
Gender	-0.19	-0.45 – 0.07	0.156
Age	0.00	-0.01 – 0.01	0.735
Observations	1212		
Tjur D	0.043		

Table A40: URL Historian 2024 Base Model: Donation

URL Historian 2024 Base Model: Donation			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	-0.35	-0.83 – 0.14	0.142
Ideology (5-Point Scale)	-0.25	-0.38 – -0.12	**<0.001**
Party ID (7-Point Scale)	-0.02	-0.09 – 0.05	0.632
Race: Black	0.00	-0.33 – 0.33	0.986
Race: Hispanic	-0.26	-0.71 – 0.20	0.265
Income Quintile	-0.15	-0.23 – -0.06	**<0.001**
Has BA Degree	0.25	0.01 – 0.50	**0.041**
Gender	-0.23	-0.46 – -0.00	**0.046**
Age	-0.01	-0.02 – -0.01	**<0.001**
Observations	3377		
Tjur D	0.022		

B.4.4 2024 Trust Models

Table A41: URL Historian 2024 General Trust Model: Consent

URL Historian 2024 General Trust Model: Consent			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	1.35	0.90 – 1.80	**<0.001**
Ideology (5-Point Scale)	-0.14	-0.22 – -0.06	**<0.001**
General Trust	-0.06	-0.25 – 0.14	0.577
Race: Black	0.47	0.19 – 0.74	**<0.001**
Race: Hispanic	-0.31	-0.67 – 0.06	0.105
Income Quintile	-0.16	-0.23 – -0.08	**<0.001**
Has BA Degree	-0.11	-0.31 – 0.09	0.294
Gender	-0.21	-0.40 – -0.02	**0.030**
Age	-0.02	-0.02 – -0.01	**<0.001**
Observations	2069		
Tjur D	0.052		

Table A42: URL Historian 2024 Trust Model: Consent

URL Historian 2024 Trust Model: Consent			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	1.22	0.77 – 1.67	**<0.001**
Ideology (5-Point Scale)	-0.13	-0.21 – -0.05	**<0.001**
Government Trust	0.24	0.01 – 0.48	**0.043**
Race: Black	0.45	0.17 – 0.72	**0.002**
Race: Hispanic	-0.30	-0.67 – 0.06	0.106
Income Quintile	-0.16	-0.24 – -0.09	**<0.001**
Has BA Degree	-0.10	-0.31 – 0.10	0.314
Gender	-0.19	-0.38 – -0.00	**0.048**
Age	-0.02	-0.02 – -0.01	**<0.001**
Observations	2069		
Tjur D	0.054		

Interaction check: We also estimated a URL Historian consent model interacting ideology with government trust. The interaction term was not statistically distinguishable from zero, indicating that the association between government trust and consent does not appear to vary meaningfully by ideology in this specification.

Table A43: URL Historian 2024 Trust Model: Consent with Ideology x Government Trust

URL Historian 2024 Trust Model: Consent with Ideology x Government Trust			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	1.26	0.81 – 1.72	**<0.001**
Ideology (5-Point Scale)	-0.15	-0.24 – -0.07	**<0.001**
Government Trust	-0.09	-0.71 – 0.53	0.778
Race: Black	0.44	0.17 – 0.72	**0.002**
Race: Hispanic	-0.31	-0.68 – 0.06	0.099
Income Quintile	-0.16	-0.23 – -0.09	**<0.001**
Has BA Degree	-0.10	-0.31 – 0.10	0.316
Gender	-0.20	-0.38 – -0.01	**0.044**
Age	-0.02	-0.02 – -0.01	**<0.001**
ideo5:gov_trust_binaryTrusting	0.12	-0.08 – 0.32	0.252
Observations	2069		
Tjur D	0.054		

