(Dis)engagement with Politics: Evidence from Smartphone Content in the 2024 Elections

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Abstract

Smartphones have become a dominant channel through which people discuss politics and are exposed to political content. Using high-frequency, privacy-preserving data from a commercial smartphone app, we provide the first systematic analysis of exposure to and engagement with political content across all the apps that a panel of Android individuals visit around the 2024 US Election. We establish three main findings. First, despite the highly contested nature of the election, people had limited exposure to political content on their smartphones. On a typical day in September and October 2024, the median individual encounters under one minute of political content—equivalent to less than half the terms they would encounter if they read a single New York Times article about the elections. Second, this disengagement remains remarkably stable through the election cycle, except for brief spikes following the first presidential debate, Taylor Swift's endorsement, and on Election Day itself. Third, despite the low individual engagement with political content, we document that there is a large share of exposures to Elon Musk and Donald Trump on applications such as X, while only a small amount of political content on applications such as Facebook and Instagram. Despite this, a variance decomposition exercise shows that individuals' behavior and tastes are a more important driver than systematic social media app-driven effects in determining political exposures.

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1 Introduction

> "If a nation expects to be ignorant & free, in a state of civilisation, it expects what never was & never will be." – Thomas Jefferson

A vibrant democracy depends on active citizen involvement. In the U.S., staying well-informed about candidates and voting in elections are fundamental aspects of political participation. However, the dramatic political changes we have witnessed in recent years have led to growing concerns that consumers are increasingly receiving information from non-authoritative sources and that a large share of information is controlled by the algorithmic choices of a few dominant online platforms. To assess whether these concerns are warranted, it is important to measure and quantify public engagement in elections, which has traditionally relied heavily on surveys. However, surveys are prone to recall bias, expressive responding, and experimenter demand effects.[1] Furthermore, surveys are limited to specific questions and typically cannot provide rich information about the different types of content people are exposed to over time and across sources.[2]

This paper leverages the content observed on smartphones to provide a more comprehensive measure of political engagement. Smartphones have become a dominant channel for communication and information. Individuals around the world spend, on average, 16.7% of their daily lives on their smartphones – consuming news and entertainment, communicating with friends, and searching for information and goods.[3] In the U.S., 92% of the population owns a smartphone and spends over 4.5 hours per day on their device (Kemp, 2024).[4] Furthermore, these devices have become an important portal for news consumption – with 57% of Americans report using digital devices (including smartphones) as a source of news consumption.[5] The ubiquity of smartphones and the digitization of information consumption and production creates a valuable opportunity to obtain objective measures of political exposure and engagement, as they capture a significant portion of individuals' information diets and conversations. Due to the technical challenges typically associated with observing smartphone content, smartphones have so far largely remained a black box.

[1] Surveys on news consumption reveal that respondents frequently report consuming more news than they actually do (Prior, 2009), and those who say news consumption is important are more likely to overstate their news consumption (Barthel et al., 2020). A meta-analysis of 106 studies focusing on digital use found that "self-reported media use correlates only moderately with logged measurements" (Parry et al., 2021).

[2] For example, they typically present respondents with a limited set of potential news sources, and thus both affect the ranking of sources (by making these options salient) and make news consumption seem more concentrated than it actually is (González-Bailón and Xenos, 2023).

[3] `https://backlinko.com/smartphone-usage-statistics`

[4] `https://www.consumeraffairs.com/cell_phones/how-many-americans-own-a-smartphone.html`

[5] This is in comparison to 33% on TV, 11% on radio, and 6% through print media (`https://www.pewresearch.org/journalism/fact-sheet/news-platform-fact-sheet`).

Our paper uses novel data to overcome this challenge and presents new evidence on political exposure and engagement from September through November in the 2024 U.S. elections. Roughly three-quarters of Americans believe the 2024 presidential election will determine the fate of U.S. democracy (AP-NORC Center for Public Affairs Research, 2024). By focusing on this pivotal event, we document political engagement during a period of heightened attention to politics in the media environment and intensified public discourse. Furthermore, we document how this engagement varies across different types of applications (e.g., social media and communication) as well as assess the concerns that the magnitude and nature of this engagement are driven by the algorithmic choices of social media applications.

Our data comes from a commercial smartphone app that helps individuals track and manage their screen time. With explicit individual consent, the app seamlessly tracks content that appears on their phones, without recording or storing personal data to ensure privacy. Specifically, the app collects a list of keywords we pre-specify and provides information on each instance where a keyword appears, including the app in which it was observed and the relevant context (through surrounding keywords). For example, we can track where and how often people encounter discussions about Kamala Harris or Donald Trump over the election cycle. Thus, this method informs—with a high ecological validity—the content that individuals see on their screens *across* many different types of apps, including social media and communication applications where previous research had limited visibility. Using this method, we measure the magnitude of political engagement by observing the occurrences for our pre-specified set of keywords. Our primary list of political words includes words related to the elections (polls, ballot, campaign, debate, democracy, Republican, Democrat, Congress, swing, vote, election, electoral, mail-in), presidential and vice-presidential candidates, and virtually all congressmembers and governors.

We begin our investigation by documenting the magnitude of political engagement. We document a striking fact: despite the highly contested nature of the election and its salience during our analysis period, most people in the U.S. had limited exposure to and engagement with political content on their smartphones. We find that the median individual encountered primary political words only 11 times, meaning they saw these words for up to 21.00 seconds on an average day in September and October 2024.[6] To put this number in perspective, the median individual in our sample spends nearly 5.54 hours a day on their phone, indicating that only 0.165% of phone time was spent observing political content. As another reference point, if they had fully read just one New York Times Article with the "2024 Elections" tag on October 31st, they would have been exposed to nearly double the amount of political content according to our measurement process.

This begs the natural question of when, if ever, does political engagement increase over the election cycle? In the lead-up to the election, there are numerous events that could result in

[6]If a word stays on the screen for more than three seconds, it is recorded again as a separate encounter.

increased engagement with political content: scandals, endorsements, debates, assassination attempts. Despite this sequence of possibilities, we find that political disengagement is remarkably stable in the leadup to the election. The only two exceptions are the day following the first presidential debate and election day itself, which led to a 56% and 494% increase in engagement, respectively compared to the week before these events, with the rest of the time period having remarkably flat engagement. We separately investigate these two spikes in engagement. We show that the spike in the first debate is partially driven by the Taylor Swift's Instagram endorsement, with nearly double the political engagement for individuals who listened to Taylor Swift on a music & video app before the endorsement, relative to those who did not. For election day, we show that most of the spike in engagement occurs in the evening after the polls closed and thus is not indicative of individuals acquiring information before voting.

With limited exposure, the exposure people do have may disportionately influence their opinion and subsequent votes. Therefore, we turn to the what and where of political content exposure and engagement, and document four stylized facts about the election period. First, the median individual is exposed to 10.40 times more content about the presidential candidates compared to *any* Congressmember in the run up to the election, highlighting just how nationalized politics is in the US. Second, when individuals do encounter politics, Donald Trump tends to dominate the conversation—about three-quarters of the mentions of the two presidential candidates were of Donald Trump. Third, dedicated news applications make up only a small portion of political encounters, with search, social media, and music & video application making up a large portion of political engagement, highlighting that, when individuals do get news, it is not necessarily from authoritative sources. Fourth, the median individual does not discuss politics, with a median of zero daily political encounters in any communication application, including messages and WhatsApp.

Given that such a large portion of the small amount of political engagement comes from applications with algorithmic curation, a natural question is what are the factors that drive this engagement. One concern is that the algorithmic choices of these prominent applications could have an outsized influence on elections by shifting the likelihood and nature of political content that individuals are exposed to. This was much discussed in the build-up to the 2024 election as, for instance, there were reports of X overly promoting conservative content and Elon Musk specifically (Graham and Andrejevic, 2024), the rise of Donald Trump's own social media platform Truth Social,[7] and Meta limiting political content across Facebook and Instagram.[8] We confirm

[7] https://www.nytimes.com/2024/04/18/technology/truth-social-right-wing-apps.html

[8] See https://www.npr.org/2024/03/26/1240737627/meta-limit-political-content-instagram-facebook-opt-out. In practice, Meta argued to not intend to suppress political content but rather to not proactively recommend political content from accounts individuals do not follow. individuals could still opt-in to see political recommendations: https://about.instagram.com/blog/announcements/continuing-our-approach-to-political-content-on-instagram-and-threads.

these anecdotal concerns in our data—we find that mentions of Donald Trump and Elon Musk are several times higher on X and Truth Social than other social media applications and that political content makes up a very small share of encounters on Facebook. Furthermore, these effects remain significantly positive even when we control for individual fixed effects.

This is potentially confirmatory of these concerns and suggestive that these platforms can significantly steer the public conversation. However, since the curation algorithms across these platforms are all personalized, it could be that apart from these special cases, the variation in the magnitude and content of political exposure is more likely to be driven by individual preferences, as opposed to application-specific biases or self-selection into different applications. In order to assess this systematically, we conduct a variance decomposition exercise which allows us to explain the variance in exposure to political content based on application-specific effects, individual-specific effects, and self-selection of individuals into applications. This procedure allows us to exploit a unique aspect of our data, relative to the existing literature, since we observe content consumption across *all* social media applications which allows us to understand differences in the *shares* of exposure across applications. Intuitively, individual effects dominate when apps fully personalize content or when there is little differentiation between them, giving individuals most of the agency in determining their exposure to political content. Conversely, app effects dominate when apps systematically expose individuals to differentiated levels of political content.

We apply this method to our data and, as a sanity check, show that individual-level effects explain a relatively larger share of the variation in communication applications, where we expect this to be the case given the lack of algorithmic curation. Our estimates show that, while the application-specific effects are larger for social media applications, individual-specific effects still dominate and explain 16% of the variance, while application-specific effects only explain 5% of the variance. The predominance of individual heterogeneity reverses in the case of news applications, explaining 38% of the variance compared to 45% explained by app heterogeneity. Furthermore, our estimates show that self-selection into applications is a large driver of variation in exposures for news applications, while this is not quantitatively important for other applications. These results suggest that both individual and app-level heterogeneity are drivers of exposure to political content, with different relative importances depending on the app type.

These results should be interpreted with caution. First, there may be self-selection bias in the use of the commercial application used by our data provider. In Section 2, we describe the steps taken to assess external validity. We show that individuals using this application exhibit smartphone use behavior similar to both population aggregates and a representative sample. In addition, our results are robust to demographic reweighting on age and gender. Second, we only capture the occurrence of pre-specified keywords. While this is unlikely to be an issue for names of politicians, businessmen, or celebrities, it may limit our ability to fully measure political engagement

when keywords are not present. Finally, while our study opens the smartphone blackbox, it does not account for political exposure and engagement occurring elsewhere.

Related Work This paper contributes to several strands of literature. First, we provide new evidence for the literature on news consumption, selective exposure, and news avoidance. Prior work has documented varying degrees of ideological selective exposure (Gentzkow and Shapiro, 2011; Flaxman et al., 2016; Peterson et al., 2019; Guess, 2021; González-Bailón et al., 2023). Beyond ideological segregation, Prior (2007) and Yang et al. (2020) highlight a deeper form of selective exposure – the divide between individuals who actively consume news and those consume none or very little. Virtually all previous work focused on one platform (typically a social media feed) or desktop browser behavior. We complement prior findings by studying news exposure across all smartphone apps, including social media feeds, search engines, communication apps, news outlets, and browsers. We find evidence supporting concerns about the widespread lack of news exposure among a significant portion of the population, despite the ease of access. We also show that when people do get exposed to political content, it is more likely to be through social media, music & video apps, or search engine, than news apps.

For the exposure that individuals do receive, some have argued that it is mainly driven by algorithms (Pariser, 2011), while others have attributed it to individual preferences (Bakshy et al., 2015). Most studies in this literature Bakshy et al. (2015); Guess et al. (2023) rely on observed content for a single social media application, whereas our paper uses the fact that we uniquely observe the content each individual sees across *all* social media applications. We therefore contribute to this literature by exploiting the fact that we can measure systematic differences in content shares across applications to separate out the explanatory role of individual preferences from the role of application-specific choices, such as algorithmic bias.

Second, we contribute to the literature documenting the role of campaigns, such as debates and endorsements, in elections.[9] Looking at 56 TV debates across 7 countries, Le Pennec and Pons (2023) find no significant effects of the debates on respondents' vote intention or vote choice. In contrast, newspaper endorsements have been shown to increase support for the recommended candidate (Chiang and Knight, 2011), and less is known about the effectiveness of celebrity endorsements in political campaigns.[10] Our high-frequency data allows us to document the dynamics of political campaigns. We show that despite the media's portrayal of various campaign events as being dramatic, news exposure is remarkably stable. Furthermore, by comparing people who are more and less likely to be exposed to endorsement, we contribute to the literature by estimating

[9]There is an large body of work in political science on this topic. See, for example, Wald and Lupfer (1978), Fridkin et al. (2007) and Brierley et al. (2020). For a review, see Jacobson (2015).

[10]In the digital media setting, Alatas et al. (2024) has shown that celebrity endorsement on social media can be effective in public health campaigns.

the causal effect of a high-profile endorsement on exposure and engagement with political news.

Third, the paper contributes to the extensive literature on the impact of media and the Internet on political outcomes (Strömberg, 2015; Zhuravskaya et al., 2020; Aridor et al., 2024). Our study adds evidence on exposure and engagement, which shape downstream outcomes commonly examined in this literature. Specifically, our work is closely linked to the literature on the role of media in voter knowledge (e.g., Snyder Jr and Strömberg 2010; Prior 2005; Angelucci and Prat 2024), including local politics. On the supply side, there has been a decline in coverage of local news since the introduction of TV (Gentzkow, 2006; Angelucci et al., 2024; Mateen and Romero, 2024). Our paper complement this with evidence on what people actually consume. Despite the highly personalized nature of smartphone content, we find that individuals receive almost no information about their local congressional representatives.

Fourth, the paper contributes to the literature on digitization. Smartphones, like other digital technologies (Goldfarb and Tucker, 2019), facilitate the recording and storage of digital activity, as well as serve as an important component of the information diet of individuals. Despite this, we know surprisingly little about how and what individuals actually engage with on these devices. Past work has used web browsing data to examine online content consumption (see, for example, Gentzkow and Shapiro 2011; Flaxman et al. 2016; Peterson et al. 2019; Guess 2021; Levy 2021; Beknazar-Yuzbashev et al. 2022). Studies that have looked at mobile consumption, such as Allcott et al. (2022) and Aridor (2025), have largely focused on the time spent on different applications, and highlight notable differences in the behavior across mobile and desktop web browsing that are important for shaping news consumption.[11] Going beyond time use, data used in this paper leverages a novel data collection method that tracks real-time smartphone *content* (Reeves et al., 2020, 2021), including to study political content exposure (Muise et al., 2024). Building on this emerging technology and using a substantially larger sample, we offer novel and comprehensive evidence on political content consumption and engagement during a highly polarized and consequential election season. Furthermore, the digitization of the information produced via smartphone consumption provides us a novel view into political *conversations*, as our data allows us to measure not just what individuals consume on social media and news applications, but also document how this differs from what they discuss with their friends and family.

This paper proceeds as follows: Section 2 describes our data sources, Section 3, 4, and 5 present new evidence on patterns of engagement and its drivers.

[11] In particular, Aridor (2025) tracks individuals on both mobile and desktop and shows significant differences in the type of applications, especially socia media applications, used across devices.

2 Data

Our analysis combines smartphone and survey data in the time period around the 2024 U.S. election.

2.1 Primary data: smartphone content

Our primary data tracks keyword occurrences across all apps on individuals' smartphones. The data covers several thousand Americans in the five months around the election, between September 1, 2024 through January 26, 2025 in the 2024 election cycle. We focus most of our analyses on the period between September 1, 2024 through November 15, 2024.

The data we use comes from Screenlake, a company that creates and maintains a proprietary database of term-encounters occurring in natural smartphone usage around the world, primarily to serve enterprise businesses in measuring their brands' organic popularity over time across apps.[12] Screenlake's data is sourced from an SDK (software development kit) which is in-turn embedded within popular smartphone applications. An individual who installs such an application on their personal device is asked for explicit additional permission to allow for anonymous on-screen keyword detection during their continuous smartphone usage. These individuals are incentivized with access to premium individual-facing app features and informed that the SDK does not collect personal information. Once permission is granted, the SDK passively checks for the presence of specific content of interest every 3 seconds continuously across apps, according to an internal library of predefined terms. If any such term is detected as being present on-screen, the SDK logs this occurrence and summarizes the sentiment and topic indications of the content surrounding the detected term on-screen.[13]

To provide additional context on the keyword appearance, we also look at the co-occurrence of a large list of surrounding words. In particular, upon observing the presence of a primary keyword on the screen, the application scans the ten observed words before and after the identified keyword and logs all of the occurrences of surrounding words within this set. For example, a specific observation could be that the word "Taylor Swift" appeared in WhatsApp on November 7 2025, with the word "vote" nearby.

[12] `http://www.screenlake.com`

[13] All such content processing is done on the smartphone device, meaning no direct identification or sensitive information is sent off of the original device. The resulting data is uploaded to the cloud periodically, to be automatically cleaned, sorted, and combined with other such data streams.

The list of keywords We track a large set of political keywords as well as a set of "control", non-political, keywords that provide us with a benchmark.[14,15]

We classify our primary political terms of interest into three groups: 1) *election terms* are words related to the elections ("polls", "ballot", "campaign", "debate", "democracy", "Republican", "Democrat", "Congress", "swing", "vote", "election", "electoral", "Mail-In"), 2) *politicians*, which include presidential and vice-presidential candidates ("Joe Biden","Robert F Kennedy Jr", "Nikki Haley", "Kamala Harris", "Donald Trump", "Tim Walz", "JD Vance") and virtually all congressmembers and governors,[16] and 3) *political issues* include the major issues discussed in the election ("climate", "court", "crime", "economy", "healthcare", "inflation", "women", "Gaza", "West Bank", "immigration", "border", "woke", "DEI", "Roe", "gun", "protest", "recount", "interference", "hoax").

Since political issues can also be mentioned in a non-political context, we only consider them political issues if they are mentioned near a political surrounding keyword. Throughout the paper, our main definition of *primary political terms* is the combination of election terms and politicians.

Application classification We classify the large set of observed apps into the following categories: communication (e.g., Gmail, WhatsApp), social media (e.g., Facebook, X), music and video (e.g., YouTube, Spotify), news (e.g., New York Times, Fox News), search (e.g., Google, Bing), browser (e.g., Samsung Browser, Google Chrome).[17] We rely on our own classification, instead of the Google Play classification, to focus on the demarcations between applications most relevant to our specific setting of political content consumption, which can differ from the Google Play classification.

Sample Representativeness We conduct several additional analyses to assess the generalizability of our results. Our sample is composed of individuals who opt to use the application offered by Screenlake. An important concern is how findings from this group can be extrapolated to the broader U.S. population. We answer this question by comparing our sample to the population on demographics, smartphone use, and political content consumption. We document the details of the exercises we conduct in Appendix D.

First, we consider the demographic composition of Screenlake individuals. The data collected by Screenlake is anonymous and disconnected from identifiers, meaning that any demographic

[14]For the full set of control keywords that we use in our analyses and our process for classifying these keywords see Section E.

[15]Some of these are added at the authors' request, but a large number of them are automatically collected by the data provider.

[16]The full list of political keywords that we track can be found in Section E.

[17]One limitation of the classification is that a substantial share of time is spent on browsers and browsing can be related to most of the app categories.

descriptors are inferred by Screenlake post-collection. Screenlake's proprietary inference method is based on the inter-demographic relative likelihood of combinations of various brands and apps appearing on-screen. For the present work, Screenlake shared weekly aggregate age and gender breakdowns of the panel and individual-level weights that allow us to reweight our aggregation across individuals to be representative of the U.S. population on these dimensions.[18] In Appendix D, we show that age and gender breakdowns are relatively stable over time, and present the re-weighted version of our main result on political engagement over time. As our results do not substantially change after this reweighting, we use the unweighted sample for the rest of the analyses.

Second, we compare our sample to the average U.S. adult in terms of app use. On the extensive margin, in Appendix D.2, we compare the set of installed applications on the individual's phone to a proxy for the market-level number of downloads via the Google Play store. We find that individuals in the sample have similar sets of applications installed, with a 0.88 correlation in the ranking of categories as well as a weighted correlation of 0.89 in the ranking of applications within our categories of interest between our sample and the Google Play Store. Screenlake individuals are more likely to have installed news applications than the broader population, suggesting that they may be potentially more engaged with news.

On the intensive margin, we compare app usage among Screenlake individuals to industry benchmarks and a representative sample collected via Prolific. As detailed in Appendix D.2, Screenlake individuals exhibit similar patterns of total phone and social media usage compared to other data sources. We find that, similar to our Prolific sample, once we remove Chrome usage in both samples, the median individual spends 5.5 hours on their phone each day.[19] When we look at social media usage, we find that the Screenlake panelists spend, on average, 3.22 hours per day on core social media applications, compared to the 2.5 hours spent by the average American reported in Kemp (2024). Thus, we conclude from these exercises that the average Screenlake individual has similar phone usage and spends more time on social media applications than the average American, which suggests that any results around (lack of) engagement with content in our analyses are not due to low phone usage.

Panel Attrition and Growth The present paper uses Screenlake's earliest data collection, a period in which Screenlake's US panel numbered under ten thousand unique adults, and experienced a moderate degree of churn. Figure A.1 documents the number of individuals observed throughout the sample period, showing that the panel grows substantially during the observation period.

[18] The weights are calculated based on data release from the U.S. Census Bureau in 2023.

[19] We remove Chrome usage in both samples because our Prolific individuals spend a substantial amount of time in Chrome – likely filling out surveys that they have received on Prolific. As such, we drop this application since the same behavior is not expected from the Screenlake panelists.

Screenlake did not substantially change its marketing strategy for the application during our sample period, ensuring a consistent degree of selection into the application throughout the period.

Naturally, there is panel churn and individuals are not consistently observed throughout the sample period. Figure A.2 plots the histogram of the number of observed active days during our sample period and finds that 59% of individuals are observed for at least two weeks. Despite the panel growth and attrition, Figure D.1 and Figure A.3 show that the demographic make-up and the overall usage of different application categories remains consistent across the sample period of interest. As a result of this, we primarily focus on aggregated daily statistics for our analyses.

3 How much Political Content are People Exposed to

3.1 The Extent of Political Exposure

A functioning democracy relies on individuals receiving high-quality information about topics and candidates, deliberating with their social networks, adjusting their beliefs, and making choices accordingly. Indeed, this is the basic structure of most political economy models. However, in the modern media environment, this basic model might not hold for at least two reasons. First, surveys have revealed a sharp decline in the demand for news (Newman et al., 2023). Second, individuals may be exposed to biased or low-quality information. Until recently, it was almost impossible to observe the political information people were exposed to and discussed, and empirically test these claims.

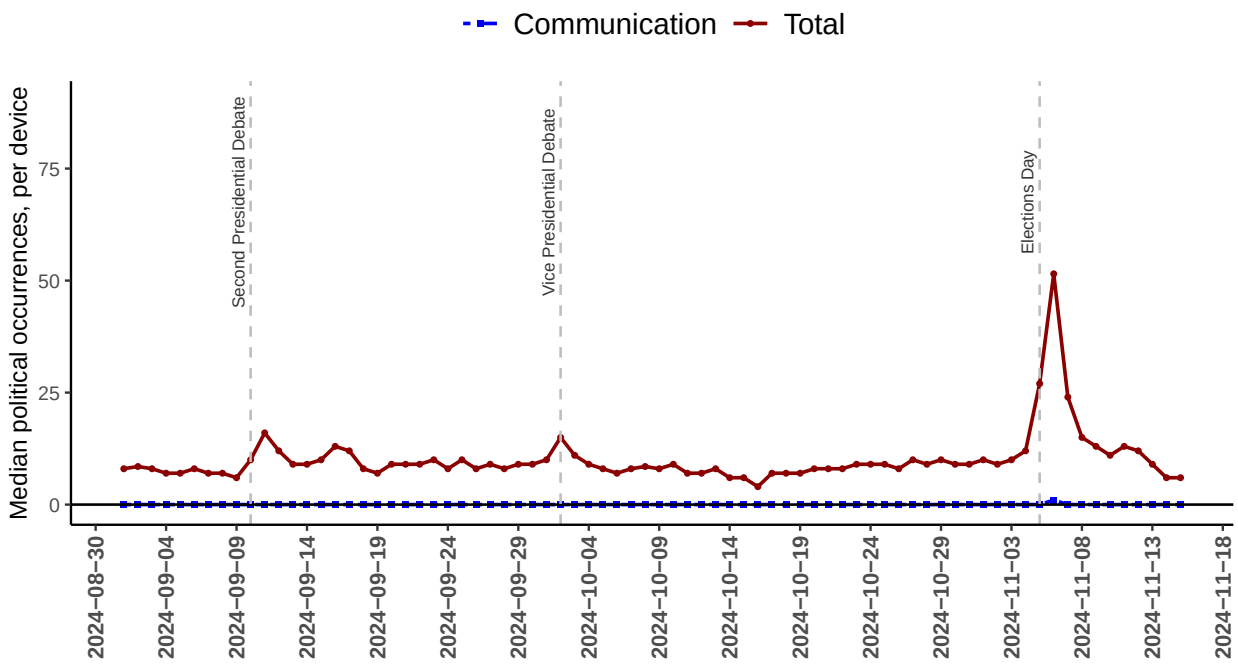
We begin our analyses by analyzing to what extent individuals are exposed to political content before elections. We define a "political" encounter as an encounter with a election term or a politician (e.g., 'elections' or 'Trump'). In Figure 1 we plot the median number of encounters per day, computed over the set of active devices in a given day, from September 1st until November 15th. We use this plot to establish several new facts.[20]

First, the median number of political encounters is arguably low. On an average day in September and October 2024, the median individual was only exposed to 9 political terms. If we expand the set of keywords to include encounters with political issues, the number is still only 12.27. These are the total number of times a political keyword was mentioned in any app, including social media posts, headlines appearing in a website's homepage, or someone mentioning the word 'Trump' in a text message.[21]

[20] We include a version of this plot in Figure D.2 that uses our demographic weights to compute a version of this that is reweighted to match a representative sample based on age and gender. The overall trend and magnitude of the effects are similar to the one reported here.