Table A44: URL Historian 2024 Trust Model: Follow-Through

URL Historian 2024 Trust Model: Follow-Through			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	0.68	-0.06 – 1.42	0.082
Ideology (5-Point Scale)	-0.35	-0.49 – -0.21	**<0.001**
Government Trust	-0.76	-1.17 – -0.35	**<0.001**
Race: Black	-0.49	-0.94 – -0.04	**0.032**
Race: Hispanic	-0.13	-0.79 – 0.53	0.703
Income Quintile	0.05	-0.07 – 0.18	0.422
Has BA Degree	0.43	0.09 – 0.78	**0.015**
Gender	-0.20	-0.53 – 0.13	0.238
Age	-0.01	-0.02 – 0.00	0.280
Observations	741		
Tjur D	0.085		

Table A45: URL Historian 2024 General Trust Model: Follow-Through

URL Historian 2024 General Trust Model: Follow-Through			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	0.33	-0.42 – 1.08	0.385
Ideology (5-Point Scale)	-0.34	-0.48 – -0.20	**<0.001**
General Trust	0.03	-0.30 – 0.36	0.854
Race: Black	-0.49	-0.94 – -0.04	**0.031**
Race: Hispanic	-0.13	-0.78 – 0.52	0.700
Income Quintile	0.03	-0.09 – 0.16	0.621
Has BA Degree	0.45	0.10 – 0.79	**0.011**
Gender	-0.14	-0.47 – 0.18	0.388
Age	-0.00	-0.01 – 0.01	0.616
Observations	741		
Tjur D	0.066		

B.4.5 2024 FIRE Models

Table A46: URL Historian 2024 FIRE Model

URL Historian 2024 FIRE Model			
Predictors	*Log-Odds*	*CI*	*p*
Intercept	0.55	-0.13 – 1.22	0.113
Ideology (5-Point Scale)	-0.26	-0.42 – -0.10	**0.001**
FIRE index	-0.23	-0.46 – -0.01	**0.044**
Race: Black	-0.52	-0.96 – -0.08	**0.022**
Race: Hispanic	-0.09	-0.74 – 0.56	0.783
Income Quintile	0.03	-0.09 – 0.16	0.596
Has BA Degree	0.41	0.07 – 0.75	**0.019**
Gender	-0.21	-0.53 – 0.12	0.213
Observations	741		
Tjur D	0.071		

B.4.6 2024 Sensitive Content Models

Table A47: URL Historian 2024 Sensitive Content Models: Graphic violence / sexual / extreme political content

Predictors	*Log-Odds*	*CI*	*p*
Intercept	0.30	-0.64 – 1.25	0.527
Ideology (5-Point Scale)	-0.32	-0.50 – -0.14	**<0.001**
Sensitive content: graphic violence/sexual/extreme political	-0.02	-0.16 – 0.11	0.715
Race: Black	-0.69	-1.32 – -0.05	**0.034**
Race: Hispanic	0.19	-0.68 – 1.07	0.662
Income Quintile	-0.01	-0.18 – 0.17	0.946
Has BA Degree	0.35	-0.13 – 0.83	0.149
Gender	0.01	-0.44 – 0.47	0.963
Observations	378		
Tjur D	0.065		

Table A48: URL Historian 2024 Sensitive Content Models: Content not suitable for children

Predictors	*Log-Odds*	*CI*	*p*
Intercept	0.46	-0.59 – 1.51	0.390
Ideology (5-Point Scale)	-0.39	-0.59 – -0.19	**<0.001**
Sensitive content: not suitable for children	-0.03	-0.17 – 0.11	0.654
Race: Black	-0.33	-0.96 – 0.30	0.299
Race: Hispanic	-0.49	-1.49 – 0.51	0.334
Income Quintile	0.07	-0.11 – 0.24	0.441
Has BA Degree	0.50	0.00 – 0.99	**0.049**
Gender	-0.28	-0.75 – 0.18	0.237
Observations	363		
Tjur D	0.079		

B.5 Digital Trace Requests

B.5.1 URL Historian Request Language

Table A49 reproduces the URL Historian consent request language. The wording of this request was the same in 2022 and 2024.

Table A49: URL Historian request language used in 2022 and 2024.