[21] In Figure B.3 we check the robustness of our results to alternative definitions of political encounters: using only election terms, election terms and issues, or election terms, issues, and politicians. The results are very similar.

Figure 1: Median daily political encounters



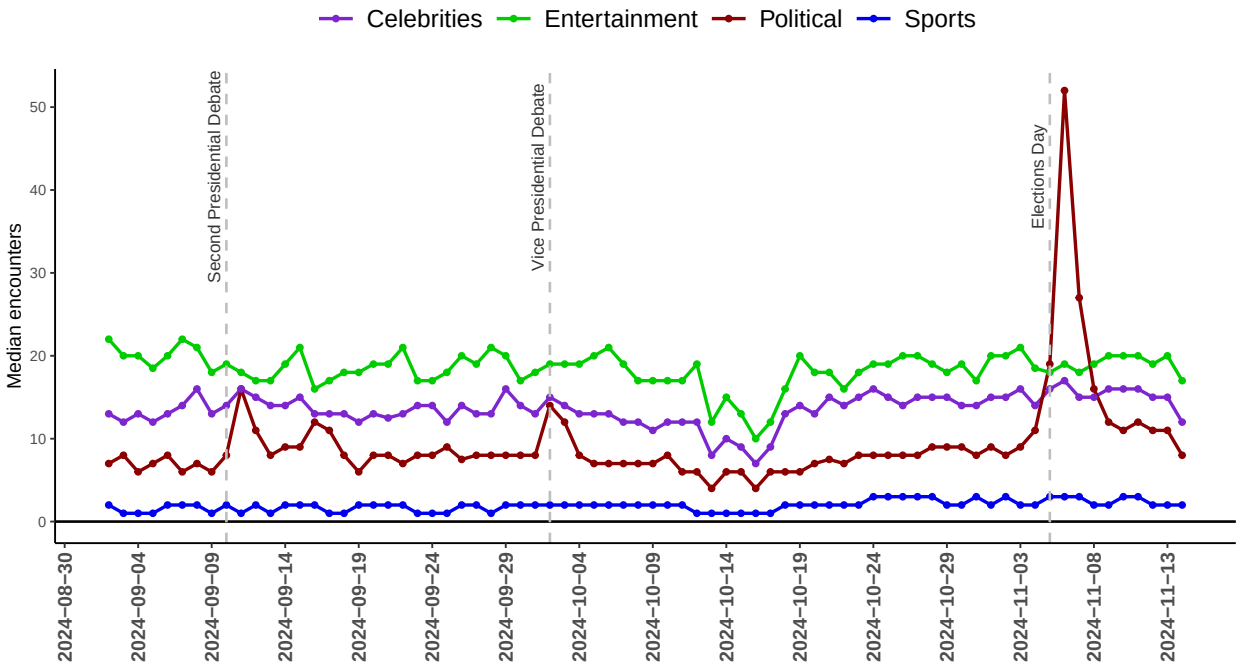
NOTES: The figure reports the median number of primary political encounters among all active devices on a given day from September 1 to November 15, 2024. The red solid line ("Total") represents all political encounters, while the blue dashed line ("Communication") tracks political encounters within communication-related apps. Vertical dashed lines highlight key political events, including the Second Presidential Debate (September 11), the Vice Presidential Debate (October 2), and Election Day (November 5). See Section 2.1 for the definition of primary political terms.

We use several benchmarks to provide context for this number. First, Figure 2 shows the median engagement with politics compared to the control keyword encounters, capturing engagement with sports, entertainment (e.g., movies, TV shows), and celebrities. This exercise suggests that the median individual encounters politics less than celebrities and entertainment keywords, but more than sports.[22]

Second, we find that on average the median individual spent approximately 21.00 seconds on their phone seeing political terms. To determine this number, we first calculate the number of unique seconds when individuals saw political terms and then multiply this number by three because keywords are captured every three seconds or less (this provides an upper bound since keywords can be captured more often if they appear multiple times in a three-second window and individuals do not necessarily spend the full three seconds exposed to the keyword). Overall, the median participant spends on average approximately 5.54 hours on their phone suggesting that

[22]We provide the mean in Appendix Figure B.2 which results in a similar conclusion of low political engagement, but find that the means are more similar due to the skewed distribution of political engagement.

Figure 2: Median daily political encounters vs. Control words



NOTES: The figure reports the median number of primary political encounters among all active devices on a given day from September 1 to November 15, 2024. The red line ("Political") represents all political encounters, while the blue, purple, and green lines represent the encounters with sports, celebrities, and entertainment keywords, respectively. Vertical dashed lines highlight key political events, including the Second Presidential Debate (September 11), the Vice Presidential Debate (October 2), and Election Day (November 5). See Section 2.1 for the definition of primary political terms and Section E for the set of keywords used for the other categories.

participants saw political terms only 0.165% of the time.[23]

Third, we compare the number of encounters to news articles and find that if someone had fully read just one New York Times article with the 2024 Elections tag on Oct 31, they would encounter 23.5 political terms on average.[24] In other words, on a given day, the median person encounters political terms less than half the times that they appear in a single New York Times article about the elections.

[23]We calculate the total amount of time spent on the phone based on data from December 19th, 2024 until January 25th, 2025 since our time use data is more accurate for this time period, however, total time use is similar in other dates. We can also use the total time the average American spends on their phone (4.5 hours) from industry benchmarks as the denominator: the participants saw political terms only 0.204% of the time. As an additional robustness exercise, we calculate time spent on the phone based on a set of 2,500 keywords. We use the same method where we multiply the number of unique seconds in which keywords appear by three. We find that at most 2.54% of total phone time was spent observing political keywords. This is an upper bound since people also spend time on their phone without seeing those 2,500 words so the actual denominator should be larger.

[24]To calculate this number we checked how often election terms or politicians appeared on the screen of someone reading these articles. The words mostly appear in the article text, but also appear in the header, title, picture caption, and additional details about the author and topic at the end of the article.

The lack of political engagement is even more stark if we define an encounter as an *engaged* encounter, where we condition only on political encounters that last at least 3 seconds. On every day besides election day and the day after, the median number of engaged political encounters is zero. Appendix Figure B.5 plots the mean number of engaged encounters in a given day and shows that it is smaller than one apart from the days surrounding the election.

Finally, we find that on a given day, most individuals do not discuss politics on their phone at all. The blue line in panel (a) show the median number of political encounters on communication apps, including both instant messaging and emails. On the vast majority of days, the median number of encounters is zero.

Overall, these results suggest that the political engagement for the median individual is low. However, this is not to say that political engagement is non-existent or uniform. Figure B.1 plots the histogram of the total number of political encounters across individuals in September and October 2024. While most individuals encounter 5-30 terms, over one in five individuals encounter less than five terms per day, and one in four individuals encounter more than 30 terms per day. Furthermore, the figures show that about 5% of consumers almost completely disengaged from politics are exposed to less than one political encounter per day and another 5% are heavy news consumers and encounter at least 100 political terms per day.[25]

3.2 Changes in Engagement Over Time

The second stylized fact we document is that political engagement is remarkably stable. Figure 1 shows that despite the numerous events that happened in September-November (for example, the second attempt to assassinate Trump, the Washington Post deciding not to endorse a candidate, Musk's increased involvement in the campaign, and the Madison Square Garden rally where Puerto Ricans were called garbage), encounters with politics did not budge.[26] There are two exceptions to this trend: the debates and election day.

On the day of the first presidential debate, individuals encountered 16 political terms on their phone, an increase of 56% compared to the previous week. The increase was much more dramatic around election day. The median number of encounters increased by 494% from the average number of encounters in September-October to the peak occurring the day after the election. We now turn to investigate in more depth these two events: the presidential debate, which coincided with Taylor Swift's endorsement, and election day.

[25]Because engagement is so highly skewed with few participants with extreme engagement we focus throughout the paper on median encounters. Appendix Figure B.4 provides the time series of political encounters for the mean, instead of median, and finds a mean of 53.35 encounters per day in September and October. While this number is larger than the median, as expected, it still represents only 0.88% of total phone time.

[26]See `https://www.ft.com/content/1010cf62-932e-4a19-9510-f5033c1c7fa5` for an extended discussion and timeline.

3.2.1 Presidential Debate and Taylor Swift's Endorsement

The highest increase in engagement before election day occurs after the only presidential debate between Harris and Trump, which also coincides with Taylor Swift's endorsement. The increase in encounters we find on election day dovetails previous literature showing that debates draw large audiences (Le Pennec and Pons, 2023). However, it is less clear if other events, such as political endorsements, are able to substantially affect engagement with politics. We focus on the most high-profile endorsement of 2024 campaign—Swift's Endorsement of Harris. Since this endorsement happened occurred on the same night of the debate, it could explain some of the increased encounters, but the timing also makes it especially challenging to study.

The presidential debate between Kamala Harris and Donald Trump was highly anticipated as it was the first debate since Kamala Harris had replaced Joe Biden and occurred on the evening of September 10th at 9 PM ET. Taylor Swift's endorsement occurred minutes after the conclusion of the debate at 10:30 PM ET when she posted her endorsement of Kamala Harris on Instagram[27] and directed her followers to register to vote.[28] Appendix Figure C.1a present political encounters by hour and shows that encounters spiked when the debate started and increased again when the debate ended and Swift made her endorsement.

To study whether Swift's endorsement could have affected interest in politics, we begin by documenting the number of mentions for the term 'Taylor Swift', highlighting that individuals in our sample were exposed to the endorsement event. Figure 3a shows that overall mentions of Taylor Swift were fairly flat from September 1st until September 10th, while the number of mentions for Taylor Swift dramatically spiked on September 11th, increasing by over 100%.[29] The overall mentions of Taylor Swift does not return back to pre-endorsement levels until September 20th, nearly 10 days after the endorsement, suggesting that the event could also have a persistent effect on engagement. While the spikes for Taylor Swift on news applications only persist for the day following the endorsement, the breakdown by category suggests longer-lasting elevated exposures to Taylor Swift on social media and communication applications, highlighting possible heterogeneous effects of engagement by app categories.

In order to separate out the effects of the debate with the endorsement, we exploit a unique aspect of the Taylor Swift endorsement, which is that she is a musical artist, and so individuals can have non-political keyword encounters for the term 'Taylor Swift' before the endorsement.

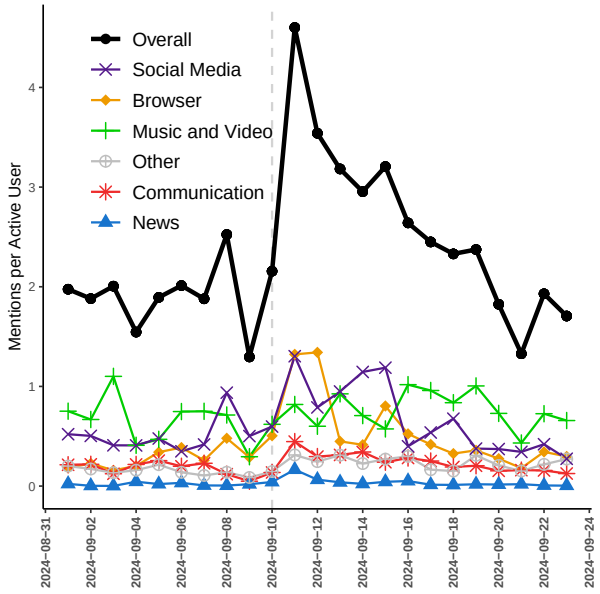
[27] https://www.nytimes.com/2024/09/10/us/taylor-swift-endorses-kamala-harris.html

[28] Reportedly the number of visits to 'vote.gov' increased dramatically following the debate and the endorsement. See https://www.cbsnews.com/news/taylor-swift-kamala-harris-endorsement-vote-gov/.

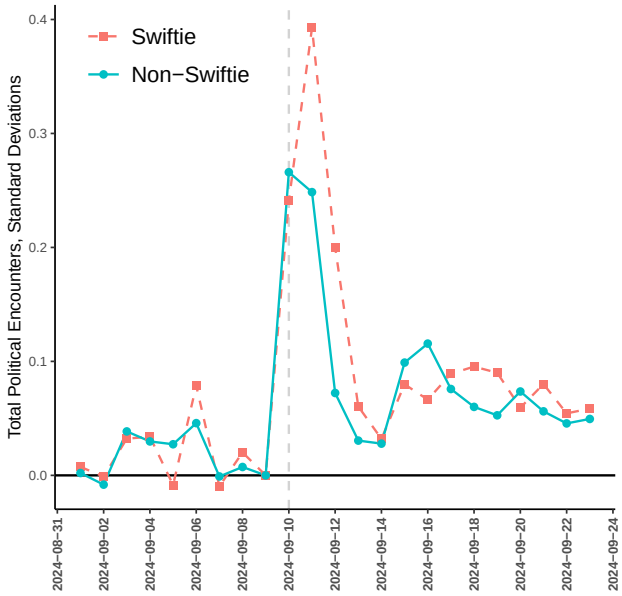
[29] As the endorsement was made late in the evening on September 10th, this is when we expect to see that most individuals would initially be exposed to it. Appendix Figure C.1b shows the number of encounters with the term 'Taylor Swift' by hour and confirms the interest spiked exactly when Swift made her endorsement.

Figure 3: Taylor Swift's Endorsement

(a) Taylor Swift Encounters



(b) Political Encounters



NOTES: Subfigure (a) describes the average daily mentions of the term "Taylor Swift" per active individual across different app categories. Subfigure (b) illustrates the occurrences of political encounters over time, in standard deviations, comparing activity between Swiftie and non-Swiftie individuals. Political encounters are defined by those using the core political terms and politician names, excluding issues. We normalize occurrences to zero on the day before the endorsement. The dashed vertical line in both panels marks the timing of Swift's endorsement.

Namely, we define 'Swifties' as individuals in our dataset that had at least one non-political occurrence of the Taylor Swift keyword in the Music & Video category (e.g., Spotify, YouTube) before the endorsement and consider them to be more likely to be influenced by the endorsement. Given the popularity of Taylor Swift, this leads to 30.5% of the individuals that we observe being classified as 'Swifties'. We measure the short-term effect of the endorsement on "Swifties" (treated individuals) and "non-Swifties" (control).

Figure 3(b) shows the occurence of political encounters (defined similarly as in Section 3.1) for Swifties vs. non-Swifties. The results show a clear increase in political engagement for Swifties the following three days after the endorsement, with the effects dissipating and becoming similar between Swifties and non-Swifties afterwards. Notably, the increase in engagement with political encounters on September 10th (0.25 standard deviation increase for both groups) – when we expect both groups to be influenced by the debate – is similar, but increases further for the Swifties on September 11th to 0.4 standard deviations, compared to 0.2 standard deviations for the non-Swifties.

In Appendix Figure C.2 we plot the time series for the following four keywords: 'Taylor Swift',

'vote', 'Donald Trump' and 'Kamala Harris'. We find a considerable increase in the occurrences of 'Taylor Swift', even for non-Swifties, which indicates that even non-Swifties were exposed to the endorsement, and that the comparison of Swifties and non-Swifties is probably a lower bound for the effect of the endorsement. This figure also suggests that the effect of the endorsement was especially strong for the term vote, which the endorsement focused on, and relatively weak for Trump, which makes sense since Swift endorsed Harris. Thus, while the focus on individual words is noisy, it provides further evidence that the increased encounters among Swifties was probably a result of the endorsement.

These results suggest that *both* the presidential debate and the Taylor Swift endorsement had increased political engagement. We provide an econometric difference-in-differences analyses of the endorsement in Appendix C.1 which confirms the same findings as Figure 3 and further explores the persistent engagement effect across different categories.

3.2.2 Election Day

After the election, there were anecdotal reports that some Americans had very little information on the candidates, to the point where searches for 'Did Joe Biden drop out' spiked on election day and the day after.[30] Of course, most Americans probably knew who the presidential candidates were but the concern remains that individuals voted without sufficient information and learned important information about candidates after they were elected.

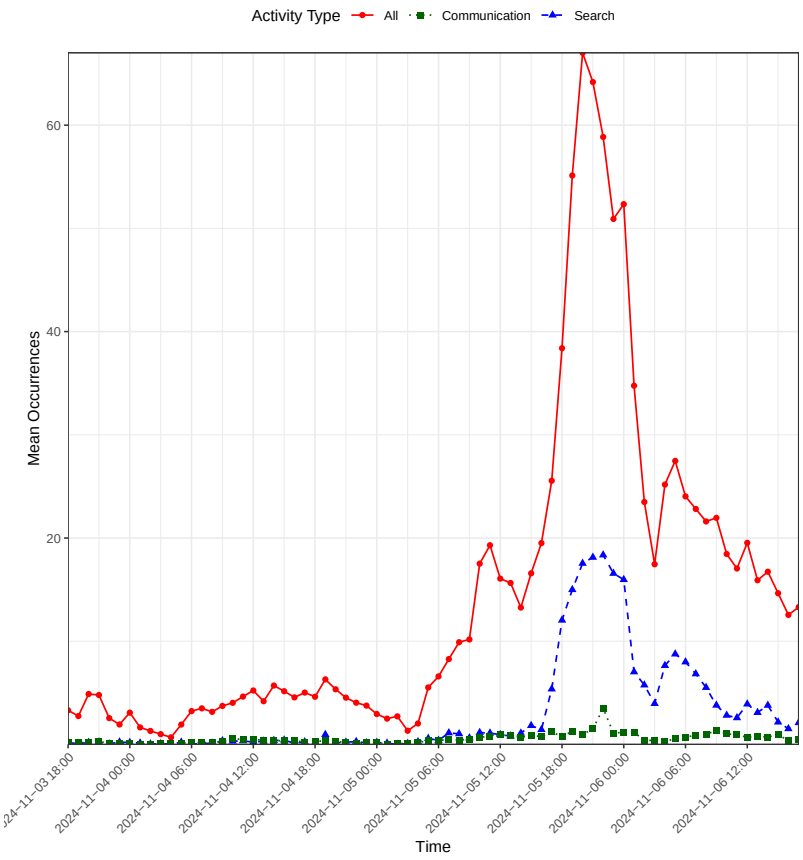
In our data, we also find a dramatic interest in encounters with politics around election day. This interest could be due to people encountering information only after they voted, but could also be consistent with individuals searching for relevant information before going to the polls. To better understand the peak interest around election day, we analyze political encounters by hour.

Figure 4 shows that most political engagement occurred *after* polls closed. The figure plots the mean political encounters by hour in the days before and after the election. It shows that political encounters were elevated throughout the day of the election, but that interest peaked around 8PM when or after polls closed.[31] Finding increased interest when polls close is not surprising. People probably want to read about the results and find out who won the election. At the same time, this result indicates that the majority of the increase in political encounters around election day is not due to people searching for relevant information before they vote. Indeed, the blue and green lines in Figure 4 focus specifically on channels where individuals may have been actively looking for information on candidates (search and communication). While searches and communication

[30] For example: `https://fortune.com/2024/11/05/did-joe-biden-drop-out-presidential-race-2024/`

[31] The vast majority of polls close at 7 or 8PM local time. Of course election results are available beforehand for people not living in the eastern time zone. For example, participants in California might have encountered political engagement at 4 PM local time just by checking election results.

Figure 4: Hourly Political Encounters



NOTES: This plot shows the average number of encounters from the beginning of November 4th until November 6th, including the day of and the day following election day. We compute the average number of primary political encounters on all applications (red) for each hour, as well as the average number of primary political encounters on communication (green) and search (blue) applications respectively. We include all active individuals on these dates for the computation.

increased on election day, the vast majority of search and communication engagement occurred after the polls closed. These figures strengthen our conclusion that individuals were exposed to limited information before election day, and that the dramatic increased in engagement around the elections is due to people reading about the results rather than gathering information to make a more informed decision.

4 What political content do people get and where do they get it

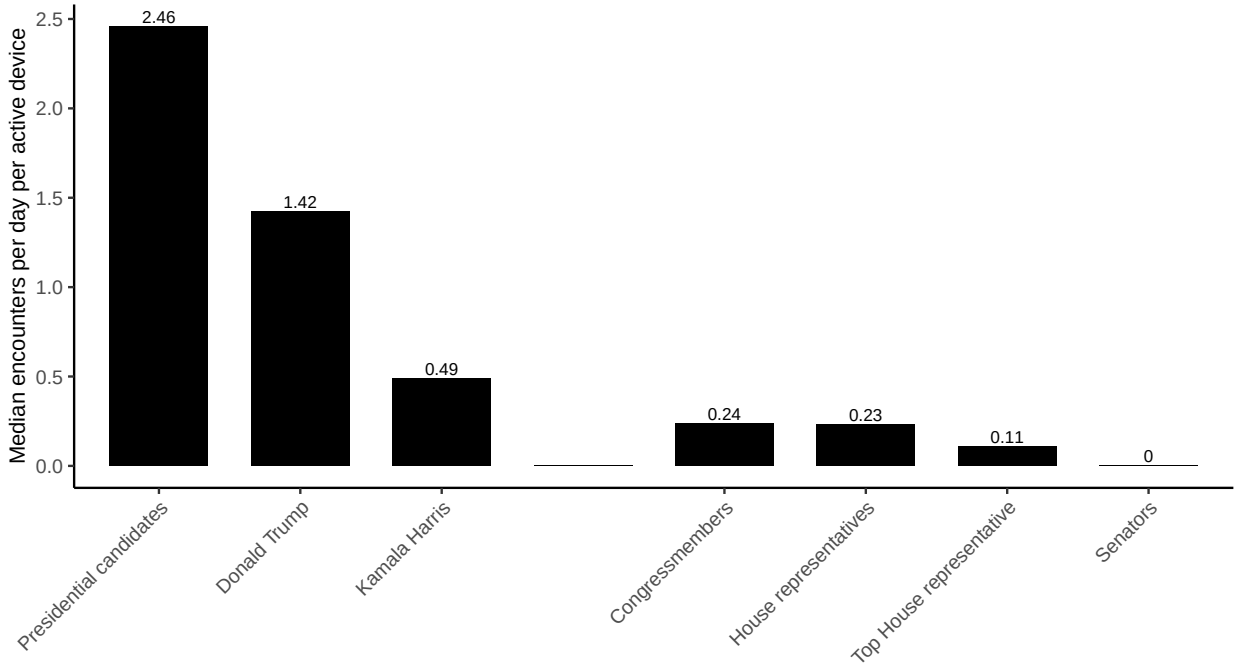
Our results thus far indicate that individuals' level of political engagement is fairly low. The limited content they are exposed to, therefore, may disproportionately influence their political knowledge

and behavior. This raises the important question of what type of political content individuals *are* exposed to and where do they consume it.

4.1 Political Content

In the presidential election, voters probably had at least some knowledge of the candidates even if their political engagement is low. That is not necessarily the case in congressional races. Most Americans cannot name their representative in the House of Representatives so clearly congressional races are a low-information environment where any political engagement is especially important.

Figure 5: Median daily encounters with politicians



NOTES: This figure presents median daily encounters with various categories of politicians per active device, calculated for individuals active on at least 20 days between September and October 2024. The results are based on the appearance of political terms, aggregated at the device level and standardized by the number of active days per individual. The analysis includes political figures and groups, such as presidential candidates, congressmembers, and senators, with House representatives' encounters further distinguished by the most frequently encountered representative per individual.

Figure 5 shows that individuals are exposed to minimal information on congressmembers compared to presidential candidates. The gap is astonishing: in September and October 2024, for every mention of a congressmember there are 10.40 mentions of presidential candidates.[32] This gap is

[32]Since not all individuals are active on all days, we only consider this table for individuals with at least 20 active

especially large when considering the fact that we include virtually all active congressmembers.[33] When we conservatively assume that the congressmembers individuals encountered the most are their local congressmember, the gap grows to 22.94 mentions of presidential candidates for each congressmember mention.[34] While it is known that politics in the US have become nationalized, this figure shows how extreme the phenomenon is and how little information individuals observe about their local elections.

Figure 5 also demonstrates a dramatic difference between encounters with Trump and Harris. 74% of all mentions of Donald Trump and Kamala Harris were of Donald Trump. Jason Miller, a senior advisor in Trump's 2024 campaign said the campaign "wanted to make sure this is going to be all Trump, all the time. The reason being that the media is going to focus on Trump because Trump generates clicks" (Bade, 2024). Based on Figure 5 this strategy was successful.

Appendix Figure D.2 shows that Trump dominated the conversation across the board. The figure shows the distribution of the share of Trump encounters among individuals who were active for at least twenty days. The results are striking as they indicate that, even individuals on the lower end of this distribution, still saw Donald Trump more than Kamala Harris. Overall, for 94% of individuals, Trump constituted over 60% of Trump or Harris encounters.

4.2 Sources of information

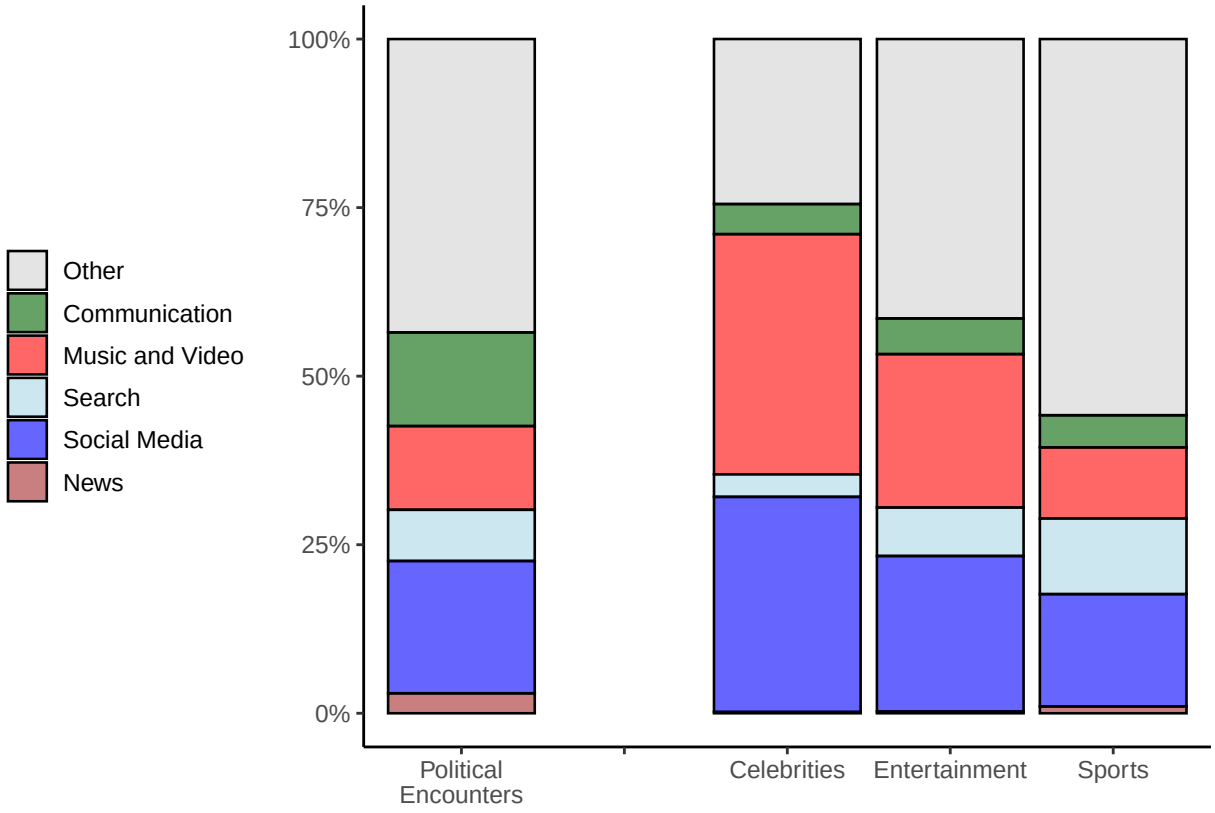
Figure 6 shows that individuals receive only 3 percent of political encounters from news apps and that most political exposure comes from social media and music & video applications. To the best of our knowledge, this is the first analysis of exposure to content across different apps, revealing that concerns about the decline of traditional media are well-founded. In Appendix Figure B.7 we focus on individual apps instead of app categories (excluding browsers), and shows that Google, YouTube, Instagram, Reddit, and TikTok are important sources of political content. Notably only two news apps appear in the top 20 (NYTimes, BBC).

days of usage, and for those with less usage than the full sample period, we scale up their usage to get a measure of the number of expected encounters for the full sample period. Our results are robust to considering this without the minimum usage requirement.

[33] We do not observe the participant's address, and therefore, cannot focus on their congressmember.

[34] In Appendix C.2 we analyze the dynamics around interest in congressmembers. We show that exposure to congressmembers is constantly low throughout September and October. Exposure does increase when around election day, but only when focusing on all congressmembers and not on the congressmember that received the most interest. This suggests that the increase in encounters stems to some degree from individuals reading about multiple congressmembers after the election, and not from individuals receiving information about their own congressmembers.

Figure 6: Share of Encounters by Category



NOTES: This figure presents the share of encounters by app category for different content types: political encounters, celebrities, entertainment, and sports. App categories include News, Social Media, Search, Music and Video, Communication, and Other (mostly Browser). Encounters are aggregated across devices between September 1 and November 15, 2024. The figure reflects aggregate content exposure patterns rather than individual-specific behavior. Political encounters exhibit a distinct distribution pattern compared to other content types, with a relatevly higher share of encounters occurring within News and Communication apps.

These results suggest that people get a large share of their information from sources that are not necessarily reliable, including social media and video apps. There are two important caveats to this result. First, individuals probably encounter news outlets indirectly on social media and music & video applications (e.g., a CNN post on Facebook or a New York Times video on YouTube). However, there are important differences between seeing content through these applications and through news apps (Aridor et al., 2024), including the content being ranked by algorithms or friends, instead of being curated by editors and individuals often seeing only headlines instead of reading full articles. A second caveat is that individuals may observe news through their browsers, which are included in the 'Other' category. While it is likely that some encounters occur through browsers, based on previous research (Aridor, 2025), most of the time spent browsing is spent on search (Google), music and video (YouTube), and various social media applications. If we assume that

the share of encounters across categories when people use their browser is similar to the overall share of encounters across categories, then the share of encounters through news apps and their website only increases from 3% to 5.2%.

The results in this section raise the concern that the content individuals are exposed to has changed dramatically because they no longer receive substantial information from traditional sources. However, it is also possible that individuals choose what content they prefer, regardless of the source where the information appears. For example, if they are interested in the Gaza war, they can read New York Times articles about it and follow social media accounts that post about the topic. In the next section we study what drives news exposure.

5 Drivers of Political Engagement

Our results thus far indicate both that the median individual has a low amount of political engagement (Section 3.1) and that most of this engagement occurs on social media and music & video applications that are driven primarily by algorithmic curation (Section 4.2). Thus, in this section we ask what drives differences in exposure across individuals: the curation of content in apps or individual preferences?

The rise of algorithms ranking content in various apps has led to concerns over biased algorithmic curation (Pariser, 2011). If indeed apps are biased in their coverage (either due to algorithms or editorial decisions) then individuals using different apps may be exposed to different magnitudes and types of political content. At the same time, the vast amount of content and personalization allow individuals to only encounter content they prefer (regardless of the app they use), for example by following specific accounts on social media. While this personalization may increase individual utility, it could lead to increased segregation in exposure to political content (Bakshy et al., 2015).

Ultimately, the content that individuals are exposed to is a result of a combination of demand-side factors and supply-side factors. On the demand side, content exposure may be driven by individual preferences, either through direct individual curation or algorithmic personalization tailored to their tastes. This could result, for example, in liberals choosing to consume more liberal content than conservatives, a concern that has been raised since the advent of the internet. On the supply side, content exposure may be influenced by platform-driven content preferencing or algorithmic bias. For example, X individuals may observe more content related to Elon Musk, if X's algorithm prioritizes such content.

To fix ideas, we consider the following stylized example we reference throughout this section.

Example 1. *Consider a world with two applications, X and Facebook, and two political keywords of interest, Harris and Trump. We examine two extreme cases for how content is sorted:*

1. ***Case 1: Preference-Driven Sorting.*** *In this scenario, on the supply side, apps either offer full algorithmic curation—perfectly responding to individual tastes and behavior—or they do not systematically prioritize certain types of content. For example, either X and Facebook have fully personalized algorithms or they both prioritize Harris and Trump equally. Thus, individuals will see the same dosage of Trump or Harris content on both applications.*

   In this scenario, individual heterogeneity will play a larger role than app heterogeneity in determining exposure to content: individuals will shape the content they see either directly through the apps they visit and their scrolling patterns or by letting algorithms respond to their tastes.

2. ***Case 2: Platform-Driven Sorting.*** *In this scenario, the content that individuals see is determined by the application they visit rather than by their individual preferences. On the supply side, apps are differentiated and seek to systematically expose individuals to certain types of content. For example, X prioritizes Trump-related content, while Facebook prioritizes Harris-related content.*

   In this scenario, app heterogeneity will play a larger role than individual heterogeneity: algorithmic biases and platform-level curation dictate content exposure, effectively overriding individual sorting by preference.

The reality in the 2024 election likely sits between these two extreme scenarios described in Example 1. We begin by providing descriptive evidence of both application-level and individual-level heterogeneity in political content exposure and then turn to quantifying which of these forces explains more of the variation in political content exposure.

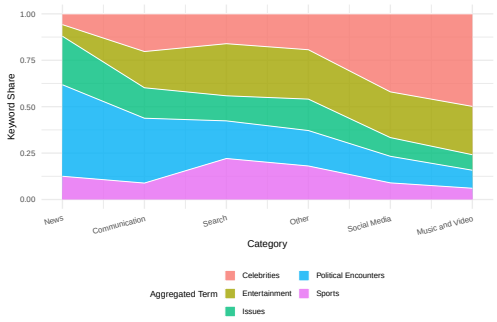
5.1 Heterogeneity in Content Exposure

In order to differentiate which of the forces in Example 1 plays a larger role, we first want to provide descriptive evidence for the presence of each. Thus, we first investigate the feasibility of Case 2 in Example 1 by documenting the differences in the magnitude and type of political content consumption across different applications. We then want to investigate the feasibility of Case 1 in Example 1 by documenting that different individuals have different shares of political content exposure. If there was no heterogeneity in either the magnitude or type of political content, then there would be little scope for possible differentiation across applications.

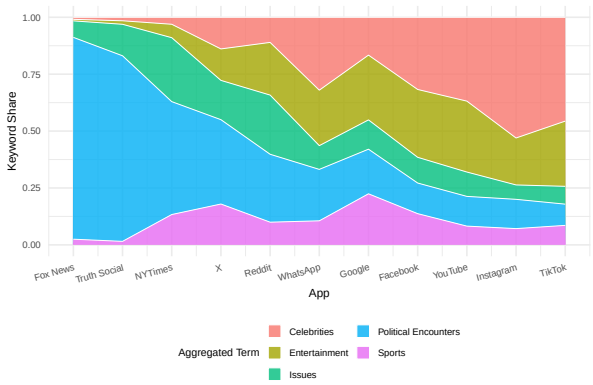
5.1.1 Heterogeneity across Applications and Categories

Figure 7: Heterogeneity in Magnitude and Type of Political Encounters Applications

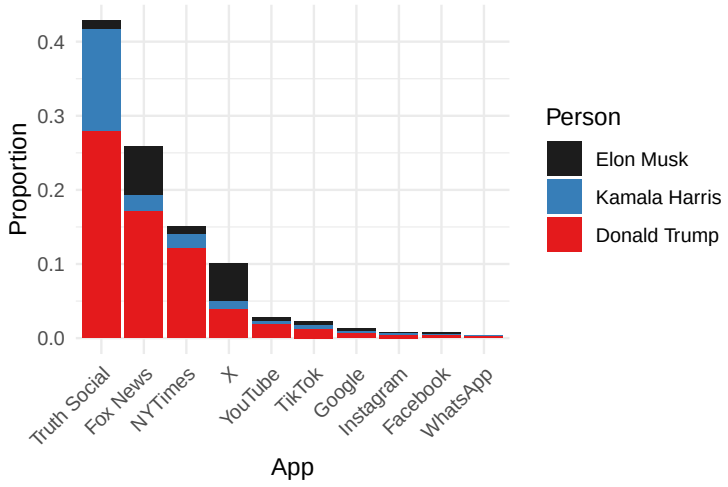
(a) Share of Encounters Within Category



(b) Political Encounters by App



(c) Political Topics by App



NOTES: Panels (a) and (b) plot the share of encounters by application category and application, respectively. Within each application (category), we compute the overall share of celebrity, entertainment, issues, sports, and political encounters. At the application (category) level, we define "share" as the ratio of encounters for a specific term category (e.g., celebrities, political) to the total encounters across all term categories within that level. Panels (a) and (b) are arranged on the x-axis in decreasing order of the share of political encounters. Panel (c) plots the overall fraction of encounters, compared to the universe of keywords we track, for Elon Musk, Kamala Harris, and Donald Trump, respectively, across each of the applications of interest. We plot this in decreasing order of the share of Donald Trump.

We begin by assessing differences at the application category level. This serves as a reasonable starting benchmark since the process by which individuals encounter keywords is very different across each of them. At one extreme, the topics that individuals encounter on communication

and search can be considered "demand-driven" since individuals explicitly have to seek out this content. At another extreme, news applications primarily contain political content and it is known that different news outlets have a different slant (Gentzkow and Shapiro, 2010). Social media and music & video fit in the middle since these platforms rely (primarily) on algorithmic curation that is intended to be geared towards individual preferences, but has the prospect to deviate based on platform design.

We characterize the differences in content consumption between the share of political content and the set of control categories that we considered earlier within each of these categories. Figure 7a plots the differences across categories, sorted in descending order on the x-axis based on the relative importance of political encounters. News applications have the highest share of encounters that are political, while categories with the lowest share of political encounters are music & video as well as social media, while "active" categories such as search and communication sit in the middle between these two.[35]

The discrepancy in political content shares across categories – particularly between social media and communication – suggests that individuals may see less political content than they may want, with communication apps serving as a cleaner measure of demand. To examine this, we compare political content shares on prominent social media platforms (Reddit, Facebook, Instagram, TikTok, X, Truth Social) to the share on a popular liberal and conservative news application (NYTimes, Fox News) as well as the most popular search, communication, music & video applications – Google, WhatsApp, YouTube. As shown in Figure 7b, the two news apps predominantly feature political content. Surprisingly, Truth Social and X have nearly the same fraction of political encounters as these news apps – exceeding the communication application WhatsApp and substantially larger than Instagram and TikTok. This finding aligns with Aridor (2025)[36], suggesting that the magnitude of political content exposure differs across social media applications and, apart from systematic algorithmic bias, could be driven by individuals using applications for different purposes. Thus, to map these results back to Example 1, this provides descriptive evidence that the forces behind case 2 can possibly drive differences in the levels of overall political content.

We next investigate whether some applications systematically prioritize certain topics. For instance, as previously discussed, there were concerns that Elon Musk and Donald Trump dominated the conversation on some applications such as X, while not as much on platforms such as Facebook (see footnote 8), potentially due to the algorithmic choices. This could potentially ex-

[35]In Figure B.9 we compare differences in the political content observed across categories by ranking the occurrence of prominent individuals in terms of overall number of encounters. We find that, while social media and communication applications, have a similar ranking, news differs substantially from both of these. This reflects that news applications are providing different content than that demanded by consumers, as reflected by the set of content appearing in communication applications.

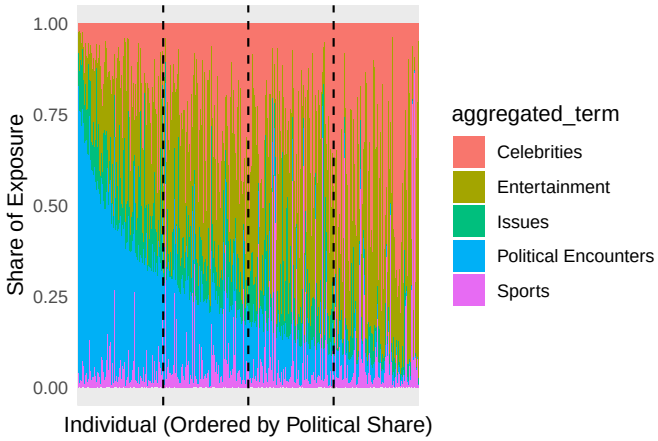
[36]See also the recent PEW survey: https://www.pewresearch.org/journalism/2024/06/12/how-americans-get-news-on-tiktok-x-facebook-and-instagram/.

plain the results in Section 4.1 as the prevalence of exposure to Donald Trump could be a result of app-specific effects. We therefore focus on the relative shares of three keywords within each application: Kamala Harris, Donald Trump, and Elon Musk. Figure 7c plots the relative shares with applications ordered in descending order of Trump share. The results show that Elon Musk has almost no encounters on social media applications, apart from X, and that Donald Trump has a large share on X, while having a very small share of encounters on Meta applications. Thus, this provides suggestive evidence for the presence of the forces in case 2 in Example 1 by confirming some of the concerns about differences in the type of political content surfaced across applications.

5.1.2 Heterogeneity across Individuals

While Section 5.1.1 shows that there are differences in content exposure across applications, it would be surprising if case 2 in Example 1 entirely dominated and there was no role for individual choices to play a role in determining exposure levels. Therefore, we now turn to studying the differences in the overall political content diet across individuals.

Figure 8: Heterogeneity in Share of Political Encounters Across Individuals



NOTES: This figure plots the share of individual content diet across celebrity, entertainment, issues, sports, and political encounters. We define the share as the fraction, at the individual level, of encounters within each category compared to the total set of encounters across all of these categories. We compute this over the period of September and October 2024 for the set of individuals who are present in the data for at least 20 days and then plot the individuals in decreasing order of political share. The three dotted lines indicate the 25th, 50th, and 75th percentile, respectively.

Figure 8 plots the same breakdown as Figures 7a and 7b except, instead of applications, considering individuals that are in our sample for at least 20 days. Individuals are ordered in decreasing order of share of political encounters with the dotted lines demarcating the 25th, 50th, and 75th percentile of individuals. The results are somewhat striking as they suggest wide heterogeneity across individuals – with some individuals having most of their content consumption consist of

political encounters. At one extreme, some individuals' content diet is dominated by political content, relative to entertainment and sports, while for nearly half the sample it makes up only a very small proportion. Thus, while the applications that individuals use is clearly important, wide heterogeneity across individuals is viable and indeed present in our data. Thus, relating it back to Example 1, this may arise because, if reality is closer to case 1, then the personalized component of algorithmic curation can enable individuals to match their desired demand for the magnitude of political content.

5.2 Unpacking the role of applications vs. individuals

The results from Section 5.1 provide descriptive evidence that suggests that applications themselves could play a large role in driving the content that individuals observe. At the same time, it suggests that there is substantial heterogeneity in the share of political consumption across individuals. Thus, we have provided evidence for the viability of both cases 1 and 2 in Example 1 and now turn to answering the question of which of the two forces is more important in driving the observed variation in exposure to political content. To answer this question, we compare the relative contribution of individual versus application heterogeneity. To do so, we conduct a variance decomposition in the spirit of Abowd et al. (1999)—hereby, AKM. Our estimation uses data of the weeks prior to the election and around the election, from September 1 to November 15. To reduce noise, we aggregate our data at the weekly level.

Empirical Specification. Concretely, we consider the following empirical specification that we estimate for each keyword k:

$$y_{iat}^k = \alpha_i^k + \beta_a^k + \gamma_t^k + \varepsilon_{iat}^k, \tag{1}$$

where y_{ia}^k represents a measure of exposure, given by the number of times that individual i encounters keyword (or group of keywords) k on app a on period t as a share of the total encounters of the indiviual on that app and period across all keywords. This normalization is useful because it accounts for differences in usage across individuals and applications. By conditioning on total exposures, we can better understand the differences in the *composition* of the content that individuals are exposed to.[37]

The parameter α_i^k represents individual fixed effects, and can be interpreted as a combination of (time-invariant) portable individual characteristics that results in equal exposure to k across all apps. For example, it may be the result of different apps serving a given share of exposures to a individual due to their personalized algorithms or due to the individual's portable scrolling patterns.

[37] The logic for using this measure is conceptually similar to the reason why the literature on echo chambers focuses on the *percent* of content of different political affiliations that individuals are exposed to (Bakshy et al., 2015).

The parameter β_a^k denotes app fixed effects, which captures the possibility that some apps expose their individuals systematically to certain types of content. For example, this parameter will capture any algorithmic bias that is uniform across individuals. Lastly, the parameter γ_t^k denotes time fixed effects, which allows a given keyword to be particularly popular across all individuals and apps on a given time period.

This methodology imposes three main assumptions (Card et al., 2018). First, we assume that the error terms ε_{iat}^k are mean-independent from the individual, app, and time-fixed effects. While this "exogenous mobility" assumption rules out that individuals sort into apps and keywords based on the shocks, it allows for unrestricted sorting patterns of individuals into apps based on any function of their own and the app fixed-effects—these can be arbitrarily correlated. Second, we impose an additive separability assumption, which rules out interactions—and thereby, complementarity—between individuals and apps.[38] Third, as explained in Abowd et al. (2002), the app effects are only identified up to a constant within a "connected set" of apps—indirectly or directly connected via individual "moves." In our context, the largest connected set encompasses over 99.9% of the individuals and of the apps. Moreover, due to multi-homing, our setting is unlikely to suffer from the limited mobility bias caused in settings with a limited amount of mobility (Abowd et al., 2004). Nevertheless, we restrict our sample to individuals who visit at least 30 apps and, subsequently, to apps visited by at least 30 of these individuals.

Case Studies. We primarily use this specification for the variance decomposition, documented in more detail below, but first want to understand whether, once we control for individual and time effects, the differences in applications that would be suggestive of the forces behind Case 2 in Example 1 driving observed encounters, still persist. Thus, we revisit two of the results from Section 5.1.1: the over-representation of Trump and Musk on X and the discrepancy between news and communication apps. We present our main results on Figure 9, which presents app fixed effects from Equation (1), focusing on social media apps (Figure 9a) and more broadly apps across different categories (Figure 9b). We use Facebook as the reference category in light of Meta's decision in early 2024 to stop actively recommending political content (see footnote 8). To the extent that Meta claims that this change enables individuals to have more agency in their exposure to political content, it is a useful reference point.

First, Figure 9a shows that, even after controlling for the rate of content observed across social media applications at an individual level, individuals have a higher weekly exposure to Trump of 4 pp and 12 pp on X and Truth Social, respectively, compared to Facebook. These magnitudes represent a 84% and 401% increase, respectively, from the weekly mean exposures to Trump

[38] This assumption does not rule out the possibility of content personalization; it rather rules out *differential* personalization, such as individuals with a strong preference for a given keyword experiencing relatively more exposures on higher-exposure apps than in lower-exposure apps.

across all social media apps—or the difference between the 87 and 94 percentiles in exposures, respectively, and the median.[39] These patterns across applications persist when looking at the overall share of political content, as illustrated in Appendix Figure C.6.

Notably, relative to Harris, Trump is overrepresented on X and YouTube, and to a lesser extent on Reddit. On these applications there is a 213%, 181%, and 63% higher exposure, respectively, of Donald Trump relative to the mean weekly exposures of Kamala Harris. Strikingly, Harris was relatively over-represented on Truth Social; obtaining 63% higher exposures relative to Trump. This figure also shows that exposure to Elon Musk was 6 pp higher on X than on Facebook, representing 490% of the weekly mean exposures to Musk across all social media apps. This pattern did not apply to other apps or to CEOs of other applications—that were not subject to anecdotal reports of bias.

Furthermore, Figure 9b provides evidence along the lines of Figure 7a, of the relatively higher prominence of political keywords such as Donald Trump, Kamala Harris, or Elon Musk on news applications relative to other apps. Particularly noteworthy is the prominent exposure of Trump on news apps, receiving over 7 times more exposures than Harris on the same apps. In contrast with Figure 7a, however, social media apps seem to systematically over-expose individuals to Trump and Harris, compared to search and communication apps. This pattern is consistent with a story of search and communication apps being more "demand-driven," with no evidence of systematic biases in these app's algorithms.[40]

Thus, our results suggest that, even once we control for individual fixed effects, some of the effects documented in Section 5.1 still persist and are large. This pattern suggests that it is possible that applications themselves played a big role in determining the content that individuals were exposed to. We therefore turn to investigating how much of the observed variation in exposures can be explained by individual preferences versus application effects, providing a more rigorous and holistic measurement of the overall influence of both in determining the political content diets of individuals.

Variance Decomposition. As in AKM, we decompose the variance of our outcome variable using Equation (1):

$$\begin{aligned}\text{Var}(y_{iat}^k) =& \text{Var}(\alpha_i^k) + \text{Var}(\beta_a^k) + \text{Var}(\gamma_t^k) + \text{Var}(\varepsilon_{iat}^k) \\ &+ 2\text{Cov}(\alpha_i^k, \beta_a^k) + 2\text{Cov}(\alpha_i^k, \gamma_t^k) + 2\text{Cov}(\beta_a^k, \gamma_t^k). \end{aligned} \tag{2}$$

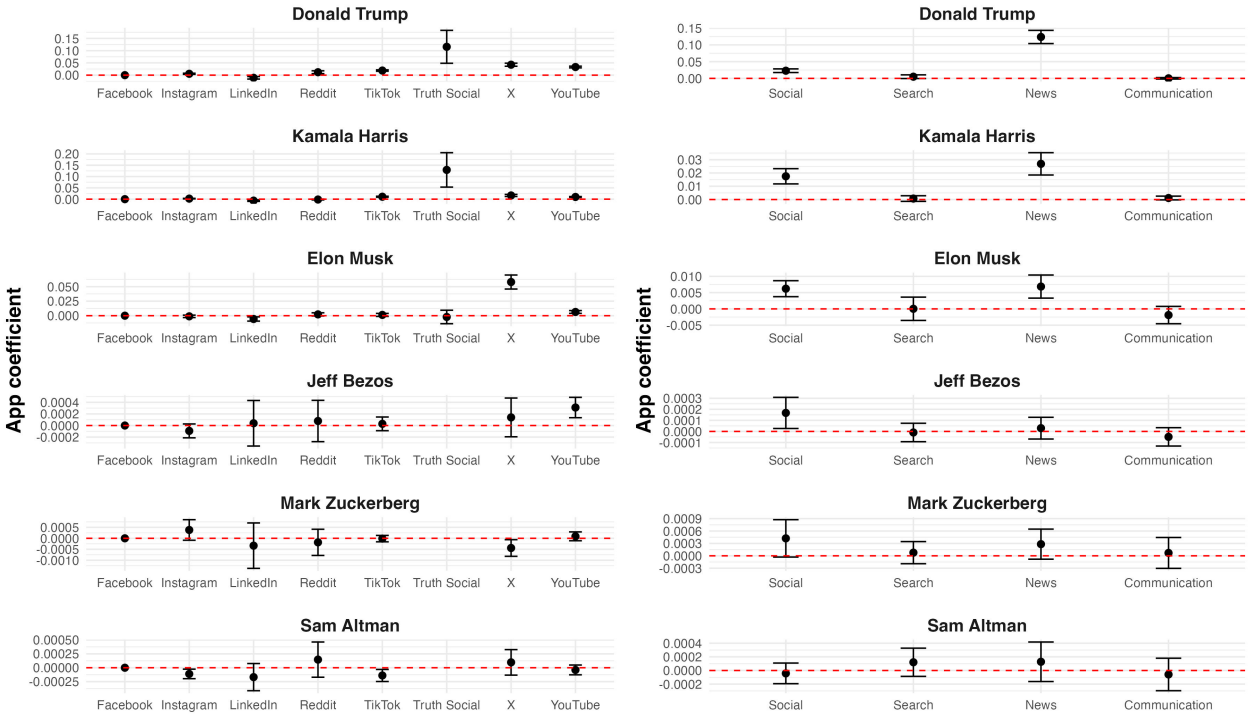
[39] As can be seen more clearly in Appendix Figure C.5 (which omits Truth Social for clarity), besides X, applications such as YouTube and TikTok seem to systematically over-expose their individuals to Trump and Harris, relative to other social applications.