Item	**Request text**
Instrument	‘url_hist_interest‘
Years used	2022 and 2024
2024 IRB	IRB-FY2023-7861
Primary ask	Would you be willing to download the free Chrome browser extension “URL Historian”? If you install the extension and contribute data to the study, you will be compensated an additional amount of YouGov points per month that your extension is active.
Tool description	URL Historian was developed by *source anonymized for peer review*. This extension can be installed on Chrome browsers and allows participants to share their web browsing history.
Optional feature	In addition, participants can choose to opt-in and share additional content that appears on their social media feeds. This feature is not required for using URL Historian and earning rewards.
Privacy and data handling	The collected data is for research purposes only and is stored in a secure database server under a unique ID assigned to each participant. This data is only accessible to *source anonymized for peer review* researchers. The extension allows participants to pause data collection and limit the domains collected. If a participant wishes to stop sharing their web history data with the study, they can pause and/or remove the extension at any time.

B.5.2 Twitter Request Language

Table A50: Twitter request language used in 2024.

Item	**Request text**
Instrument	Twitter 2024 consent item
Years used	2024
IRB	IRB-FY2023-7861
Primary ask	Do you consent to share your Twitter ID with researchers at YouGov and New York University for the purposes of this study?
Response format	Single selection
Compensation note	No additional compensation

B.5.3 YouTube Request Language

Table A51: YouTube request language used in 2024.

Item	**Request text**
Instrument	YouTube interest request
Years used	2024
IRB	IRB-FY2023-7861
Eligibility language	We are interested in the content you see on YouTube. If you have a YouTube account, and watched more than 10 YouTube videos prior to November 5 while logged into your account, we are offering a one time incentive of a $10 Visa gift card or 10,000 YouGov points if you share your YouTube data with us.
Participation language	If you are willing to help us with this research we will provide detailed steps to participate. Would you like to share your YouTube data with researchers?
Response options	Yes, I intend to share my data with researchers for a $10 Visa gift card; Yes, I intend to share my data with researchers for a bonus of 10,000 YouGov points; No thank you

B.5.4 TikTok Request Language

Table A52: TikTok request language used in 2024.

Item	**Request text**
Instrument	TikTok interest request
Years used	2024
IRB	IRB-FY2023-7861
Eligibility language	We are interested in the content you see on TikTok. If you have had a TikTok account for over 30 days, and spent more than 5 minutes using TikTok while logged into your account, we are offering a one time incentive of a $15 Visa gift card or 15,000 YouGov points if you share your TikTok data with us.
Participation language	If you are willing to help us with this research we will provide detailed steps to participate. Would you like to share your TikTok data with researchers?
Response options	Yes, I intend to share my data with researchers for a $15 Visa gift card; Yes, I intend to share my data with researchers for a bonus of 15,000 YouGov points; No thank you

Table A54: Descriptives for 2024 (W15) by donor group.

metric	Whole sample	YouTube donors	TikTok donors	URL donors
N	3754.00	453.00	184.00	397.00
Ideology mean	2.98	2.55	2.48	2.57
PID mean	3.72	3.13	3.06	3.18
Age mean	47.58	44.59	37.97	43.23
BA pct	41.13	47.46	39.67	45.84
Woman pct	50.11	46.14	54.35	45.59
White pct	79.63	79.56	63.31	78.74
Black pct	12.88	14.84	26.63	14.66
Hispanic pct	7.49	5.60	10.06	6.61
Income quintile mean	3.03	2.88	2.74	2.85
Gov trust trusting pct	18.63	17.39	20.74	16.26

B.6 Reference Descriptives

B.6.1 Covariates by Year and Platform Donor Group

Table A53: Reference Descriptives for 2022 (W11) by donor group.

metric	Whole sample	YouTube donors	Facebook donors	Twitter donors
N	2201.00	405.00	619.00	1158.00
Ideology mean	2.88	2.44	2.65	2.58
PID mean	3.53	2.95	3.25	3.07
Age mean	57.37	49.25	54.63	54.19
BA pct	49.61	51.36	48.47	52.50
Woman pct	50.84	46.90	48.79	51.64
White pct	86.75	82.51	85.51	85.93
Black pct	8.03	10.66	8.38	7.98
Hispanic pct	5.22	6.83	6.11	6.08
Income quintile mean	3.07	3.02	2.99	3.09
Gov trust trusting pct	NA	NA	NA	NA