[40] As before, these patterns persist when looking at the overall share of political content, as illustrated in Appendix Figure C.7.

Figure 9: Normalized Exposure Counts Across Apps

(a) Trump, Harris, and CEOs: Social Media

(b) Trump, Harris, and CEOs: By App Category



Notes: Panel (a) presents the estimated coefficients of the app fixed effects from Equation (1). We estimate this equation separately for each keyword corresponding to each person, restricting the analysis to the social media apps shown in the figure. Panel (b) extends this analysis by including all social, search, news, and communication apps. We first estimate Equation (1) at the app level and then aggregate the results at the app category level. In both panels, Facebook is the omitted category, serving as the reference group. The 95% confidence intervals are constructed using standard errors clustered at the individual level.

By comparing Var(α_i^k) and Var(β_a^k), we assess whether individual characteristics or behaviors or systematic app-specific factors play a larger role in shaping content exposure. The covariance term Cov(α_i^k, β_a^k) indicates the pattern of individual sorting into apps. For example, if this component is positive, it reflects that individuals with a particulary strong exposure to keyword k also tend to use apps that provide a frequent coverage of that keyword.[41]

	All apps		Social		Communication		News	
	T & H	All	T & H	All	T & H	All	T & H	All
$Var(\alpha_i^k)$	0.06	0.05	0.18	0.16	0.18	0.19	0.41	0.38
$Var(\beta_a^k)$	0.07	0.10	0.05	0.05	0.00	0.03	0.56	0.45
$Var(\gamma_t^k)$	0.01	0.01	0.02	0.02	0.01	0.01	0.04	0.06
$Var(\varepsilon_{ia})$	0.85	0.84	0.74	0.78	0.80	0.77	0.57	0.52
$2Cov(\alpha_i^k, \beta_a^k)$	0.00	-0.00	0.01	-0.00	0.00	0.01	-0.58	-0.42
$2Cov(\alpha_i^k, \gamma_t^k)$	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.01	0.00
$2Cov(\beta_a^k, \gamma_t^k)$	0.00	0.00	0.00	0.00	-0.00	-0.00	-0.01	-0.00
N apps	2399	2399	11	11	15	15	21	21
N individuals	3579	3579	3579	3579	3579	3579	3579	3579

Table 1: Variance decomposition, percent of variance

Table 1 shows the variance decomposition exercise, using as outcome variable either the weekly share of exposures to Donald Trump and Kamala Harris or the weekly share of political content that individuals are exposed to on different apps. We estimate the variance decomposition within each set of apps: across all apps, among social apps, among communication apps, and among news apps.

There are four main findings from this exercise. First, when considering all apps, app heterogeneity is more important than individual heterogeneity, explaining up to double the variance of the share of political content. Second, this pattern is reversed when focusing on social and communication apps, where individual fixed effects explain from 3 to 6 times the variance than app fixed effects. Intuitively, these app categories belong to the first scenario we described in Example 1: content curation is pervasive on social media, and algorithms that could introduce persistent biases are largely absent from communication apps. This finding is consistent with early work from the social media echo chamber literature documenting a larger role of individual decisions relative to the algorithm (Bakshy et al., 2015) in determining exposure to like-minded content.

Third, news applications lie somewhere in between these scenarios, with app heterogeneity explaining only 18% more variance than individual heterogeneity. These findings are consistent

[41] We conduct a simulation exercise that assumes that the true data generating process for keywords follows either Case 1 or Case 2 from Example 1 and confirm that our variance decomposition correctly identifies that application-specific effects dominate in Case 2, while individual-specific effects dominate in Case 1.

with recent work documenting substantial variance in slant not only between news outlets but also within news outlets, driven in part by individual ideological sorting within outlets (Braghieri et al., 2024). Fourth, individual sorting patterns are generally unimportant in explaining variance in exposures, except for news apps, where there is evidence of a substantial *negative* assortative matching between individuals and apps. This pattern reflects that individuals with relatively lower exposure to political content tend to sort into news apps with relatively higher exposure to political content, or vice versa. In other words, there is a "counterbalancing" pattern where if a individual naturally tends to see less political content, they may be using news apps that push more of that content—or, alternatively, individuals with a high baseline exposure might select less politically charged news apps.

In sum, we find that app-specific and individual-level factors have a similar contribution to the overall variation in political content exposure, but their relative importance differs by app type. For social and communication apps, which make up a large share of political encounters (see Figure 6), individual-level factors are the dominant drivers of exposure. In contrast, for news apps, app-specific characteristics play a larger role. Our overall estimates do not account for the absolute magnitude of usage, as our analyses considers within-application shares, but our results are suggestive that for applications where individuals spend most of their time, individual-specific factors are driving the force.

6 Conclusion

In this paper, we uncovered new facts on political exposure and engagement during a highly consequential election season. We find that overall exposure remains limited and stable in the two months leading up to the election, with brief spikes occurring around key events such as the presidential debate and celebrity endorsement, and election day. The little exposure that does occur is largely centered on national politics, predominantly focused on Trump rather than Harris, and a significant portion of it comes from social media and video apps. We uncover substantial heterogeneity in political exposures across apps and across individuals. To better understand the relative importance of these channels, we conduct a variance decomposition exercise and find that individual behavior and preferences are the primary drivers of political exposure on social and communication apps, while the reverse is true on news apps.

These findings represent a first step in leveraging a novel data collection method to study political exposure and engagement. Several open questions remain to be explored. Given that smartphones provide easy access to a large range of apps, does certain types of exposure – such as positive versus negative content or news versus social media exposure – lead to more discussions in communication apps? Are individuals simply not encountering political content, or are they

actively avoiding it? Answering these questions will provide insights into the evolving landscape of political engagement and the state of American democracy.

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Appendix

A Screenlake Panel Composition over Time

In this section we provide additional figures and plots of the composition in the Screenlake panel.

Figure A.1: Total number of panelists across time

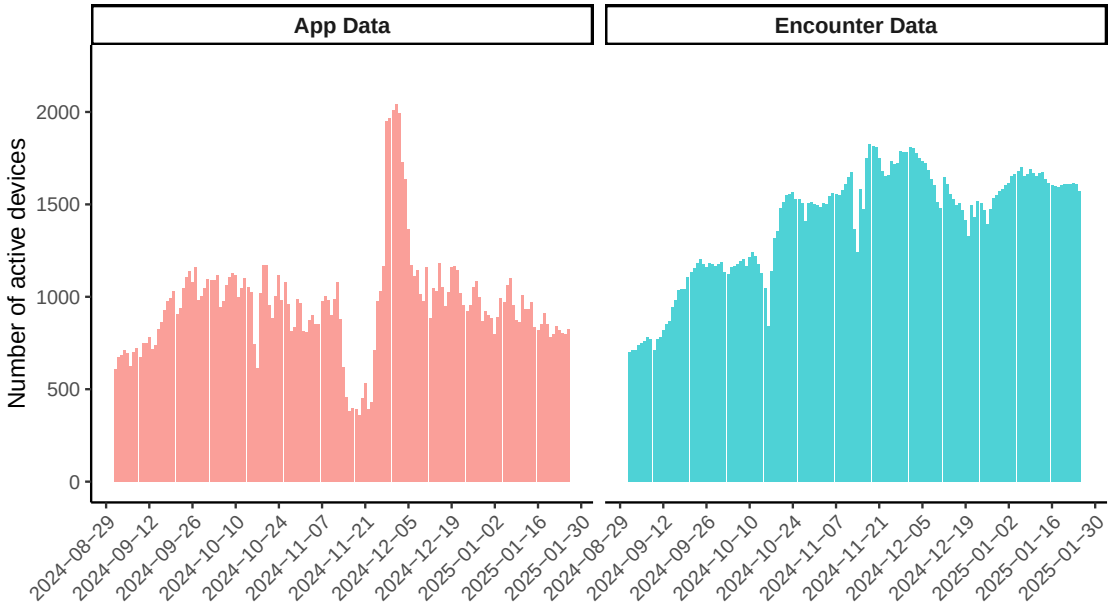


Figure A.2: Number of days panelists are active

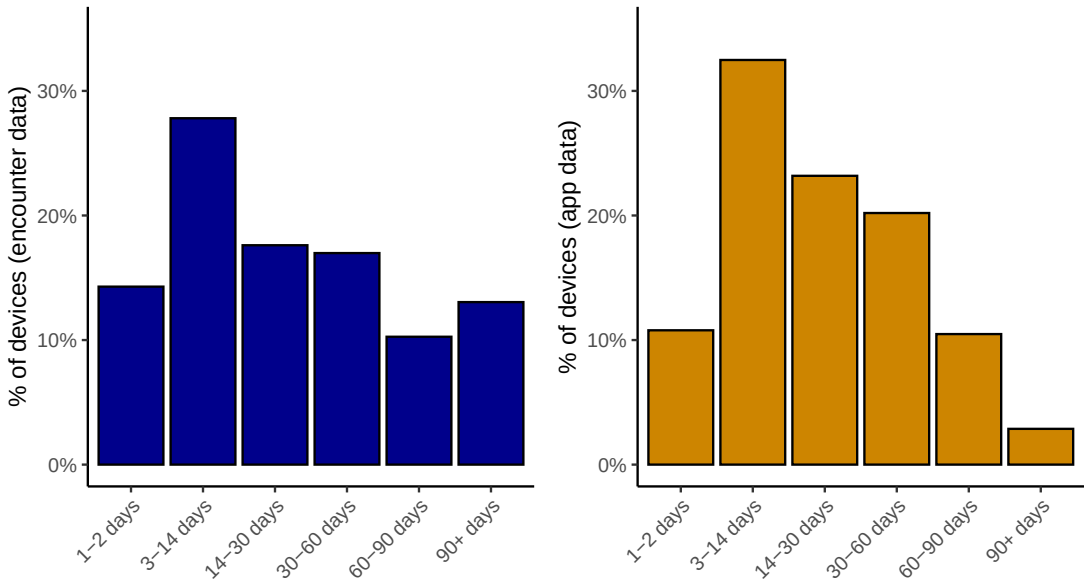
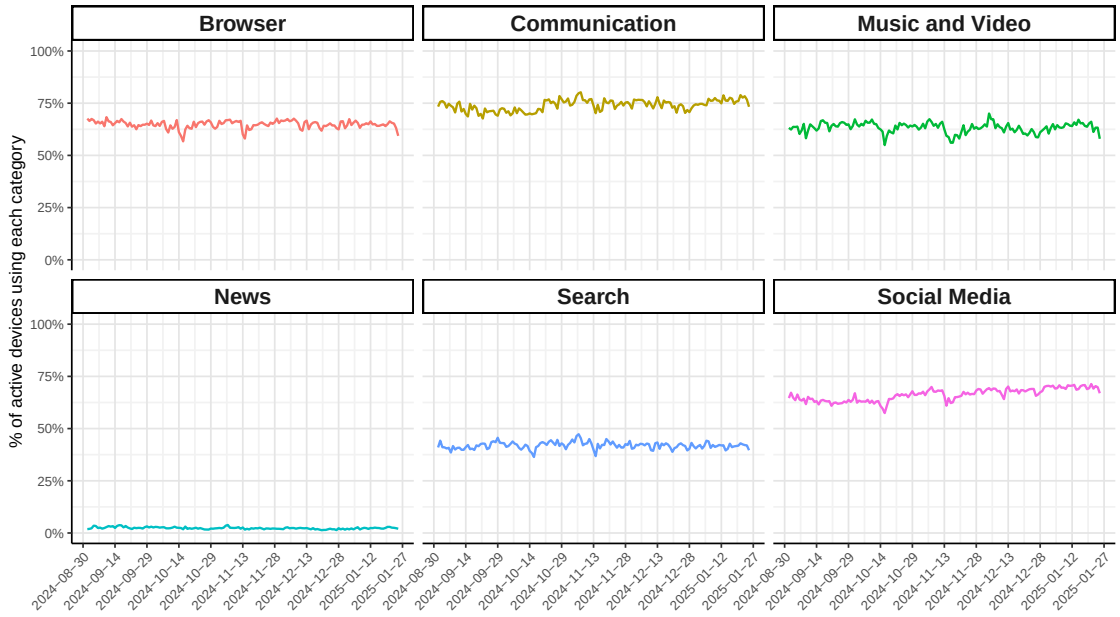


Figure A.3: Application category encounters across time



B Additional Analyses for Political Engagement

Figure B.1: Distribution of political encounters

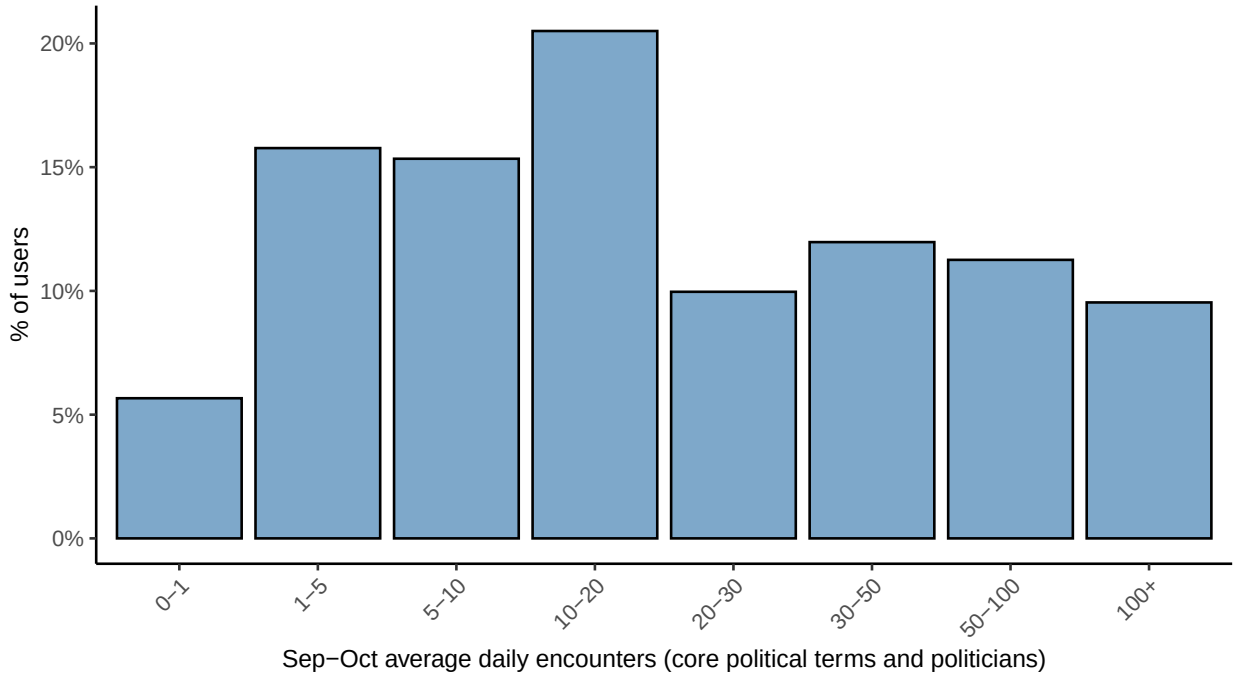


Figure B.2: Mean comparison between political and control encounters

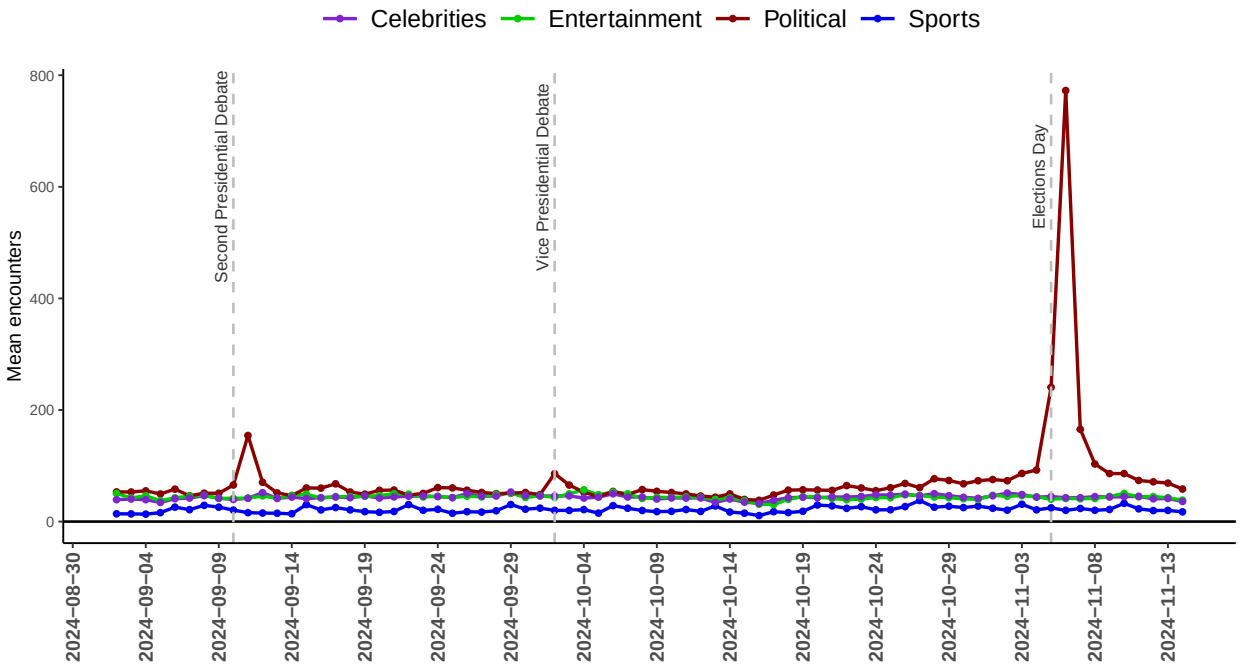
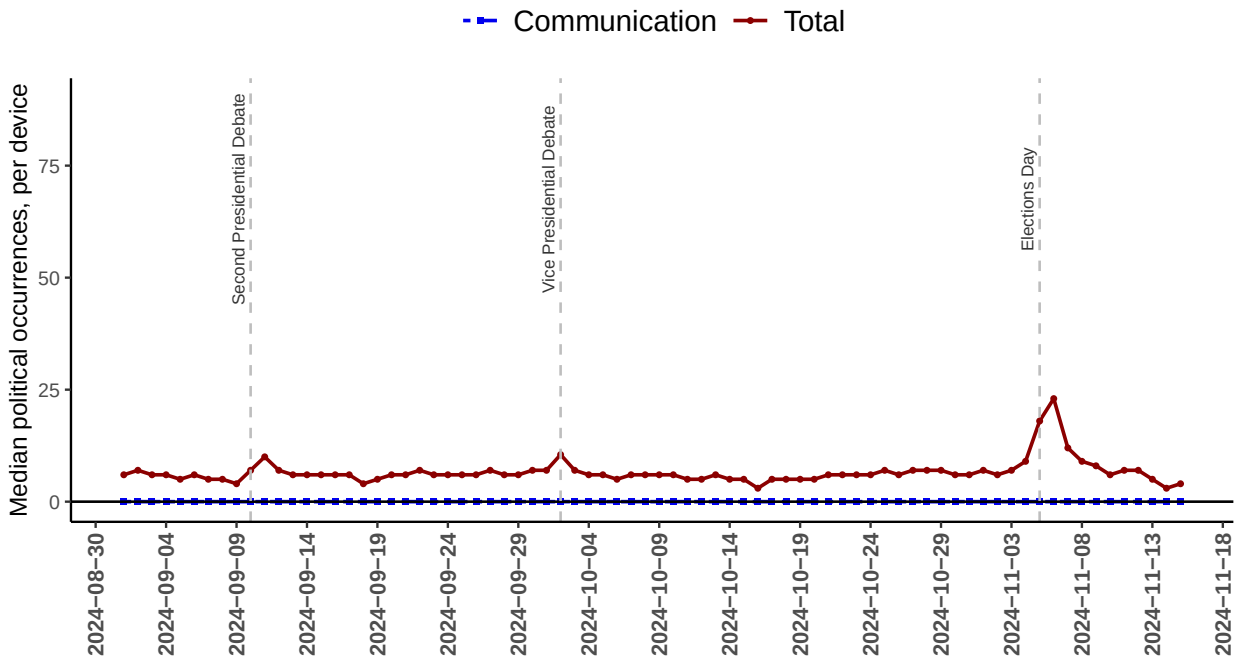
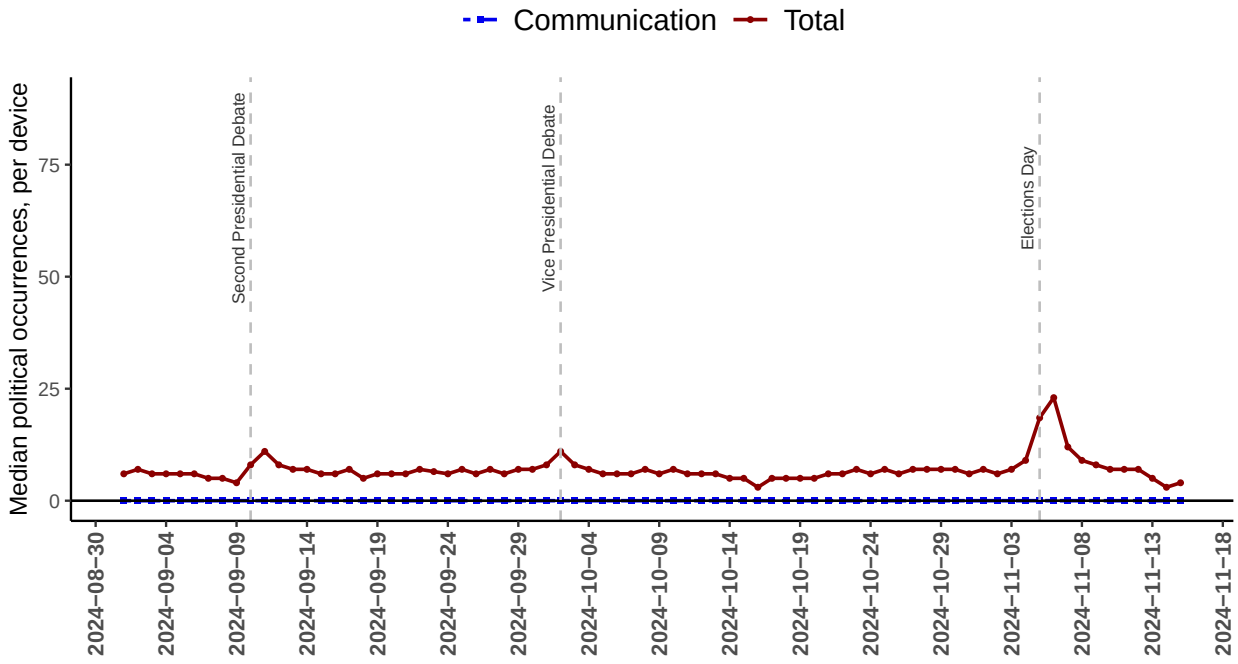