C Affective Polarization: Supplementary Figure

C.1 Feeling Thermometer Distribution by Donation Status

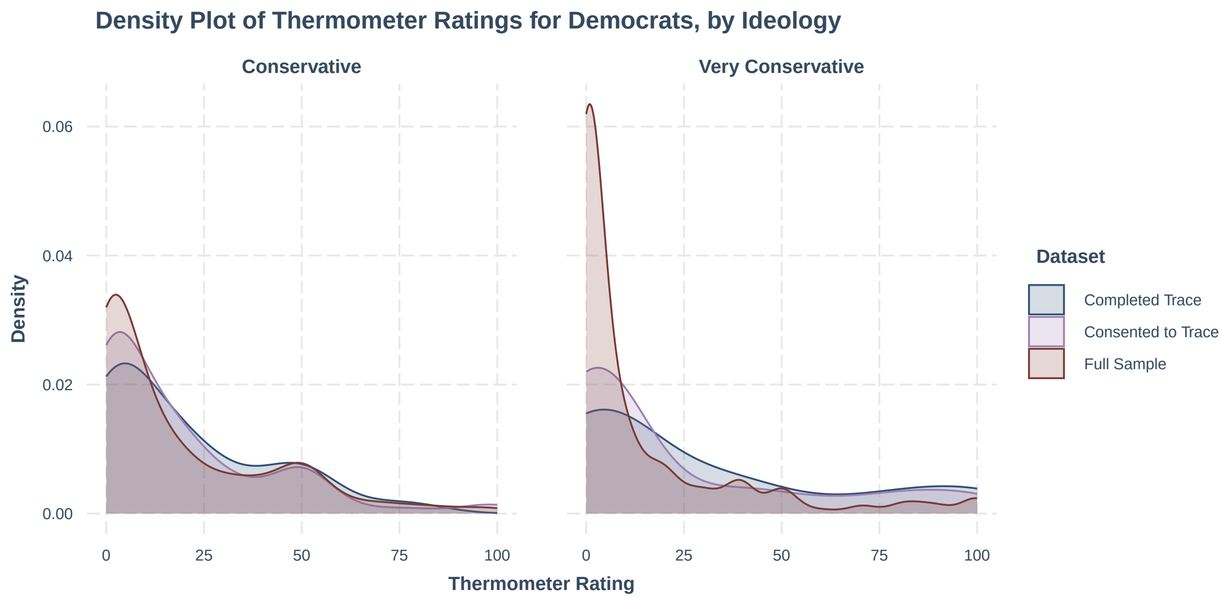

Figure A1: Density of feeling thermometer ratings toward Democrats among conservative and very conservative respondents, by donation status. Respondents who did not donate skew toward lower thermometer scores, indicating that non-donors hold more negative attitudes toward Democrats than the donor sample suggests. This pattern motivates the reweighting strategy described in Section 6.

D Gradient Boosting Variable Importance

D.1 Cross-Platform Gradient Boosting Predictors among Self-Identified Conservatives

Table A55: Top predictors of data donation among self-identified conservatives, 2022

	Cl.	Variable	YouTube 2022 ($N = 365$, donors = 65) Rank	Gain	Facebook 2022 ($N = 548$, donors = 150) Rank	Gain
Group and racial attitudes						
∗	G	GOP immigration stance	12	3.8%	2	7.1%
∗	G	Thermometer: Republican Party	2	5.9%	4	6.1%
	G	Importance of immigration issue	3	5.7%	—	—
∗	G	Thermometer: undocumented immigrants	15	3.6%	3	7.1%
	G	Thermometer: police	—	—	8	4.0%
	G	Thermometer: Asian Americans	—	—	10	3.8%
	G	Thermometer: Republicans	11	4.0%	—	—
	G	Trump's immigration stance	19	3.0%	—	—
	G	Thermometer: White nationalists	21	2.8%	—	—
Policy, partisan, and candidate attitudes						
	P	GOP social ideology (perceived)	—	—	1	7.3%
∗	P	Own stance: size of government	4	5.7%	14	3.3%
∗	P	Trump's tax-the-wealthy stance	5	5.4%	5	5.3%
∗∗	P	Own stance: single-payer health care	—	—	6	4.7%
∗	P	Retrospective personal-finance evaluation	6	5.3%	20	2.9%
	P	Thermometer: DeSantis	—	—	7	4.6%
∗∗	P	Trump's single-payer stance	7	5.1%	—	—
	P	Few big interests run government	9	4.5%	—	—
	P	Ideology: Republican Party placement (7-pt)	—	—	9	4.0%
	P	Importance of abortion issue	—	—	11	3.7%
	P	Politics as good-versus-evil conflict	13	3.8%	—	—
	P	Importance of jobs issue	14	3.7%	—	—
∗∗	P	Own stance: government intervention	—	—	15	3.2%
∗	P	Biden's single-payer stance	18	3.1%	16	3.1%
∗	P	GOP size-of-government stance	16	3.4%	23	2.8%
	P	Biden as tool of AOC item	—	—	17	3.0%
∗∗	P	Trump's size-of-government stance	17	3.4%	21	2.9%
∗∗	P	GOP single-payer stance	—	—	18	3.0%
∗∗	P	Trump's government-role stance	—	—	19	3.0%
	P	Government spending responsibility	20	2.8%	—	—
	P	GOP tax-the-wealthy stance	22	2.7%	—	—
	P	Issue priority: gun policy	—	—	22	2.8%
	P	Importance of government-health issue	23	2.4%	—	—
	P	Importance of political reform issue	—	—	24	2.7%
	P	Responsibility for Ukraine war	24	2.3%	—	—
	P	Support for wealth tax	25	2.3%	—	—
Network homophily and political exposure						
	N	Cable news political-information use	1	6.2%	—	—
	N	Twitter friends' political posts	8	5.1%	—	—
	N	Talk radio frequency	10	4.0%	—	—
	N	Political content on Facebook	—	—	12	3.5%
	N	News voice behavior	—	—	13	3.3%
	N	Friends' political posts on Facebook	—	—	25	2.7%

Notes: Self-identified conservative respondents only. Predictors are survey items from the same or preceding wave; age, demographics, identity-salience items, and platform-use variables are excluded.
Gain is each variable's normalized share of top-25 predictive improvement (`xgboost` Gain), averaged across $m = 5$ MICE-imputed datasets.
Stars: ∗ appears in both 2022 platform top-25 lists; ∗∗ also appears in a 2024 platform top-25 list.
Clusters: G = group and racial attitudes; P = policy, partisan, and candidate attitudes; N = network homophily and political exposure.

Table A56: Top predictors of data donation among self-identified conservatives, 2024