Figure B.3: Alternative Definitions of Political Encounters

(a) Core political terms



(b) Primary political terms and political issues



(c) Core political terms, political issues, politicians

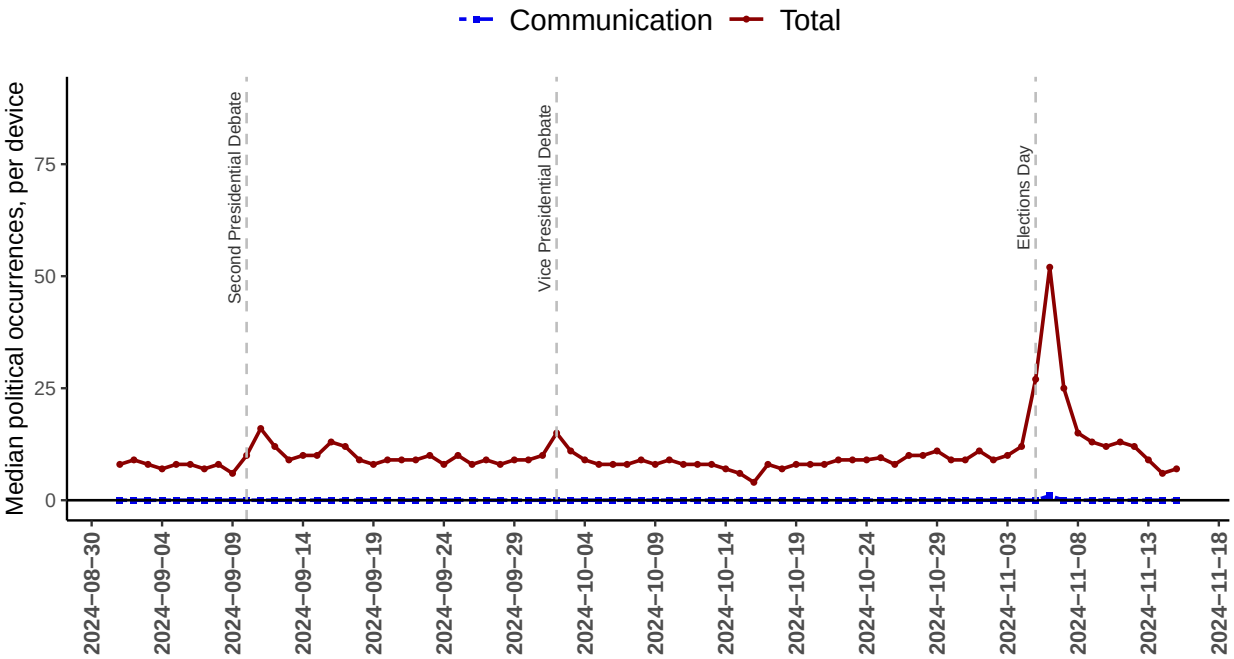


Figure B.4: Mean political encounters over time

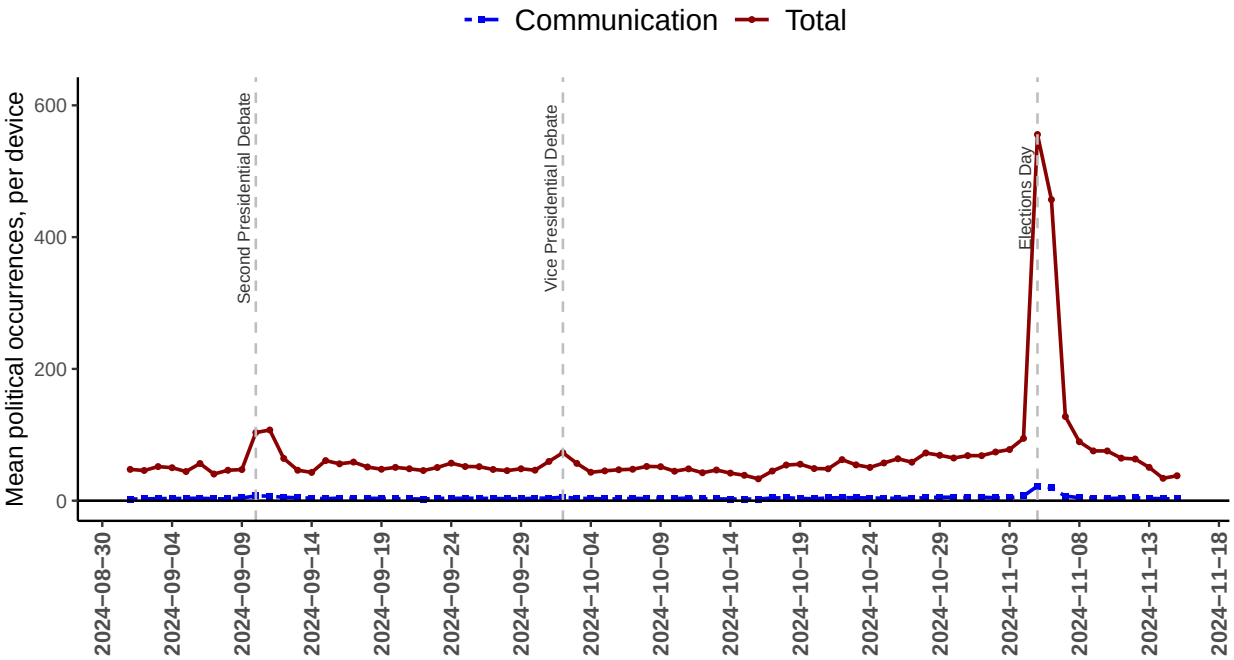


Figure B.5: Engaged (> 3 seconds) political encounters

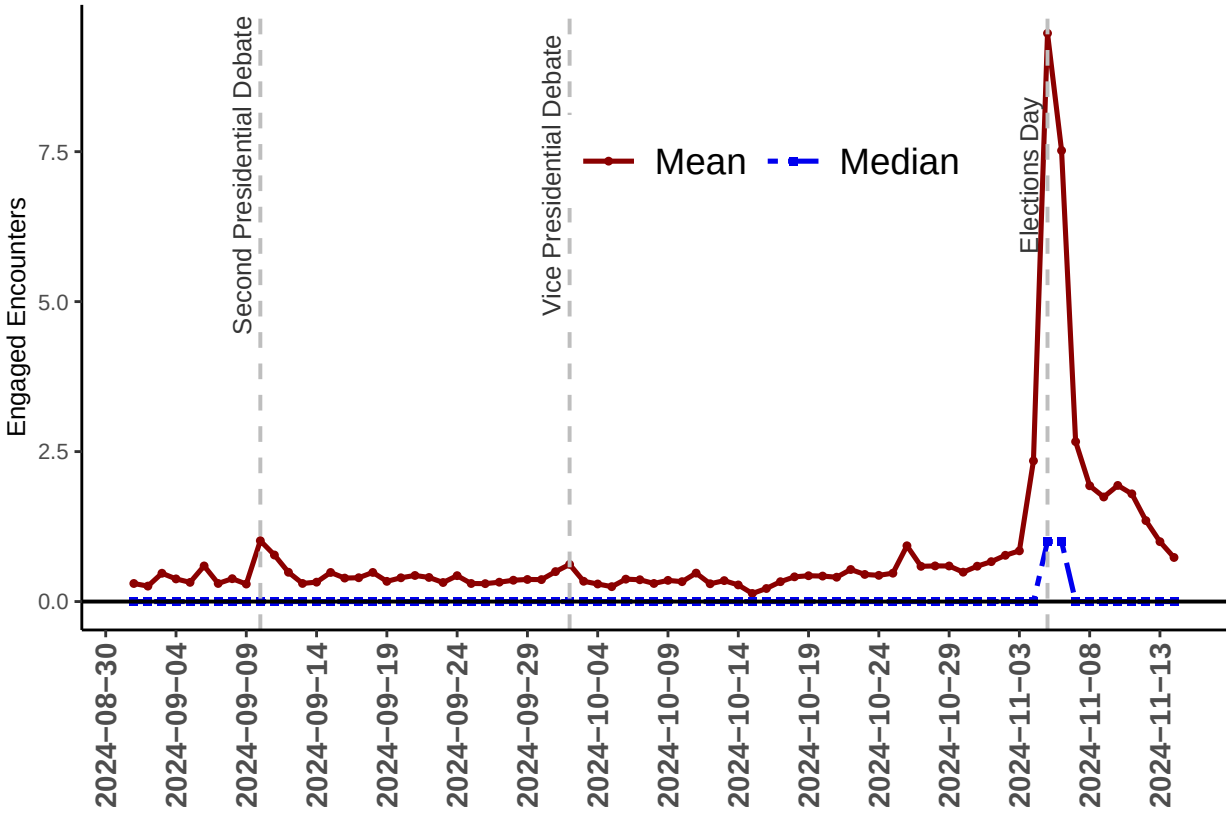
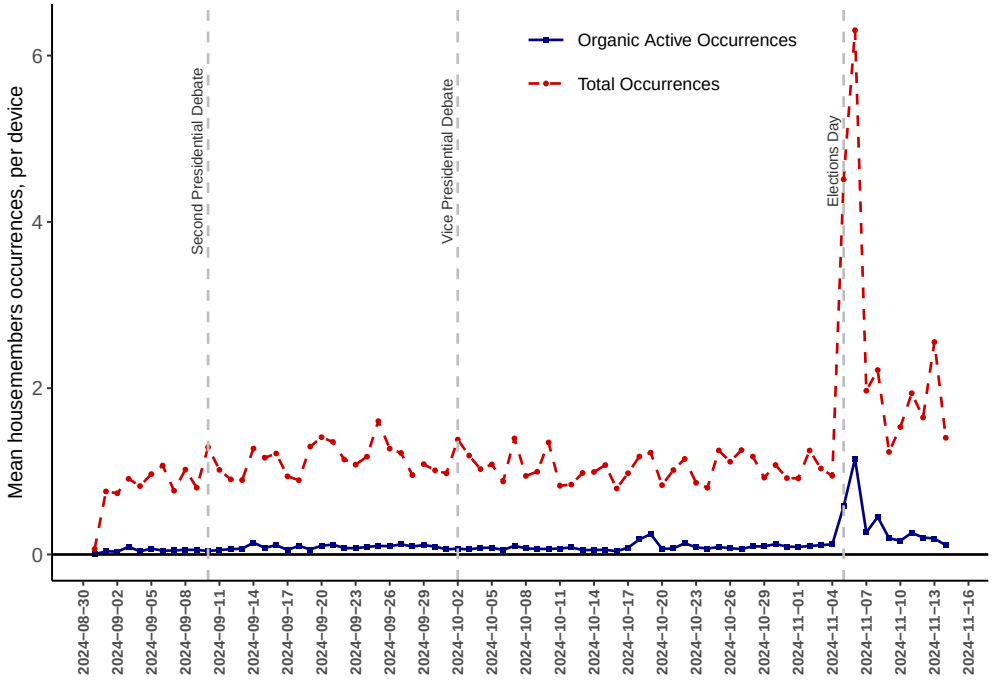


Figure B.6: Congressmembers over time

(a) Congressmember encounters over time



(b) Local congressmember encounters over time

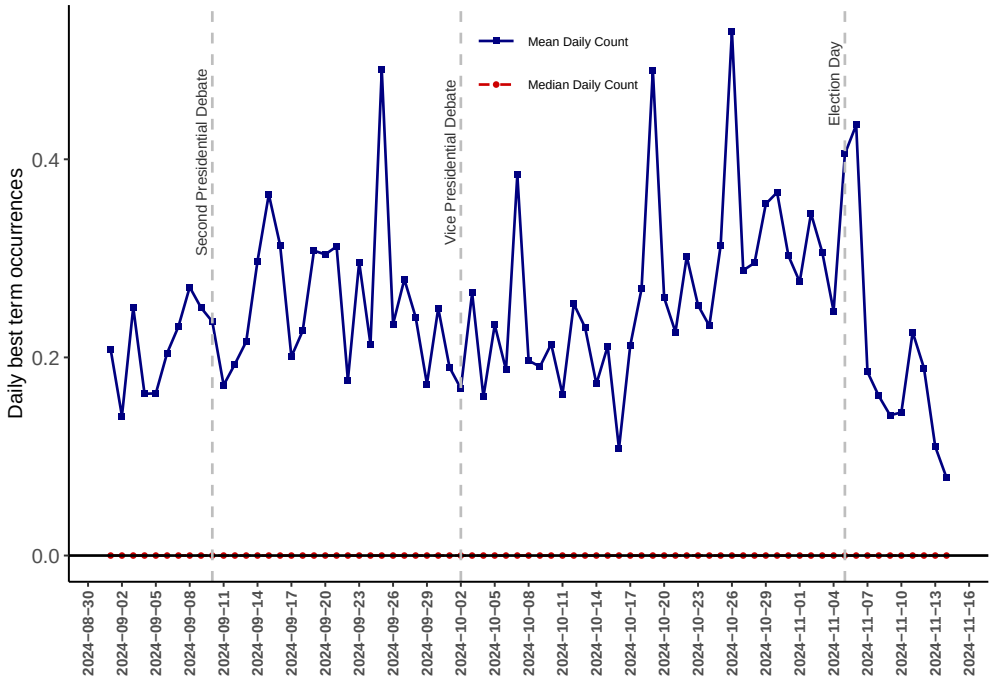


Figure B.7: Top 20 Applications for Political Encounters

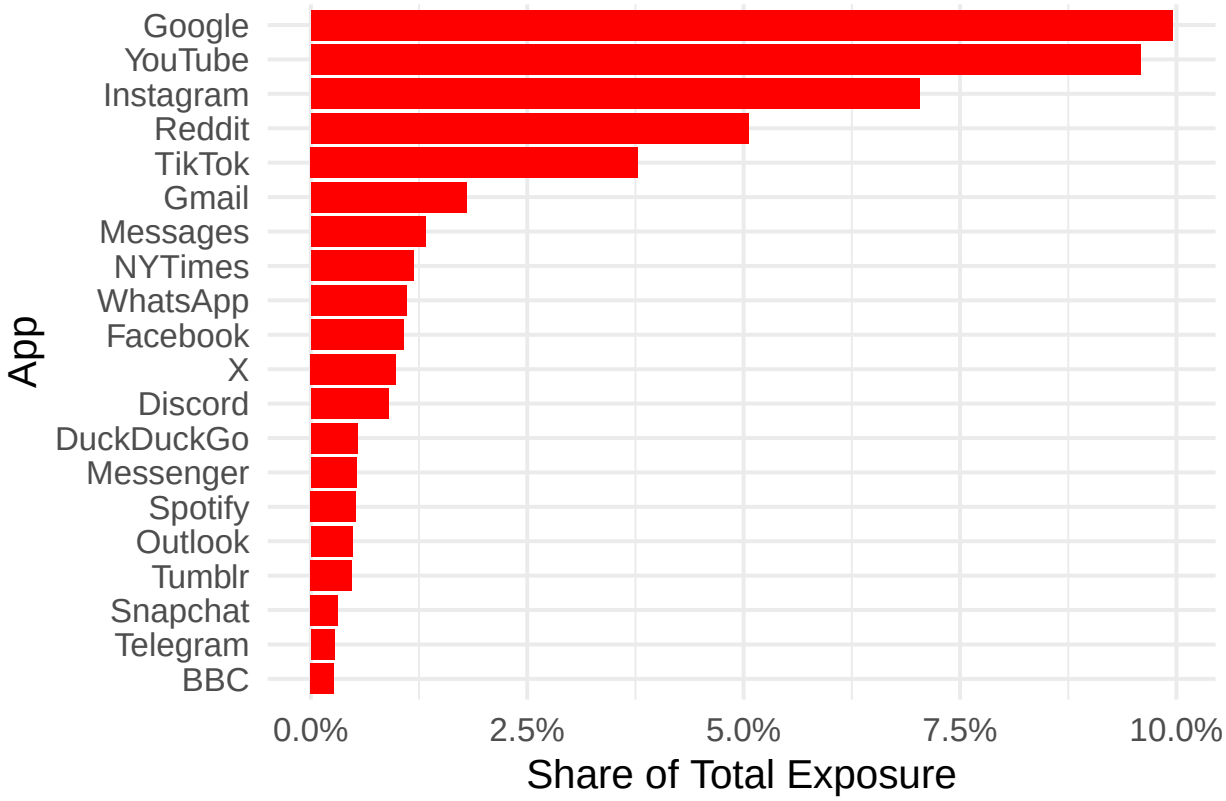


Figure B.8: Trump vs. Kamala Share

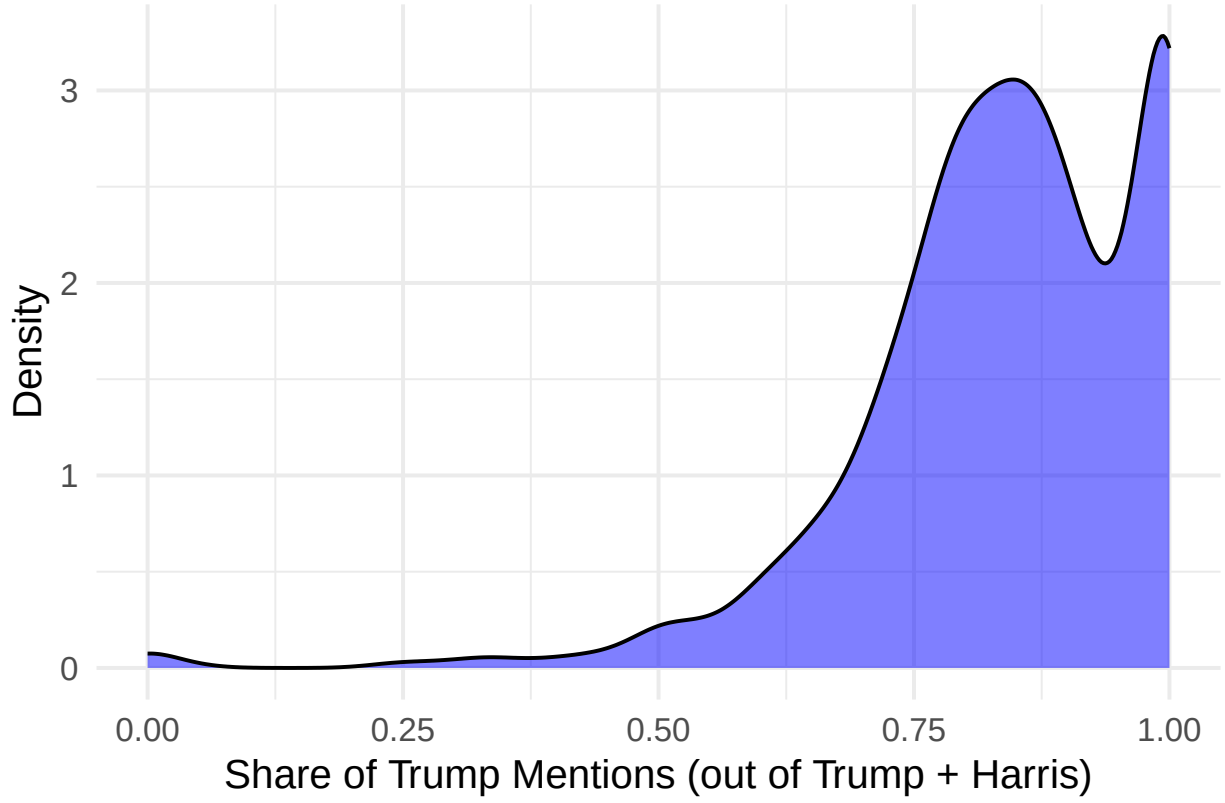
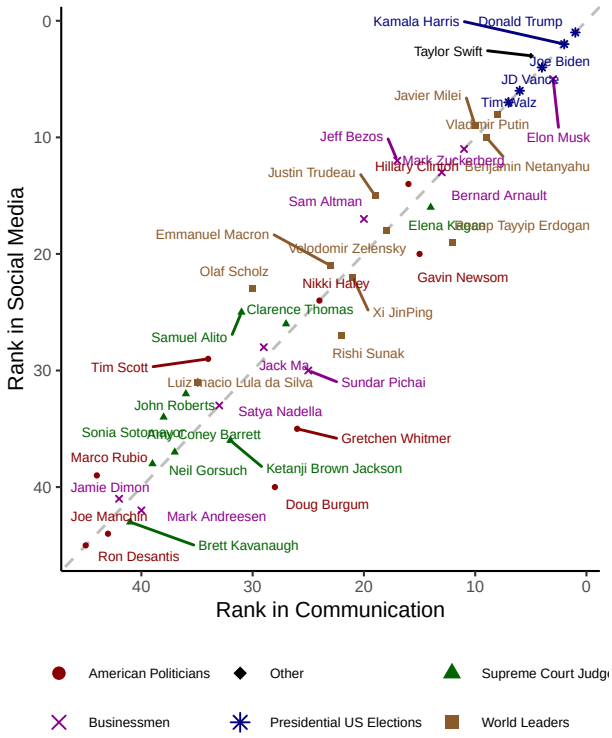
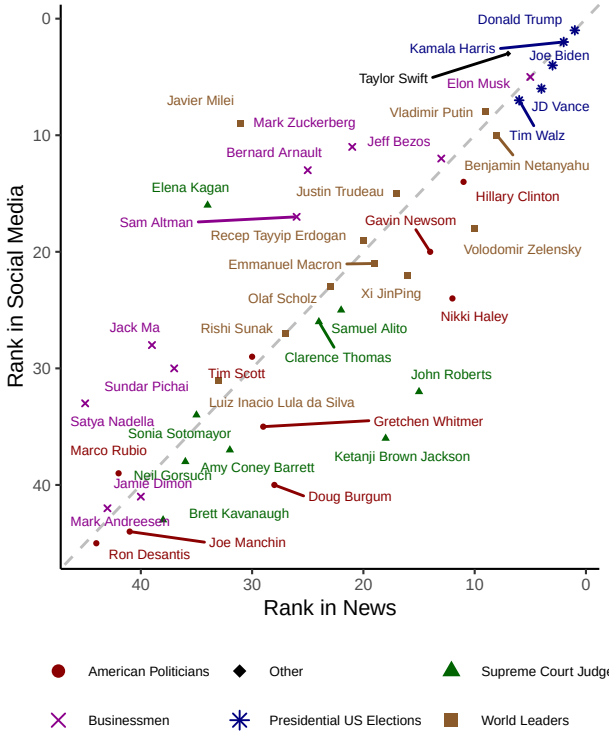


Figure B.9: Ranking of Prominent Individuals Across categories

(a) Ranking of Prominent Individuals (Communication)



(b) Ranking of Prominent Individuals (News)



C Additional Analysis

C.1 Empirical Analyses for the Taylor Swift Endorsement

In this section we perform econometric analyses to more rigorously assess the effect of the Taylor Swift endorsement. We consider the following regression model to assess the overall causal effect of the endorsement for a given individual i and time period t:

$$Y_{it} = \sum_t \beta_t \Big(\text{Day}_t \times S_i \Big) + \alpha_i + \kappa_t + \epsilon_{it}, \tag{3}$$

where S_i indicates that individual i is a Swiftie, α_i denotes individual fixed effects, and κ_t denotes month fixed effects. We cluster standard errors at the individual level. We consider three dependent variabes: the overall number of political encounters, the fraction of encounters that are political, and whether a individual has any political encounters. The first variable captures the overall magnitude of political engagement, the second captures the "dosage" of overall content that is political,

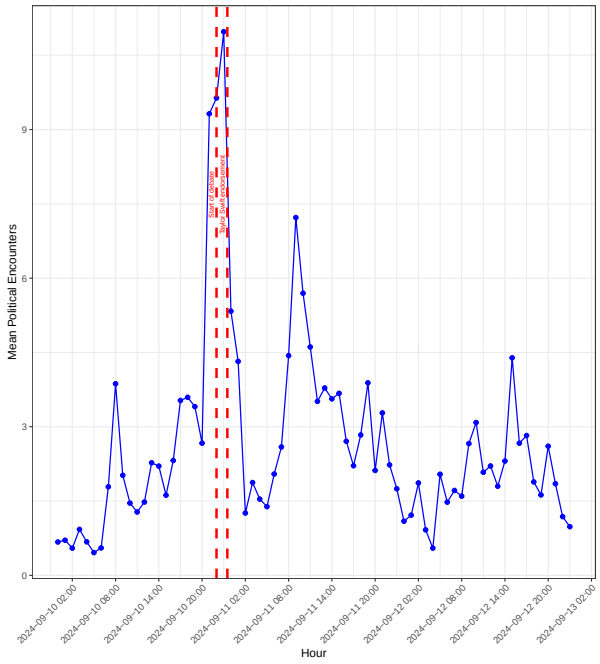
and the third captures the extensive margin of whether the individual observes any political content. Motivated by the patterns in Figure 3a, we consider this specification over all applications, active (i.e., search/communication), social media, and music & video.

We present the results for the overall magnitude of political engagement in Appendix Figure C.3(a) which show the same pattern as Figure 3 – a statistically significant of political encounters by 0.28 and 0.17 SD for the first two days, respectively, for Swifties vs. non-Swifties with an increased, but not statistically significant level of engagement following this.

A natural concern is that the results of Appendix Figure C.3 may be driven by increased engagement of already highly engaged individuals. Furthermore, as noted in Appendix Figure B.1, the distribution of political encounters is heavily skewed. Therefore, in Appendix FiguresC.4 we measure the fraction of encounters that are political. We find a similar effect as before – there is a large and statistically significant effect for the fraction of encounters that are political in the two days following the endorsement. We see some suggestive evidence in Figure C.4(a) that there is a persistent increase in the fraction of encounters that are political overall. Figures C.4(c) and (d) suggest that this can potentially be driven by increased exposure in social media and music & video applications, with larger effects in social media. While we cannot discern the mechanism here, a possible explanation could be that engagement with Taylor Swift's endorsement could lead to increased political exposure on these platforms (e.g., via following Kamala Harris or providing a signal of interest in political content through post engagement).

Figure C.1: Taylor Swift endorsement - encounters by hour, around the debate

(a) Political encounters



(b) Taylor Swift encounters

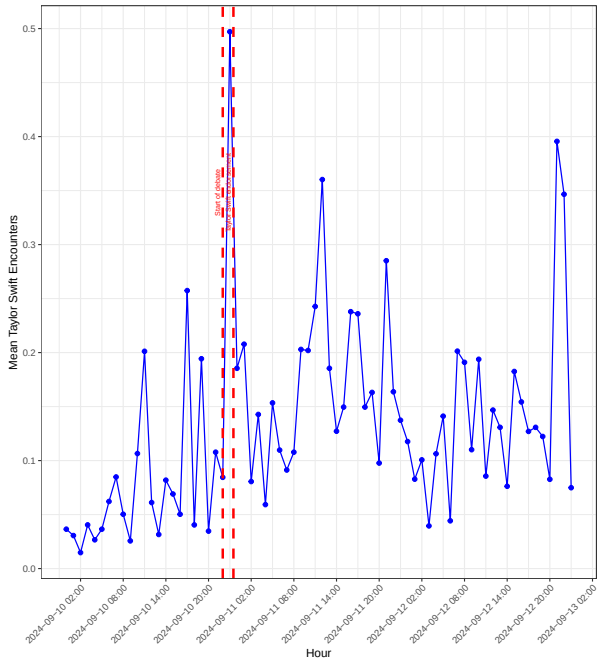
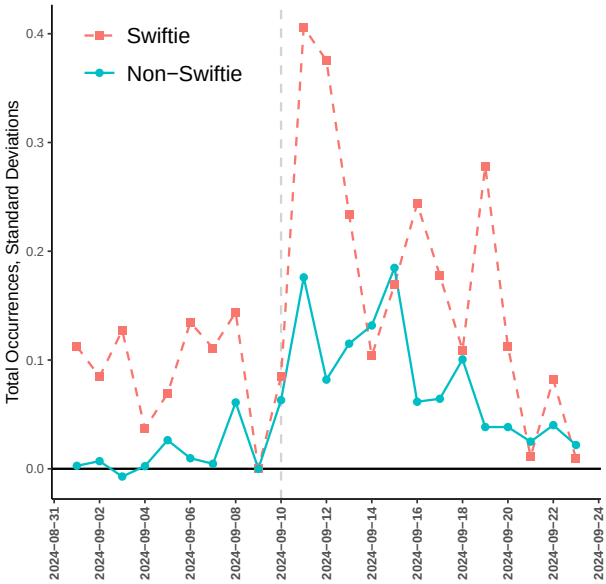
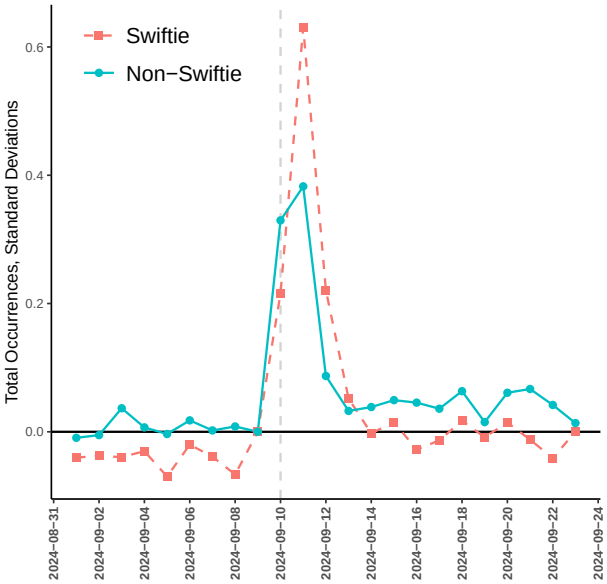


Figure C.2: Taylor Swift Endorsement – Raw Data Plots

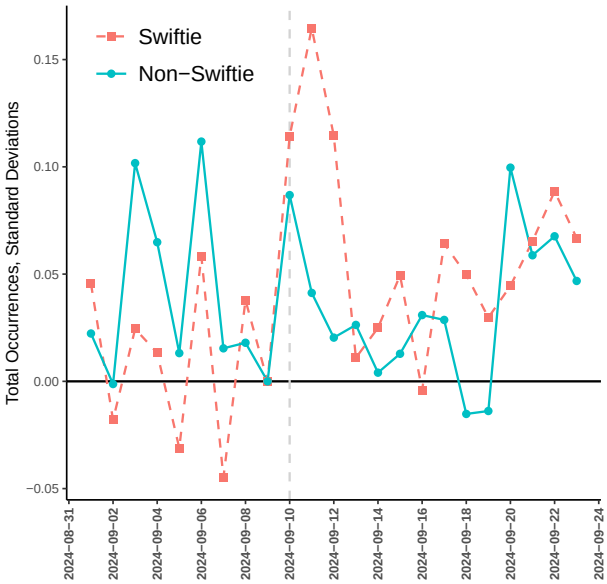
(a) Raw Data - Taylor Swift Occurrences



(c) Raw Data - Kamala Harris Occurrences



(b) Raw Data - Vote Occurrences



(d) Raw Data - Donald Trump Occurrences

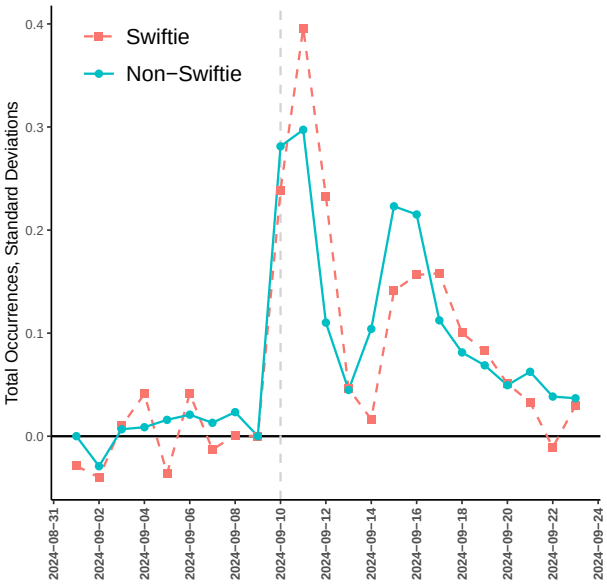
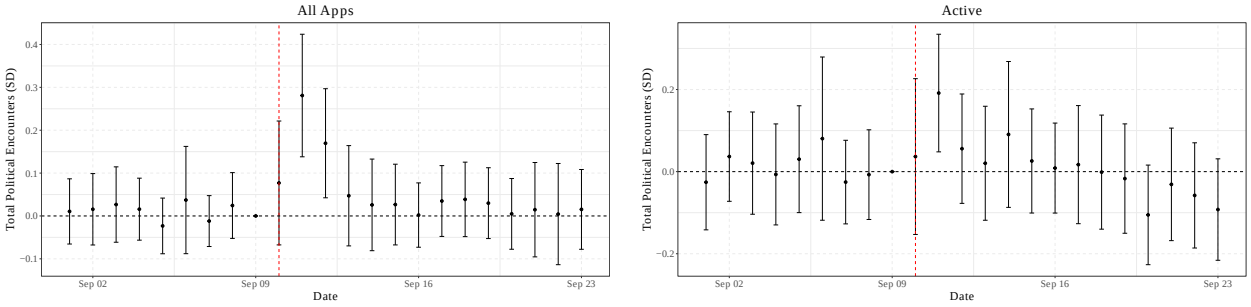


Figure C.3: Taylor Swift Endorsement DiD Estimates on Total Political Occurrences

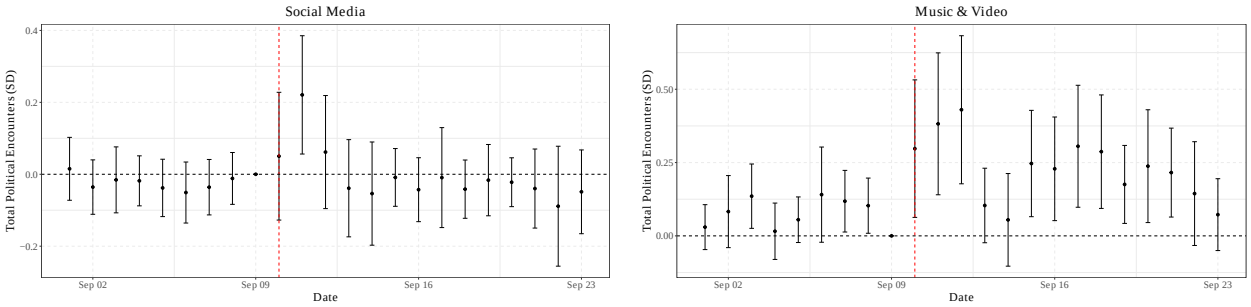
(a) DiD Estimates - All Applications

(b) DiD Estimates - Active Encounters



(c) DiD Estimates - Social Media

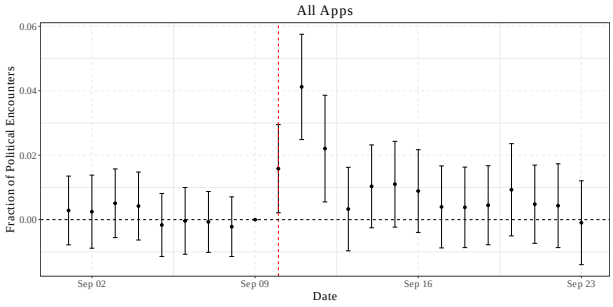
(d) DiD Estimates - Music and Video



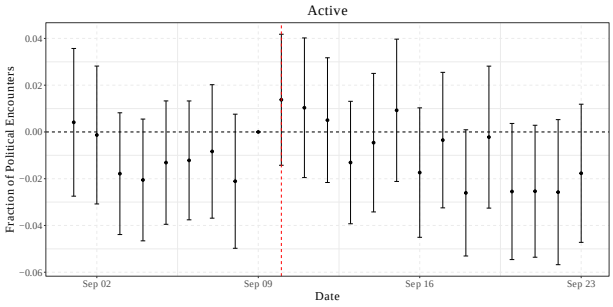
Notes: TWFE DiD estimates. Using the total number of political occurrences (all apps, search/communication, social media, music & video). Standard errors clustered at individual level.

Figure C.4: Taylor Swift Endorsement DiD Estimates on Fraction of Encounters that are Political

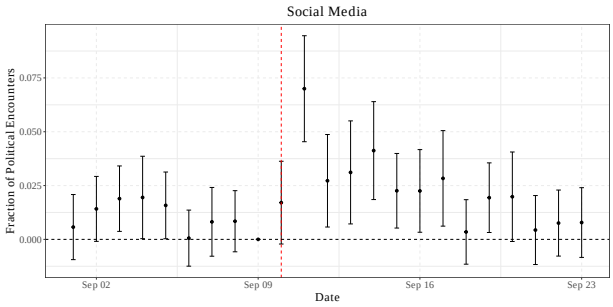
(a) DiD Estimates - All Applications



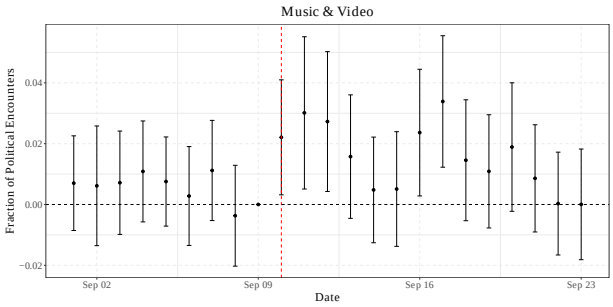
(b) DiD Estimates - Active Encounters



(c) DiD Estimates - Social Media



(d) DiD Estimates - Music and Video



Notes: TWFE DiD estimates. Using the total number of political occurrences (all apps, search/communication, social media, music & video). Standard errors clustered at individual level.

C.2 Dynamics in Exposure to Congressmembers

Encounter Category	House Encounters (Sep-Oct)	House Encounters (Election Day)	Ratio (Sep-Oct)	Ratio (Election Day)
Total	71.68	12.28	0.48	0.08
Search	9.67	5.25	0.29	0.03
Communication	18.71	2.65	0.59	0.10
News	11.84	7.82	0.01	0.11
Social Media	17.00	2.33	0.40	0.16

Table C.1: Mean Scaled House Encounters and Congress/Presidential Ratio by Encounter Category

Appendix Figure B.6a shows that the mean number of encounters with congressmembers over time is very low. In this figure we include virtually all active congressmembers.[42], On an average day, the median individual encountered a Congressmember 0 times on their phone with the mean only having encountering a congressmember on their phone 1.17 times. Again, we see a sharp increase around election day. Figure 4 shows that this increase occurred almost entirely after polls closed. In Appendix Figure B.6b we plot this figure again for the congressmembers who each individual encountered the most. We conservatively assume that this is their local congressmember.

[42]We do not observe the participant's address, and therefore, cannot focus on their congressmember.

The figure shows that engagement around election day is no different from the days preceding election day when we focus on only one congressmember, suggesting that the increase in encounters stems to some degree from individuals reading about multiple congressmembers after the election, and not from individuals receiving information about their own congressmembers.

While the peak in search interest is similar for political terms and congressmembers, the magnitudes are completely different. In Appendix Table C.1, we break down the political encounters based on the number of occurrences, across individuals, for house members and across app categories.[43] The table provides the mean across individuals in our sample, both in the leadup to Election Day (09/01-10/31) and the days surrounding Election Day (11/04-11/06) for *all* House members.[44] It shows that the mean individual had 71.68 encounters with House Members for the entire period between September 1st and October 31st, which is at most 3.58 minutes. On election day, this is 12.28 encounters which is at most 36.84 seconds. As a comparison, we provide the ratio of encounters between presidential candidates and *all* House Members, showing that, between September 1st and October 31st, the presidential candidates were encountered 24.63 times more than all House Members. On election day this spikes to 62.12.

Encounter Category	House Encounters (Sep-Oct)	House Encounters (Election Day)	Ratio (Sep-Oct)	Ratio (Election Day)
Total	14.88	0.00	0.06	0.00
Search	1.65	0.00	0.02	0.00
Communication	0.00	0.00	0.00	0.00
News	0.00	1.50	0.00	0.01
Social Media	2.65	0.00	0.03	0.00

Table C.2: Median Scaled House Encounters and Congress/Presidential Ratio by Encounter Category

[43] We only consider this table for individuals with at least 20 active days of usage, and for those with less usage than the full sample period, we scale up their usage to get a measure of the number of encounters for the full sample period. Our results are robust to considering this without the minimum usage requirement.

[44] The median is presented in Table C.2.

C.3 Variance Decomposition

Figure C.5: Normalized Exposure Counts Across Social Media Apps

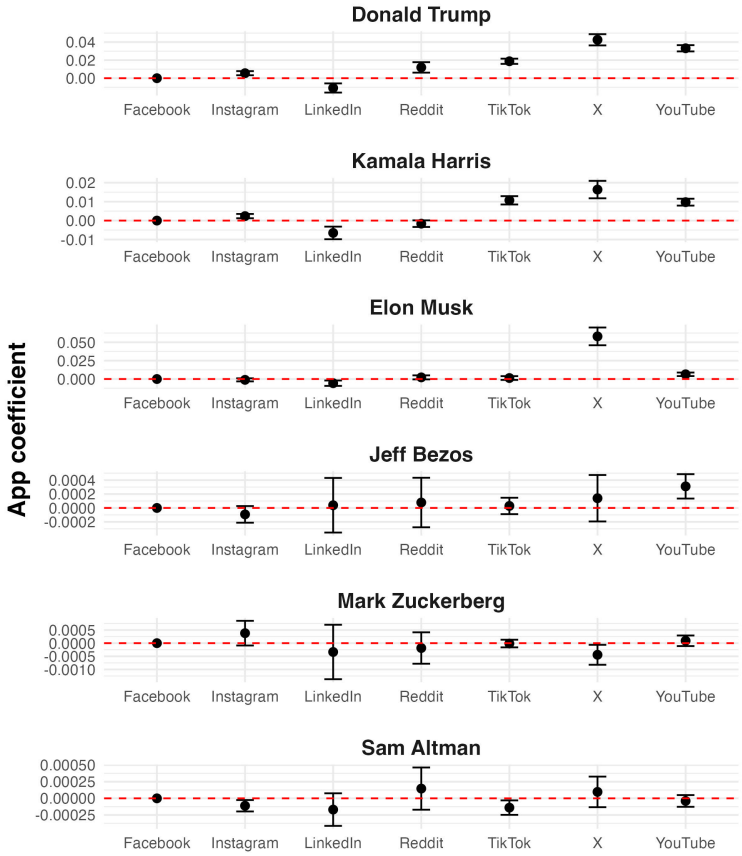
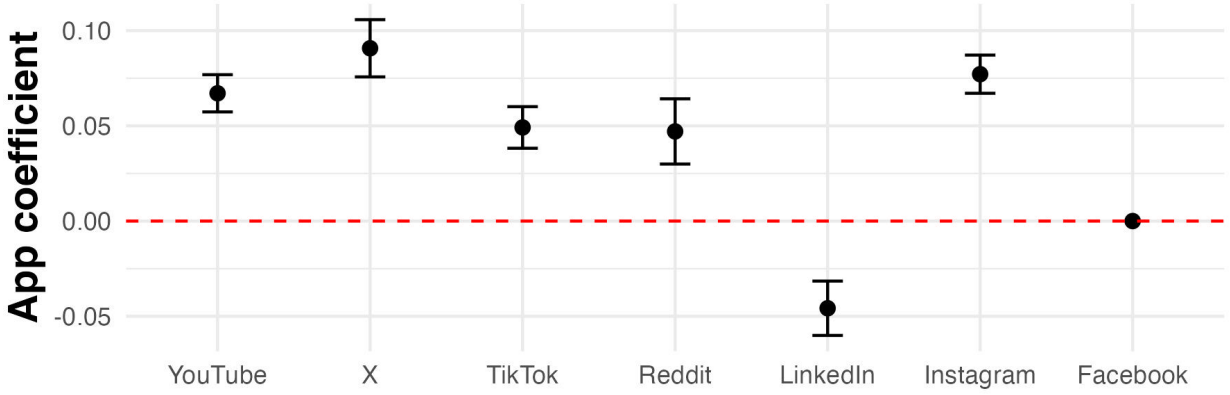
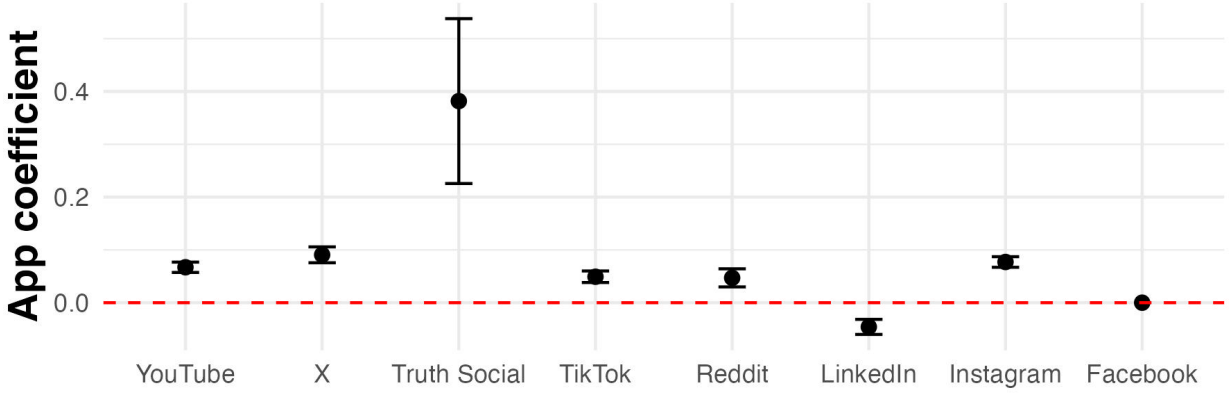


Figure C.6: Exposure to Political Content across Social Media

(a) Without Truth Social

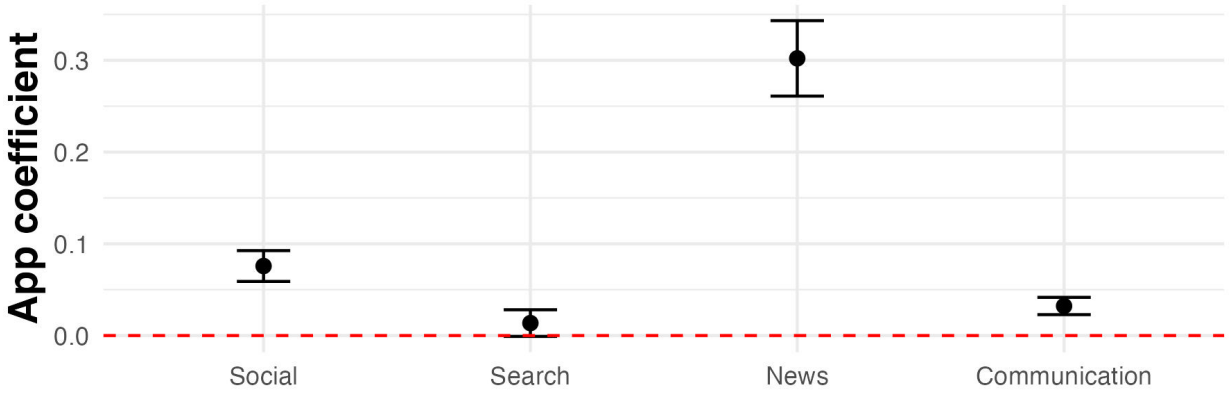


(b) With Truth Social



Notes: This figure presents the estimated coefficients of the app fixed effects from Equation (1). We estimate this equation for the share of political content as outcome variable, restricting the analysis to the social media apps shown in the figure. Panel (a) includes Truth Social and Panel (b) excludes it for visualization purposes (but still includes it in the estimation). In both panels, Facebook is the omitted category, serving as the reference group. The 95% confidence intervals are constructed using standard errors clustered at the individual level.

Figure C.7: Exposure to Political Content across Apps



	All apps		Popular		Social		Communication		News	
	T & H	All	T & H	All	T & H	All	T & H	All	T & H	All
$E(Var(\alpha_i^k\|k))$	0.09	0.07	0.23	0.23	0.39	0.38	0.39	0.37	0.90	0.93
$E(Var(\beta_a^k\|k))$	0.10	0.11	0.07	0.05	0.06	0.06	0.00	0.03	0.50	0.32
$E(Var(\gamma_t^k\|k))$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$E(Var(\varepsilon_{ia}\|k))$	0.81	0.82	0.69	0.71	0.55	0.56	0.60	0.60	0.09	0.07
$E(2Cov(\alpha_i^k, \beta_a^k\|k))$	-0.00	-0.00	0.01	0.00	0.00	-0.00	-0.00	0.00	-0.49	-0.32
$E(2Cov(\alpha_i^k, \gamma_t^k\|k))$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$E(2Cov(\beta_a^k, \gamma_t^k\|k))$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N apps	2399	2399	51	51	11	11	15	15	21	21
N individuals	3579	3579	3579	3579	3579	3579	3579	3579	3579	3579

Table C.3: Variance decomposition, no time FE

	All apps		Popular		Social		Communication		News	
	T & H	All	T & H	All	T & H	All	T & H	All	T & H	All
$E(Var(\alpha_i^k\|k))$	0.04	0.03	0.06	0.05	0.11	0.08	0.10	0.10	0.31	0.29
$E(Var(\beta_a^k\|k))$	0.04	0.05	0.03	0.03	0.03	0.03	0.00	0.02	0.54	0.34
$E(Var(\gamma_t^k\|k))$	0.01	0.01	0.02	0.01	0.02	0.01	0.01	0.00	0.10	0.09
$E(Var(\varepsilon_{ia}\|k))$	0.90	0.92	0.89	0.91	0.84	0.88	0.89	0.87	0.63	0.64
$E(2Cov(\alpha_i^k, \beta_a^k\|k))$	0.00	-0.00	0.00	0.00	0.01	0.00	0.00	0.00	-0.57	-0.37
$E(2Cov(\alpha_i^k, \gamma_t^k\|k))$	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.01	-0.00
$E(2Cov(\beta_a^k, \gamma_t^k\|k))$	0.00	0.00	0.00	0.00	0.00	0.00	-0.00	0.00	-0.01	-0.00
N apps	2399	2399	51	51	11	11	15	15	21	21
N individuals	3579	3579	3579	3579	3579	3579	3579	3579	3579	3579

Table C.4: Variance decomposition, daily FE

D External Validity

In this appendix, we use two methods to assess the external validity of our analysis. First, we provide aggregate demographics of our sample and reweigh our results. Second, we compare the set of applications installed and time spent to external benchmarks.

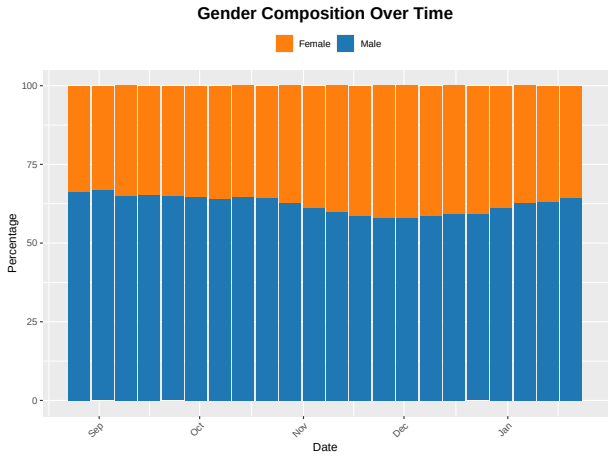
D.1 Demographic Comparisons

We received weekly aggregated data on age and gender distribution for the panel. As shown in Figure D.1, the sample tends to skew younger and male. While there are slight variations over time, the overall distribution remains relatively stable.

To address potential sampling biases, we reweight our results using individual-level weights provided by Screenlake (calculated based on 2023 data from the U.S. Census Bureau). In Figure D.2, we present the reweighted version of Figure 1. While the reweighted data shows slightly elevated levels, the overall trend remains consistent.