	Cl.	Variable	YouTube 2024 ($N = 792$, donors = 98) Rank	Gain	TikTok 2024 ($N = 289$, donors = 30) Rank	Gain
Group and racial attitudes						
	G	Own stance: Muslim ban	2	7.8%	—	—
	G	Group finances: college graduates	5	5.1%	—	—
∗	G	Group finances: people with similar jobs	6	4.2%	14	3.7%
	G	Own immigration stance	—	—	6	4.5%
	G	Group finances: non-college adults	8	3.8%	—	—
	G	Support increased border-wall funding	—	—	8	4.1%
	G	Group finances: Asian Americans	11	3.5%	—	—
	G	Trump's Muslim-ban stance	15	3.4%	—	—
	G	Acquaintances: immigrants	17	3.3%	—	—
	G	Group finances: Hispanic Americans	18	3.2%	—	—
∗	G	Trump's border-wall stance	19	3.1%	25	2.8%
	G	FIRE: Fearful of people of other races	—	—	20	3.1%
Policy, partisan, and candidate attitudes						
	P	Trump's ideological position	1	8.4%	—	—
	P	Trump's size-of-government stance	—	—	2	6.7%
	P	Biden evaluation: Israel	—	—	3	5.2%
	P	Trump's military-force stance	3	6.0%	—	—
	P	Trump's government-role stance	—	—	4	4.9%
	P	Trump's single-payer stance	4	5.3%	—	—
	P	Own stance: government intervention	7	4.1%	—	—
	P	Trump evaluation: terrorism	—	—	7	4.3%
	P	Support tuition-free college	—	—	9	4.0%
	P	Biden's China-tariff stance	—	—	11	4.0%
∗	P	GOP China-tariff stance	24	2.9%	12	3.9%
	P	Own stance: single-payer health care	—	—	13	3.8%
	P	Harris weak-on-China-trade item	14	3.5%	—	—
	P	Biden's trade stance	16	3.4%	—	—
	P	Trump's trade stance	—	—	16	3.4%
	P	Biden's military-force stance	—	—	18	3.3%
	P	Harris single-payer stance	20	3.1%	—	—
	P	Belief in absentee voter fraud	21	3.0%	—	—
	P	Biden's ideological position	—	—	22	3.0%
∗	P	GOP single-payer stance	22	3.0%	24	2.9%
	P	Thermometer: Trump	23	2.9%	—	—
	P	Own stance: military force	25	2.8%	—	—
Network homophily and political exposure						
	N	Instagram commenting frequency	—	—	1	7.4%
	N	Atlanta Journal-Constitution campaign info	—	—	5	4.8%
	N	Facebook feed: left-right placement	10	3.5%	—	—
	N	YouTube content: no viewpoint diversity	—	—	10	4.0%
	N	TikTok news-organization political information	12	3.5%	—	—
	N	Facebook feed: views similar to own	13	3.5%	—	—
	N	Twitter content: views similar to own	—	—	15	3.4%
	N	Online political discussion frequency	—	—	17	3.3%
	N	Instagram groups frequency	—	—	19	3.3%
	N	Twitter news-viewing frequency	—	—	21	3.0%
	N	MSNBC news/opinion viewing	—	—	23	3.0%

Notes: Self-identified conservative respondents only. Predictors are survey items from the same or preceding waves; age, demographics, identity-salience items, and platform-use variables are excluded.
Gain is each variable's normalized share of top-25 predictive improvement (`xgboost` Gain), averaged across $m = 5$ MICE-imputed datasets.
The single-payer placement item was fielded in two randomized forms, and both entered the YouTube 2024 top 25. They appear here as one row, so that column lists 24 rows and its gains sum to 96.3 rather than 100.
Stars: $*$ appears in both 2024 platform top-25 lists.
Clusters: G = group and racial attitudes; P = policy, partisan, and candidate attitudes; N = network homophily and political exposure.

D.2 Affective Polarization Models Underlying Figure 5 and 7

Table A57: Predicted Affective Polarization by Sample (OLS)

Predictors	Full Sample	YouTube Donors	Reweighted YouTube Donors
Has BA Degree	-1.64	-10.35***	-13.27***
	(1.68)	(3.11)	(3.11)
Woman	6.75***	11.62***	11.25***
	(1.63)	(3.03)	(3.15)
Race: Black	-3.47	6.37	6.85
	(2.76)	(4.68)	(5.23)
Race: Hispanic	-11.21***	-10.38*	-5.13
	(2.54)	(4.76)	(5.20)
Race: Other	1.38	12.72*	14.54**
	(2.74)	(5.28)	(4.99)
Ideology (5-Point Scale)	-4.17***	-4.85*	-4.94**
	(0.98)	(1.95)	(1.87)
Party ID (7-Point Scale)	-30.06***	-25.60***	-27.85***
	(1.78)	(3.26)	(3.30)
Party ID Squared	3.71***	2.82***	3.42***
	(0.22)	(0.42)	(0.44)
Observations	1158	340	340
R-squared	0.271	0.341	0.341

Note: OLS model predicting affective polarization (absolute difference between thermometer for Republicans and for Democrats). Reweighted YouTube Donors applies entropy balancing to conservative/Republican (PID7 5–7) donors only, calibrating them to their corresponding non-donors; Democrat/Independent donors are unweighted.

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.