Figure D.1: Panel Demographic Composition Across Time

(a) Gender Composition



(b) Age Range Composition

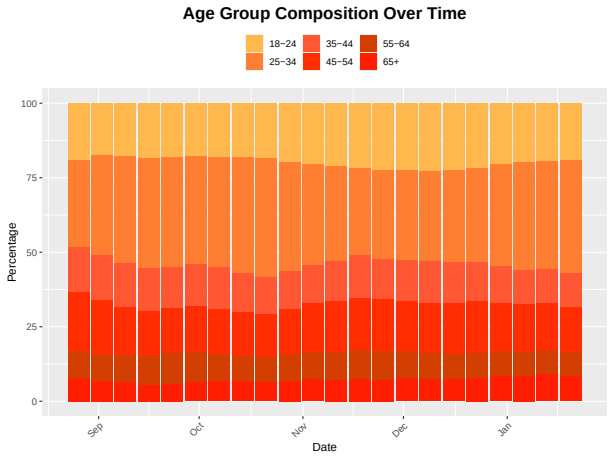
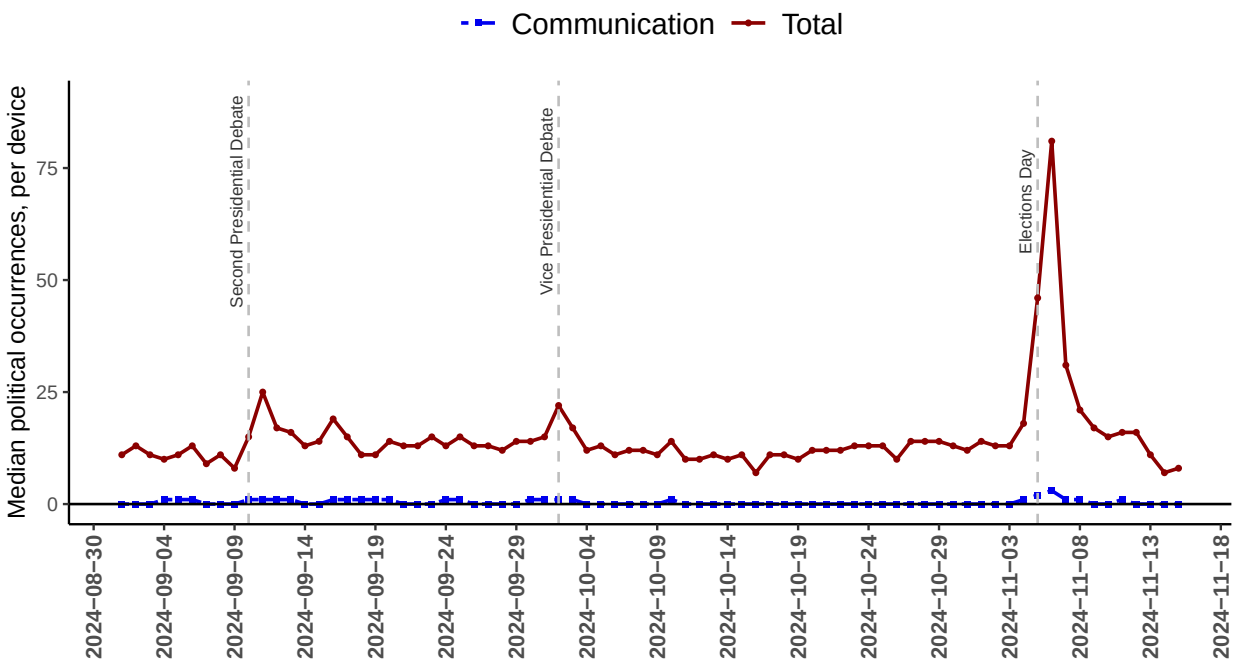


Figure D.2: Reweighted Political Engagement Over Time



D.2 Representativeness of App Distribution

We analyze the representativeness of the apps used by the Screenlake panelists. We first analyze the extensive margin, the installation of apps, and then the intensive margin, time usage.

D.2.1 Comparison of Installations to Google Play Store Data

To analyze whether the apps individuals installed are representative, we compared the distribution of app installed to population-level data available via the Google Play Store, the primary distribution channel for Android applications. We use data on the number of ratings scraped during October 2024 and January 2025 for all applications with over 1 million downloads, or in the news and social categories.[45] We follow the best practices for using this data and take the number of ratings for an application as an approximation for its overall popularity (Kesler et al., 2020; Kesler, 2023; Affeldt and Kesler, 2021; Janssen et al., 2022).[46] We consider two variants of this: total number of ratings (denoted overall ratings) measuring cumulative popularity and the difference in the number of ratings between the January 2025 and October 2024 data collection (denoted delta) measuring recent popularity.[47] We compare the overall number of downloads to the overall prevalence of the same applications within our sample. As we do not directly observe installed applications for the individuals in our sample and only measures of time usage, we mark an application as being installed for an individual if we ever observe them using the application. Finally, in order to ensure an apples-to-apples comparison, we remove any applications that are pre-installed on Android phones and ensure that we consider only the set of applications that we observe both in our dataset as well as in the Google Play data.[48]

Figure D.3a shows a remarkably strong correlation between apps used among our sample and the change in the number of Google Play rankings. Since there is wide heterogeneity in usage within categories across individuals, in this figure we compare the relative importance of categories across the two datasets. For both datasets, we sum across all of the individual applications within the dataset to obtain a total number of installations for the category and compare the relative rank across the datasets. We plot this in Figures D.3a and D.3b, using the delta measure and overall ratings respectively. These results show strong alignment in the relative set of installed applications across categories, especially according to the more reliable delta measure, indicating that the set of individuals in the sample are reasonably representative in terms of the overall category of appli-

[45] We thank Reinhold Kesler for generously sharing this data with us.

[46] Rating are typcially used since the publicly available range for the number of installations is too wide to provide a meaningful ordering of applications.

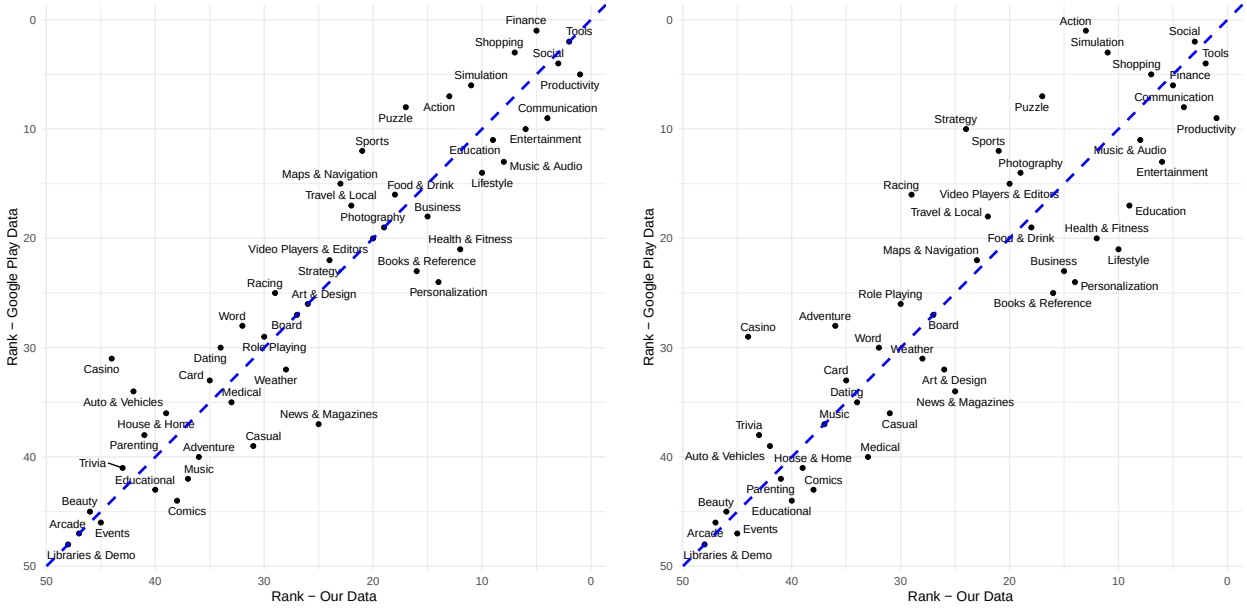
[47] For example, an application such as Among Us was very popular several years ago, and so accumulated a large number of ratings, but is not very popular during our sample period.

[48] Across all individuals in our data, we observe 25113 unique applications, so we still observe a large number of applications.

Figure D.3: Comparison between Sample and Google Play

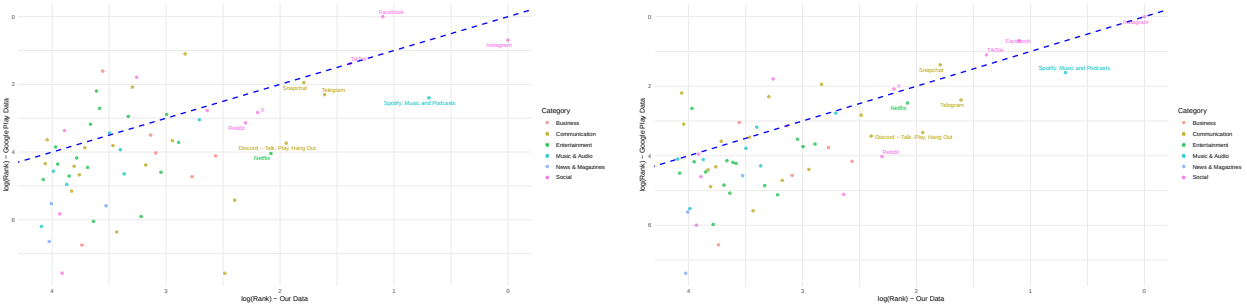
(a) Category Comparison (Delta)

(b) Category Comparison (Overall Ratings)



(c) App Comparison (Delta)

(d) App Comparison (Overall Ratings)



NOTES: Comparison plot

cations they use. We compute the Spearman correlation coefficient, a commonly used measure of accordance for ranking data, and find that it is very strong, with 0.928 for the delta measure and 0.888 for the overall rating measures. Notably, according to this analysis, our sample has a *larger* relative importance of news applications compared to the general prevalence of these applications in the population.

We then turn to comparing the ranks of applications within our categories of interest for our primary analyses – news, communication, social, business, music & audio, and entertainment. We conduct the same ranking comparison exercise between these two sets of applications and plot the results in Figures D.3c and D.3d for the Delta measure and overall ratings, respectively. We use log rank as the difference between ranks corresponds to smaller difference in absolute downloads

due to the skewed nature of app downloads as the rank increases. These figures show relative agreement in the installation between top applications. Beyond the top applications, we consider the full set of applications that we observe across the categories of interest. We compute the weighted Spearman rank correlation coefficient, considering as the weight $\frac{1}{\text{Google Play Rank}}$ in order to place more weight on accordance for higher ranks, relative to those in the long tail. This provides a correlation coefficient of 0.891 for the Delta measure and 0.921 for the overall ratings measure, indicating strong agreement in the relative rankings.

Overall, we conclude that the set of apps that the individuals in the sample use is reasonably representative of the app usage of the broader population.

D.2.2 Comparison of Time Usage to Benchmarks and a Representative Sample of individuals

While the set installed apps among our sample could be reasonably representative, our sample may still differ from the general population in how often each app is used. Therefore, We compare the time usage of Screenlake participants to an industry benchmark and a representative sample of Prolific participants. We consider time usage observed in our dataset from December 19th, 2024 until January 25th, 2025 as this represents the time period that covers the application version with the most reliable measurement of application time usage.

We Are Social (Kemp, 2024), which aggregates information from multiple sources, provides a useful industry benchmark. On average, Screenlake individuals spend slightly longer (3.2 hours a day) on a set of communication and social media apps[49] than the average individual (2.5 hours a day).

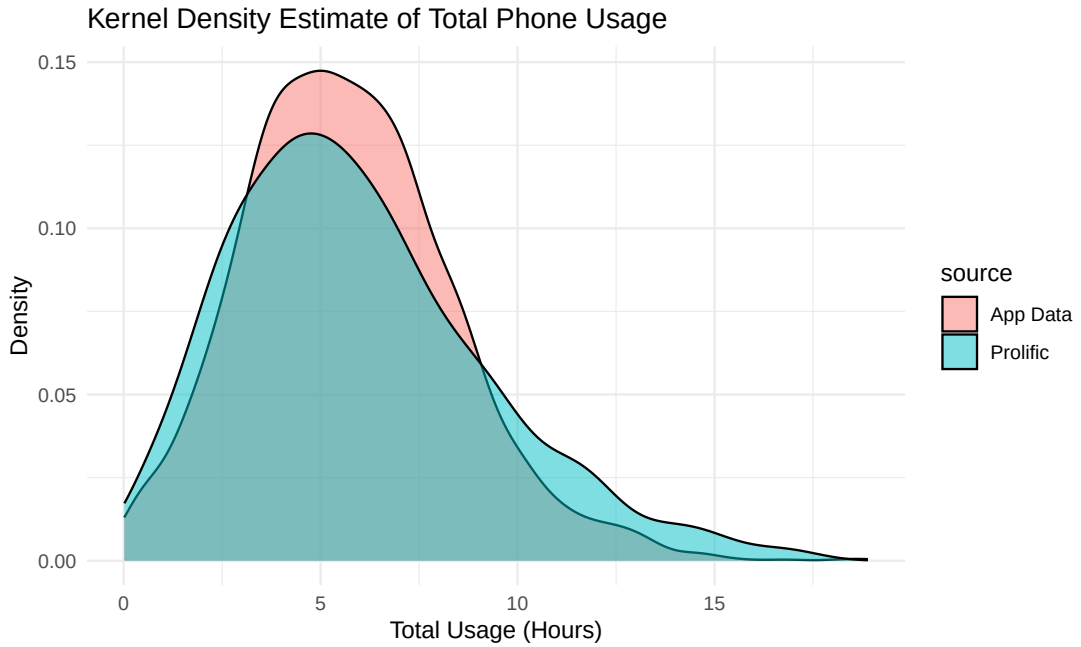
Industry benchmarks may not correspond precisely to the time period of analysis for our sample. To establish a representative baseline of smartphone usage for the same period, we recruited 813 Android individuals on Prolific from October 30 to November 3, 2024. The sample is representative in terms of average age and political affiliation. Participants are asked to complete a demographic survey and upload screenshots of their daily app-level screen time. using the Digital Wellbeing for 7 days, capturing "the entire list of apps that were used for more than 1 minute."

Figure D.4 shows that the distribution of overall phone usage is similar between our sample and the representative Prolific sample. The median individuals is both samples spend a strikingly similar amount of time on their phone, 5.46 and 5.54 hours, respectively, in the Prolific and ScreenLake samples (a 1% difference). The average individual in the Prolific sample spends 5.95 hours on their phone, while the average individual in the ScreenLake sample spends 5.71 hours (a 4% difference). Consistent with this, the Prolific sample has a higher standard deviation relative to the

[49]The set of apps include in this benchmark are Facebook, Discord, Instagram, LinkedIn, Messenger, Pinterest, Reddit, Snapchat, Telegram, Threads, TikTok, WhatsApp, X, YouTube.

ScreenLake sample. This is visually apparent in the kernel density of the estimate of the two distributions, presented in Figure D.4. Nonetheless, the results suggest that the ScreenLake population is reasonably similar in overall phone usage to the representative sample from Prolific.

Figure D.4: Distribution Comparison between Prolific and ScreenLake



Dataset	Mean	Median	SD	Q25	Q75	N
Prolific	5.95	5.46	3.27	3.51	7.86	813
ScreenLake	5.71	5.54	2.64	3.84	7.33	2499

NOTES: We compute the average daily hours spent on the phone for the days when a individual was active, both in the Prolific sample and the ScreenLake sample.

Next, we compare the time spent and usage of top applications – Facebook, Instagram, Netflix, Reddit, Snapchat, Spotify, TikTok, WhatsApp, X, and YouTube – between the samples. The results are presented in Table D.1. One notable difference between the two samples is the fraction of WhatsApp and Instagram usage for the ScreenLake sample, which is higher than both the Prolific sample as well as the PEW survey, while Facebook usage is lower. This likely reflects potential demographic differences between the two samples. The Prolific sample has an over-representation of Reddit, both relative to PEW and ScreenLake.[50] Nonetheless, conditional on using the application, the two samples show similar patterns: large time spent on YouTube and TikTok, very similar time spent on Snapchat and Spotify, and reasonably similar time spent on X and WhatsApp. Their over-

[50]This likely reflects the fact that these individuals are survey-takers.

Table D.1: Comparison of App Usage Between Prolific Data and App Data

	Average Time Per Person (Hours)		Average Time If Used (Hours)		Fraction of Nonzero Users		
	Prolific	App Data	Prolific	App Data	Prolific	App Data	Pew
Facebook	0.5022	0.1975	0.8367	0.4376	0.6002	0.4514	0.7000
Instagram	0.2055	0.6287	0.4374	0.9586	0.4699	0.6559	0.5000
LinkedIn	0.0028	0.0048	0.0458	0.0437	0.0603	0.1108	0.3200
Reddit	0.2189	0.0406	0.4972	0.2384	0.4403	0.1701	0.2400
Snapchat	0.0458	0.0669	0.2314	0.2385	0.1980	0.2805	0.2700
TikTok	0.3954	0.5462	1.2085	1.3189	0.3272	0.4142	0.3300
X	0.1016	0.0431	0.4919	0.2414	0.2066	0.1785	0.2100
WhatsApp	0.0605	0.4053	0.3752	0.5808	0.1611	0.6979	0.3000
Spotify	0.0411	0.0585	0.1506	0.1125	0.2731	0.5202	NA
YouTube	0.6044	1.0699	0.8003	1.1847	0.7552	0.9032	0.8500
Fox News	0.0007	0.0000	0.1333	0.0019	0.0049	0.0016	NA
Google News	0.0000	0.0003	0.0333	0.0140	0.0012	0.0208	NA
NYTimes	0.0025	0.0007	0.2527	0.0573	0.0098	0.0116	NA
Netflix	0.0393	0.0552	0.5073	0.2699	0.0775	0.2045	NA

all time spent on social media is around the same and comparable to additional benchmark data from Kemp (2024). Overall, the Screenlake sample differs on several dimensions from these two benchmarks, but reflects similar engagement patterns across the core applications that individuals spend time on their phones.

E The Full Set of Keywords

In this section we provide additional documentation of the full set of keywords used in our analyses. Our political keywords were largely chosen by the research team as well as a large number of pre-specified political figures provided by Screenlake. Outside of politics, Screenlake captures a large number of nonpolitical keywords, which we use as a proxy for time spent on the phone and as control categories. We begin by documenting the additional political keywords apart from those in the main text and then describe the classification process for the control words.

E.1 Full set of political keywords

The full set of political figures that we track are as follows:

- **Notable Political Figures**: Bernard Sanders, Hillary Clinton, Joe Biden, Nancy Pelosi, Nikki Haley, Robert F Kennedy Jr
- **Governors**: Albert Bryan, Andy Beshear, Arnold Palacios, Bill Lee, Brad Little, Brian Kemp, Chris Sununu, Dan McKee, Doug Burgum, Eric Holcomb, Gavin Newsom, Glenn Youngkin, Greg Abbott, Greg Gianforte, Gretchen Whitmer, Henry McMaster, Janet Mills, Jared Polis, Jay Inslee, JB Pritzker, Jim Justice, Jim Pillen, Joe Lombardo, John Carney, Josh Green, Josh Shapiro, Kathy Hochul, Katie Hobbs, Kay Ivey, Kevin Stitt, Kim Reynolds, Kristi Noem, Laura Kelly, Lemanu Peleti, Lou Leon, Mark Gordon, Maura Healey, Michelle Lujan, Mike DeWine, Mike Dunleavy, Mike Parson, Ned Lamont, Pedro Pierluisi, Phil Murphy, Phil Scott, Ron DeSantis, Roy Cooper, Sarah Huckabee, Spencer Cox, Tate Reeves, Tina Kotek, Tony Evers, Wes Moore
- **Congressmembers**: Aaron Bean, Abigail Spanberger, Adam Schiff, Adam Smith, Adrian Smith, Adriano Espaillat, Al Green, Alex Padilla, Alexandria Ocasio-Cortez, Alma Adams, Ami Bera, Amy Klobuchar, André Carson, Andrea Salinas, Andrew Clyde, Andrew Garbarino, Andy Barr, Andy Biggs, Andy Harris, Andy Kim, Andy Ogles, Angie Craig, Angus S. King, Ann Wagner, Anna Eshoo, Anna Paulina Luna, Annie Kuster, Anthony D'Esposito, Ashley Hinson, August Pfluger, Austin Scott, Ayanna Pressley, Barbara Lee, Barry Loudermilk, Barry Moore, Becca Balint, Ben Cline, Ben Ray Luján, Benjamin L. Cardin, Bennie Thompson, Bernard Sanders, Beth Van Duyne, Betty McCollum, Bill Cassidy, Bill Foster, Bill Hagerty, Bill Huizenga, Bill Keating, Bill Pascrell, Bill Posey, Blaine Luetkemeyer, Blake Moore, Bob Good, Bob Latta, Bobby Scott, Bonnie Watson Coleman, Brad Finstad, Brad Schneider, Brad Sherman, Brad Wenstrup, Brandon Williams, Brendan Boyle, Brett Guthrie, Brian Babin, Brian Fitzpatrick, Brian Mast, Brian Schatz, Brittany Pettersen, Bruce

Westerman, Bryan Steil, Buddy Carter, Burgess Owens, Byron Donalds, Carlos A. Giménez, Carlos Giménez, Carol Miller, Catherine Cortez Masto, Cathy McMorris Rodgers, Celeste Maloy, Charles E. Schumer, Chip Roy, Chris Deluzio, Chris Pappas, Chris Smith, Chris Van Hollen, Chrissy Houlahan, Christopher A. Coons, Christopher Murphy, Chuck Edwards, Chuck Fleischmann, Chuck Grassley, Chuy García, Cindy Hyde-Smith, Claudia Tenney, Clay Higgins, Cliff Bentz, Colin Allred, Cori Bush, Cory A. Booker, Cory Mills, Cynthia M. Lummis, Dale Strong, Dan Bishop, Dan Crenshaw, Dan Goldman, Dan Kildee, Dan Meindividual, Dan Newhouse, Dan Sullivan, Daniel Webster, Danny Davis, Darin LaHood, Darrell Issa, Darren Soto, David Joyce, David Kustoff, David Rouzer, David Schweikert, David Scott, David Trone, David Valadao, Dean Phillips, Deb Fischer, Debbie Dingell, Debbie Lesko, Debbie Stabenow, Debbie Wasserman Schultz, Deborah Ross, Delia Ramirez, Derek Kilmer, Derrick Van Orden, Diana DeGette, Diana Harshbarger, Dina Titus, Don Bacon, Don Beyer, Don Davis, Donald Norcross, Doris Matsui, Doug LaMalfa, Doug Lamborn, Drew Ferguson, Dusty Johnson, Dutch Ruppersberger, Dwight Evans, Ed Case, Edward J. Markey, Eli Crane, Elise Stefanik, Elissa Slotkin, Elizabeth Warren, Emanuel Cleaver, Emilia Sykes, Eric Burlison, Eric Schmitt, Eric Sorensen, Eric Swalwell, Erin Houchin, Frank Lucas, Frank Pallone, Frederica Wilson, French Hill, Gabe Vasquez, Garret Graves, Gary C. Peters, Gary Palmer, Gerry Connolly, Glenn Grothman, Glenn Ivey, Glenn Thompson, Grace Meng, Grace Napolitano, Greg Casar, Greg Landsman, Greg Lopez, Greg Murphy, Greg Pence, Greg Stanton, Greg Steube, Gregory Meeks, Gus Bilirakis, Guy Reschenthaler, Gwen Moore, Hakeem Jeffries, Hal Rogers, Haley Stevens, Hank Johnson, Harriet Hageman, Henry Cuellar, Hillary Scholten, Ilhan Omar, Jack Bergman, Jack Reed, Jacky Rosen, Jahana Hayes, Jake Ellzey, Jamaal Bowman, James Comer, James E. Risch, James Lankford, Jan Schakowsky, Jared Golden, Jared Huffman, Jared Moskowitz, Jasmine Crockett, Jason Crow, Jason Smith, Jay Obernolte, Jeanne Shaheen, Jeff Duncan, Jeff Jackson, Jeff Merkley, Jeff Van Drew, Jen Kiggans, Jennifer McClellan, Jennifer Wexton, Jerry Carl, Jerry Moran, Jerry Nadler, Jill Tokuda, Jim Baird, Jim Banks, Jim Clyburn, Jim Costa, Jim Himes, Jim Jordan, Jim McGovern, Jimmy Gomez, Jimmy Panetta, Joaquin Castro, Jodey Arrington, Joe Courtney, Joe Manchin, Joe Neguse, Joe Wilson, John B. Larson, John Barrasso, John Boozman, John Carter, John Cornyn, John Curtis, John Duarte, John Fetterman, John Garamendi, John Hoeven, John James, John Joyce, John Kennedy, John Moolenaar, John Rose, John Rutherford, John Sarbanes, John Thune, John W. Hickenlooper, Jon Ossoff, Jon Tester, Jonathan Jackson, Joni Ernst, Joseph Morelle, Josh Brecheen, Josh Gottheimer, Josh Harder, Josh Hawley, Joyce Beatty, Juan Ciscomani, Juan Vargas, Judy Chu, Julia Brownley, Julia Letlow, Kat Cammack, Katherine Clark, Kathy Castor, Kathy Manning, Katie Boyd Britt, Katie Porter, Kay Granger, Keith Self, Kelly Armstrong, Ken Calvert, Kevin Cramer,

Kevin Hern, Kevin Kiley, Kevin Mullin, Kim Schrier, Kirsten E. Gillibrand, Kyrsten Sinema, Lance Gooden, Laphonza R. Butler, Larry Bucshon, Laurel Lee, Lauren Boebert, Lauren Underwood, Linda Sánchez, Lindsey Graham, Lisa Blunt Rochester, Lisa McClain, Lisa Murkowski, Lizzie Fletcher, Lloyd Doggett, Lloyd Smucker, Lois Frankel, Lori Chavez-DeRemer, Lori Trahan, Lou Correa, Lucy McBath, Madeleine Dean, Marc Molinaro, Marc Veasey, Marco Rubio, Marcy Kaptur, Margaret Wood Hassan, Maria Cantwell, María Elvira Salazar, Mariannette Miller-Meeks, Marie Gluesenkamp Perez, Marilyn Strickland, Marjorie Taylor Greene, Mark Alford, Mark Amodei, Mark DeSaulnier, Mark E. Green, Mark Kelly, Mark Pocan, Mark R. Warner, Mark Takano, Markwayne Mullin, Marsha Blackburn, Martin Heinrich, Mary Gay Scanlon, Mary Miller, Mary Peltola, Matt Cartwright, Matt Gaetz, Matt Rosendale, Max Miller, Maxine Waters, Maxwell Frost, Mazie K. Hirono, Melanie Stansbury, Michael C. Burgess, Michael Cloud, Michael F. Bennet, Michael Guest, Michael McCaul, Michael Rulli, Michael Waltz, Michelle Steel, Mike Bost, Mike Braun, Mike Carey, Mike Crapo, Mike Ezell, Mike Flood, Mike Garcia, Mike Johnson, Mike Kelly, Mike Lawler, Mike Lee, Mike Levin, Mike Quigley, Mike Rogers, Mike Rounds, Mike Simpson, Mike Thompson, Mike Turner, Mikie Sherrill, Mitch McConnell, Mitt Romney, Monica De La Cruz, Morgan Luttrell, Morgan McGarvey, Nancy Mace, Nanette Barragán, Nathaniel Moran, Neal Dunn, Nick LaLota, Nick Langworthy, Nicole Malliotakis, Nikki Budzinski, Norma Torres, Nydia Velázquez, Pat Ryan, Patrick McHenry, Patty Murray, Paul Gosar, Paul Tonko, Pete Aguilar, Pete Ricketts, Pete Sessions, Peter Welch, Pramila Jayapal, Raja Krishnamoorthi, Ralph Norman, Rand Paul, Randy Feenstra, Randy Weber, Raphael G. Warnock, Rashida Tlaib, Raúl Grijalva, Raul Ruiz, Rich McCormick, Richard Blumenthal, Richard Hudson, Richard J. Durbin, Richard Neal, Rick Allen, Rick Crawford, Rick Larsen, Rick Scott, Ritchie Torres, Ro Khanna, Rob Menendez, Robert Aderholt, Robert Garcia, Robert Menendez, Robert P. Casey, Robin Kelly, Roger F. Wicker, Roger Marshall, Roger Williams, Ron Estes, Ron Johnson, Ron Wyden, Ronny Jackson, Rosa DeLauro, Ruben Gallego, Rudy Yakym, Russ Fulcher, Russell Fry, Ryan Zinke, Salud Carbajal, Sam Graves, Sanford Bishop, Sara Jacobs, Scott DesJarlais, Scott Fitzgerald, Scott Franklin, Scott Perry, Scott Peters, Sean Casten, Seth Magaziner, Seth Moulton, Sharice Davids, Sheila Cherfilus-McCormick, Sheldon Whitehouse, Shelley Moore Capito, Sherrod Brown, Shontel Brown, Shri Thanedar, Steny Hoyer, Stephanie Bice, Stephen F. Lynch, Steve Cohen, Steve Daines, Steve Scalise, Steve Womack, Steven Horsford, Summer Lee, Susan M. Collins, Susan Wild, Susie Lee, Suzan DelBene, Suzanne Bonamici, Sydney Kamlager-Dove, Sylvia Garcia, Tammy Baldwin, Tammy Duckworth, Ted Budd, Ted Cruz, Ted Lieu, Teresa Leger Fernandez, Terri Sewell, Thom Tillis, Thomas Kean Jr., Thomas Massie, Thomas R. Carper, Tim Burchett, Tim Kaine, Tim Kennedy, Tim Scott, Tim Walberg, Tina Smith, Todd Young,

Tom Cole, Tom Cotton, Tom Emmer, Tom McClintock, Tom Suozzi, Tom Tiffany, Tommy Tuberville, Tony Cárdenas, Tracey Mann, Trent Kelly, Troy Balderson, Troy Carter, Troy Nehls, Val Hoyle, Valerie Foushee, Vern Buchanan, Veronica Escobar, Vicente Gonzalez, Victoria Spartz, Vince Fong, Virginia Foxx, Warren Davidson, Wesley Hunt, Wiley Nickel, William Timmons, Yadira Caraveo, Young Kim, Yvette Clarke, Zach Nunn, Zoe Lofgren

- **World Leaders**: Benjamin Netanyahu, Emmanuel Macron, Javier Milei, Justin Trudeau, Luiz Inacio Lula da Silva, Olaf Scholz, Recep Tayyip Erdogan, Rishi Sunak, Vladimir Putin, Volodomir Zelensky, Xi JinPing

We use the following surrounding keywords to determine the context for some of the main keywords:

- **Fundraising**: contribute, donate, donation, fund, funding, fundraising, pacs, stop, stop2end
- **Secondary Political Keywords**: absentee, ballot, biden, campaign, campaign, candidate, conservative, constituent, contribute, debate, debates, democracy, democrat, elect, election, elections, electoral, electorate, endorsement, farleft, farright, fundraising, gerrymandering, independent, liberal, lobbying, nomination, nominee, political, polling, polls, populist, president, presidential, progressive, progressives, rally, recount, recount, redistricting, reelection, representative, republican, republicans, rights, suppression, trump, turnout, vote, voters, voting

E.2 Control Keywords

The control words are classified in the following pipeline:

1. We used gpt-4o to first categorize keywords using the following prompt: "You will be asked to classify a vector of keywords into topics. Read this vector of keywords and classify them into 11 topics. Make sure that the topic labels are easy to understand. Reply only with a tab-separated database with the 11 topics in one column and the most representative 10 keywords per topic in another column. Make sure to format the database properly. This is the comma-separated list of keywords:"
2. We manually reviewed and updated this initial list of topics into a list of 13 topics:
    - **Finalized Topics**: 1) Entertainment celebrities; 2) Sports celebrities; 3) Entertainment (excluding celebrities), including music and shows; 4) Sports excluding celebrities; 5) Technology; 6) Countries and places outside of the US; 7) Names of US states; 8)

Places in the US (excluding names of US states); 9) Brands (such as food and beverages, retail, and automobile); 10) Businesspeople; 11) Words related to weather; 12) Words that do not fall into any of these 11 categories but are often used in everyday conversations; 13) Words that do not fall into any of these 11 categories and are not often used in everyday conversations

3. We then used gpt-4o to categorize all keywords into these 13 categories using the prompt: "You will be asked to classify the category of a keyword, given a list of categories. Read this keyword and classify it into one of the following categories. This keyword comes from a dataset that captures what people see on their smartphones. If a word can be classified into multiple categories, pick the one that's most likely to be relevant for content that people would see on their smartphones. Your response should be a single number corresponding to the topic of the keyword. Do not respond with anything but a number."

4. After we have classified every word into one of the 13 categories, we inputed all keywords into ChatGPT, 1 category at a time, and asked GPT to verify the categorization, providing justification for words it believed to be misclassified. We then manually reviewed the words that were flagged.

This process generates the following set of control words that we use for entertainment, celebrities, and sports:

- **Entertainment**: #ABTalks, #blackAF, 100 Days to Indy, 6ixtynin9 The Series, 7SEEDS, A Kidnapping Scandal: The Florence Cassez Affair, A Killer Paradox, A Little Help with Carol Burnett, A Perfect Crime, A Sinister Sect: Colonia Dignidad, AC/DC, Adam Neely, Age of Tanks, Aggretsuko, Akuma Kun, Al Hayba, AlRawabi School for Girls, ALVINNN!!! And the Chipmunks, American Manhunt: The Boston Marathon Bombing, American Ninja Warrior, Americas Got Talent, Ancient Aliens, Anthracite, Aranyak, Archibalds Next Big Thing, Ari Shaffir: Double Negative, Arpo, ATEEZ, Avatar The Last Airbender, Baby Bandito, Bad Dinosaurs, Badanamu ABC TV, Badanamu Pop, Bakugan, Bandidos, Barbie Dreamhouse Adventures: Go Team Roberts, Barracuda Queens, Bashar Shorts, Battlefish, Batwheels, BEASTARS, Ben 10, Betaal, Better Call Saul, Beyblade Burst QuadDrive, Bhaag Beanie Bhaag, Big Mouth, Big Vape: The Rise and Fall of Juul, Black Mirror, Blackpink, Blippi, Blood of Zeus, Bloodride, Blue Moon, Bo on the Go!, Bodies, Bodkin, BoJack Horseman, Booba, Bottersnikes and Gumbles, Breaking Bad, Bridgerton, Brigands: The Quest for Gold, Buddi, Bulgasal: Immortal Souls, Bureau of Magical Things, Cable Girls, Captain Laserhawk: A Blood Dragon Remix, Carmel: Who Killed Maria Marta?, Carmen Sandiego, Castlevania, Cathedral of the Sea, Centaurworld, Chad and JT Go Deep, Chappell Roan,

Cheuk Wan-Chi: Two Night Stand, Chhota Bheem, Chico Bon Bon: Monkey with a Tool Belt, Choona, Clairo, Cocomelon, Countdown: Inspiration4 Mission to Space, Cracow Monsters, Crazyhead, Creedence Clearwater Revival, Crooks, Cyborg 009: Call of Justice, DAHMER, Daniel Sloss: Live Shows, Daniel Spellbound, Deadwind, DEATH NOTE, Deepa and Anoop, Degrassi: Next Class, Derry Girls, Designated Survivor, Destiny, Detective Forst, Dew Drop Diaries, DI4RIES, Dino Girl Gauko, Dinotrux, Disenchantment, Django, Do Do Sol Sol La La Sol, Doona!, Dorohedoro, DOTA: Dragons Blood, Dragon Age: Absolution, Dragon Sakura S2, Earthstorm, Eastsiders, EDENS ZERO, Edha, Elite Short Stories: Phillipe Caye Felipe, Elize Matsunaga: Once Upon a Crime, ENHYPHEN, Eternal Love, Extreme Engagement, Fall in Love with Vinyasa, Farzar, Fate: The Winx Saga, Faten Amal Harby, Fauda, Feels Like Ishq, Feria: The Darkest Light, Fiasco, FIGHTWORLD, Fishbowl Wives, Formula 1: Drive to Survive, Frank Elstner: Just One Last Question, Freeridge, Furies, GAMERA -Rebirth-, Ganglands, Gentefied, Get Gotti, Ghost in the Shell: SAC_2045, Gigantosaurus, Gilmore Girls: A Year in the Life, Ginny and Georgia, Girls5eva, Godzilla, Goedam, Green Day, Greenleaf, Grizzy et les Lemmings, Gudetama: An Eggcellent Adventure, Guns and Gulaabs, Gyeongseong Creature, Haikyu!!, Hanwoo Rhapsody, Hasmukh, Headspace Guide to Sleep, Heartstopper, Heeramandi: The Diamond Bazaar, Highland: Thailands Marijuana Awakening, Hitlers Circle of Evil, Hoarders, Holey Moley, House of Secrets: The Burari Deaths, How to Become a Tyrant, Hyperdrive, I Am Georgina, ICarly, Ignite and Inspire with Kirsty Godso, Ikebukuro West Gate Park, In the Bosom of a Thorn, Ingobernable, Ingress: The Animation, Inspector Gadget, Inspector Koo, InuYasha, Inventing Anna, ISHIKO and HANEO: Youre Suing Me?, Itaewon Class, IZombie, Izzys Koala World, Jack Whitehall: Travels with My Father, Jailbirds New Orleans, Jamtara - Sabka Number Ayega, Jeen-yuhs: A Kanye Trilogy, Jessie Murph, Jjajangmyeon Rhapsody, John Mulaney Presents: Everybody's in L.A., JoJos Bizarre Adventure, joker, Jordan Adetunji, JU-ON: Origins, Junji Ito Maniac: Japanese Tales of the Macabre, Justice League Unlimited, Kaala Paani, Kakegurui, Kantaro: The Sweet Tooth Salaryman, Kath and Kim, Katla, Kayko and Kokosh, Kazoops!, KENGAN ASHURA, Khakee: The Bihar Chapter, Khawatir, Kibaoh Klashers, Kick Off with Betina Gozo, King of Collectibles: The Goldin Touch, Kipo and the Age of Wonderbeasts, Kitti Katz, Kohrra, Komi Cant Communicate, Kongsuni and Friends, KonoSuba: Gods Blessing on This Wonderful World, Kota Factory, Kotaro Lives Alone, Kulipari: An Army of Frogs, Kuromukuro, Lady Dynamite, Larva in Mars, Last Tango in Halifax, Lava Ka Dhaava, LEGO Friends: Heartlake Stories, LEGO® DREAMZzz, Levius, Lilyhammer, Lockwood and Co., Longmire, Lookism, Love Island USA, Love Naggers, Lovestruck in the City, Ludik, Lugar de Mulher, Luke Combs, Luo Bao Bei, Lupin, Luz: The Light of the Heart, Maamla Legal Hai, Madam Secretary, Mai: A

Mothers Rage, Mako Mermaids: An H2O Adventure, Malverde el santo patrón, Marcella, Masameer County, Masha and the Bear, Mashas Spooky Stories, Maverix, McGREGOR FOREVER, MeatEater, Meekah, Melancholia, Melanie Martinez, MerPeople, Metalica, Metallica: Some Kind of Monster, Middleditch and Schwartz, Mighty Little Bheem, Mighty Morphin Power Rangers, Mighty Raju, MINDHUNTER, Miniforce, Miriam Margolyes: Almost Australian, Misaeng: Incomplete Life, Miseducation, Mismatched, MIU404, Molang, Monarca, Mononoke, Monsters Inside: The 24 Faces of Billy Milligan, Monty Pythons Almost the Truth, Morgan Drinks Coffee, Morphle, Mortel, Motown Magic, movie, Murdaugh Murders: A Southern Scandal, Murder Among the Mormons, Murderville, Mush-Mush and the Mushables, My Daemon, My Hero Academia, My Wiggly Friend, Mythomaniac, Nadiya Bakes, Nadiya's Time to Eat, Nagi-Asu: A Lull in the Sea, Narcos, Naruto, Navarasa, Navillera, NCIS, Neds Declassified School Survival Guide, Neo Yokio, Netflix, Nevenka: Breaking the Silence, Nightflyers, Nisman: The Prosecutor the President and the Spy, Norsemen, Not Quite Narwhal, NSYNC, Numberblocks, Octonauts, Oddbods, Oggy Oggy, Oktoberfest: Beer and Blood, Okupas, Oldsters, ONE PIECE, Onimusha, Onmyoji, Outlander, Overlord, Ozark, Paava Kadhaigal, Pablo Escobar el patrón del mal, Pacific Rim: The Black, Paquita Salas, Parasyte: The Grey, Patriot Act with Hasan Minhaj, Peaky Blinders, Peppa Pig, Persona: Sulli, Pinky Malinky, Pitta Kathalu, Plastic Cup Boyz: Laughing My Mask Off!, Pocoyo, Polly Pocket, Ponysitters Club, Pororo - The Little Penguin, Powerpuff Girls, Project Runway, Pui Pui Molcar, Qin Empire: Alliance, Queenmaker, Queer Eye, Rabbids Invasion, Ragnarok, Rana Naidu, Ratched, Rebelde, Red Velvet, Replacing Chef Chico, Resident Alien, Rilakkuma and Kaoru, Rilakkumas Theme Park Adventure, Riverdale, Robocar Poli, Robozuna, Romesh Ranganathan: The Cynic, Rugal, Rugrats, Rust Valley Restorers, SAINT SEIYA: Knights of the Zodiac, Saitama Host Club, Scaredy Cats, Scooby-Doo!: Mystery Incorporated, Sense8, Senzo: Murder of a Soccer Star, Sex Education, Sexify, Shaboozey, Shahmaran, Shahs of Sunset, Shaman King Flowers, Shards of Her, Sharkdog, Shaun the Sheep: Adventures from Mossy Bottom, Shimajiro: A Wonderful Adventure, Sintonia, Siren: Survive the Island, Sirius the Jaeger, Slasher, Sleepless Society: Two Pillows and A Lost Soul, Smosh, Sonic Prime, Spectros, SPRIGGAN, Spycraft, Squid Game, StarBeam, StoryBots Super Songs, StoryBots: Laugh Learn Sing, Sunderland Til I Die, Sunny Bunnies, Supa Team 4, Super Drags, Super PupZ, Superbro, Survivor, Sweet Magnolias, SWORDGAI The Animation, Tahirs House, Takki, Tayo the Little Bus, Team Zenko Go, Teasing Master Takagi-san, Teenage Mutant Ninja Turtles, Tekken: Bloodline, Teletubbies, Terrace House: Aloha State, Thai Cave Rescue, The American Barbecue Showdown, The Andy Warhol Diaries, The Asunta Case, The Batman, The Bequeathed, The Boss Baby: Back in the Crib, The Conners, The Cook of Castamar, The Cuphead Show!, The

Fairly OddParents, The Five Juanas, The Garfield Show, The Good Place, The goop lab with Gwyneth Paltrow, The Great British Baking Show, The Grimm Variations, The Haunting of Bly Manor, The Hunt for Veerappan, The Idhun Chronicles, The Iliza Shlesinger Sketch Show, The Imperfects, The InBESTigators, The Indrani Mukerjea Story: Buried Truth, The Irregulars, The Jamie Foxx Show, The Millionaire Matchmaker, The Mire, The Mole, The Outreau Case: A French Nightmare, The Pentaverate, The Princess Weiyoung, The Red Clay Strays, The Ripper, The Secret of Skinwalker Ranch, The Smurfs, The Thundermans, The Ultimatum: South Africa, The Unbroken Voice, The Uncanny Counter, The Unremarkable Juanquini, The UnXplained with William Shatner, The Upshaws, The Watcher, The Way of the Househusband, The Wiggles World, The Witcher, Thus Spoke Kishibe Rohan, Tidelands, Time: The Kalief Browder Story, Titipo Titipo, Titletown High, Tobot Galaxy Detectives, Tokyo Trial, Top Secret UFO Projects: Declassified, Toradora!, Trainwreck: Woodstock 99, Transformers: War for Cybertron: Kingdom, Trap Nation, Treehouse Detectives, Triad Princess, Trollhunters, Trolls: The Beat Goes On!, Turning Point: 9/11 and the War on Terror, Twogether, Tyler childers, Ultimate Beastmaster, Ultraman, Ultramarine Magmell, Unsuspicious, Untameable, Vai Anitta, Vasco Rossi: Living It, Vida the Vet, VINLAND SAGA, Violet Evergarden, Wakfu, Wassup Man GO!, Ween, Welcome to Samdal-ri, Welcome to the Family, Wellmania, What the Love! with Karan Johar, Wizards: Tales of Arcadia, Wynonna Earp, XO Team, Yakitori: Soldiers of Misfortune, Yanxi Palace: Princess Adventures, Yasuke, Yeh Kaali Kaali Ankhein, YG Future Strategy Office, Yoga With Adriene, Yoga with Xochilt, Yoh! Christmas, Young Sheldon, Young Wallander, Yu Yu Hakusho, Yu-Gi-Oh!, Zig and Sharko, Zom 100: Bucket List of the Dead, Zombieverse

- **Celebrities**: Addison Rae, Adele, Alia Bhatt, Avani Gregg, Bailey Zimmerman, Bayashi, Bella Poarch, Ben Azelart, Benson Boone, Beyoncé, Billie Eilish, BossMan Dlow, Brandon Lake, Brent Rivera, Bruno Mars, Bryson Tiller, BTS, Burak Özdemir, Cardi B, Carlos Feria, Charli DAmelio, Charli XCX, Chris Brown, Chris Stapleton, Christen Dominique, Cody Johnson, Coldplay, Davie 504, Deftones, Demi Lovato, Dixie DAmelio, Doja Cat, Dominik Lipa, Drake, Dua Lipa, Dude Perfect, Dwayne Johnson, Ed Sheeran, El Chapo, Ella Langley, Ellen Degeneres, Eminem, Emma Chamberlain, Escalona, Fleetwood Mac, Frank Ocean, Gal Gadot, GloRilla, Gordon Ramsay, Gracie Abrams, Griselda, Gunna, Harry Styles, Hozier, Ice Spice, Imagine Dragons, J Cole, Jack Harlow, Jack White, Jackie Aina, Jacksepticeye, JaidenAnimations, Jake Paul, James Charles, Jason Derulo, Jeff Nippard, Jelly Roll, Jennie, Jennifer Lopez, Jimin, Joe Albanese, JoJo Siwa, Jordan Davis, Justin Bieber, Kacey Musgraves, Kane Brown, Kanye, Kanye West, Karol G, Katy Perry, Kendall Jenner, Kendrick Lamar, Kevin Hart, Khabane Lame, Khloé Kardashian, Kim Kardashian, Kimberly Loaiza, Kleo, Koe Wetzel, KondZilla, Kourtney Kardashian, Kristina Collins,

Kylie Jenner, Lainey Wilson, Lana Del Rey, Lilly Singh, Linkin Park, Lisa, Liza Anokhina, Llama Llama, Logan Paul, Loren Gray, Lucas and Marcus, Mark Rober, Markiplier, Marques Brownlee, Megan Moroney, Megan Thee Stallion, Metro Boomin, Michael Jackson, Michael Le, Michelle Phan, Miley Cyrus, Morgan Wallen, MrBeast, Niana Guerrero, Nicki Minaj, NikkieTutorials, Nirvana, Noah Kahan, Noel Robinson, Olivia Rodrigo, OneRepublic, Orville Peck, PewDiePie, Post Malone, Priyanka Chopra, Reba, Ria Ricis, Rihanna, Riyaz Aly, Rod Contreras, Sabrina Carpenter, SB Mowing, Selena Gomez, Shakira, Shraddha Kapoor, SIMI, Snoop Dogg, Spencer Polanco Knight, Stray Kids, SZA, Tate McRae, Taylor Swift, Taylor Wynn, Teddy Swims, The Kid LAROI, The Weeknd, Tommy Richman, Travis Scott, Tyler The Creator, Vilmei, Vin Diesel, Whindersson, Willie Salim, Younes Zarou, Zach Bryan, Zach King, Zendaya

- **Sports**: Anaheim Ducks, Arizona Cardinals, Arizona Coyotes, Arizona Diamondbacks, Athletic, Atlanta Braves, Atlanta Falcons, Atlanta Hawks, Atlanta United FC, Austin FC, Baltimore Orioles, Baltimore Ravens, Boston Bruins, Boston Celtics, Boston Red Sox, Brooklyn Nets, Buffalo Bills, Buffalo Sabres, Calgary Flames, Carolina Hurricanes, Carolina Panthers, CF Montreal, Champions League, Charlotte FC, Charlotte Hornets, Chicago Bears, Chicago Blackhawks, Chicago Bulls, Chicago Cubs, Chicago Fire FC, Chicago White Sox, Cincinnati Bengals, Cincinnati Reds, Cleveland Browns, Cleveland Cavaliers, Cleveland Guardians, Colorado Avalanche, Colorado Rapids, Colorado Rockies, Columbus Blue Jackets, Columbus Crew Sc, D.C. United, Dallas Cowboys, Dallas Mavericks, Dallas Stars, Denver Broncos, Denver Nuggets, Detroit Lions, Detroit Pistons, Detroit Red Wings, Detroit Tigers, Eagles, Edmonton Oilers, FC Barcelona, FC Cincinnati, FC Dallas, Florida Panthers, Golden State Warriors, Green Bay Packers, Houston Astros, Houston Dynamo, Houston Rockets, Houston Texans, Indiana Pacers, Indianapolis Colts, Inter Miami CF, Jacksonville Jaguars, Kansas City Chiefs, Kansas City Royals, La Galaxy, Las Vegas Raiders, Los Angeles Angels, Los Angeles Chargers, Los Angeles Clippers, Los Angeles Dodgers, Los Angeles FC, Los Angeles Kings, Los Angeles Lakers, Los Angeles Rams, Memphis Grizzlies, Miami Dolphins, Miami Heat, Miami Marlins, Milwaukee Brewers, Milwaukee Bucks, Minnesota Timberwolves, Minnesota Twins, Minnesota Vikings, Minnesota Wild, Montreal Canadiens, NASCAR: Full Speed, Nashville Predators, NBA, New England Patriots, New England Revolution, New Jersey Devils, New Orleans Pelicans, New Orleans Saints, New York City FC, New York Giants, New York Islanders, New York Jets, New York Knicks, New York Mets, New York Rangers, New York Red Bulls, New York Yankees, NFL, Oakland Athletics, Oklahoma City Thunder, Orlando City Sc, Orlando Magic, Ottawa Senators, Paris Saint-Germain, Philadelphia 76ers, Philadelphia Eagles, Philadelphia Flyers, Philadelphia Phillies, Philadelphia Union, Phoenix Suns, Pittsburgh Penguins, Pitts-

burgh Pirates, Pittsburgh Steelers, playoffs, Portland Timbers, Portland Trail Blazers, Real Madrid CF, Real Salt Lake, Sacramento Kings, Saint Louis Blues, San Antonio Spurs, San Diego Padres, San Francisco 49ers, San Francisco Giants, San Jose Earthquakes, San Jose Sharks, Seattle Kraken, Seattle Mariners, Seattle Seahawks, Seattle Sounders FC, Sporting Kansas City, St. Louis Cardinals, Tampa Bay Buccaneers, Tampa Bay Lightning, Tampa Bay Rays, Tennessee Titans, Texas Rangers, Toronto Blue Jays, Toronto FC, Toronto Maple Leafs, Toronto Raptors, Utah Jazz, Vancouver Canucks, Vancouver Whitecaps FC, Vegas Golden Knights, Washington Capitals, Washington Football, Washington Nationals, Washington Wizards, Winnipeg Jets, WWE