The Joe Rogan Effect: Politicized Podcasts and the Youth Gender Voting Gap

First version: 31st January, 2026 Current version: 17th June, 2026

Elliott Ash[1], Sergio Galletta[2], Federico Masera[3], Lehan Zhang[1]

[1] *ETH Zürich*
[2] *Sapienza University of Rome*
[3] *University of New South Wales*

Abstract
Online creators have become a central source of political information for young adults in recent years, and over the same period, young men have shifted toward the political right relative to young women. We examine whether these two major developments are connected by focusing on "The Joe Rogan Experience", the leading long-form podcast, which has a disproportionately male audience. Our identification leverages the timing and location of Ultimate Fighting Championship (UFC) events, for which Rogan has long served as the lead commentator. In a difference-in-differences design, we find that local UFC events trigger a significant increase in Google searches and in time spent consuming Joe Rogan episodes among young men. Applying text analysis to podcast transcripts, we document a pronounced shift in Rogan's political rhetoric: until 2020, Rogan frequently expressed support for Sanders with left-populist rhetoric; starting in 2021, his commentary became supportive of Trump with a right-populist slant. Using administrative voter files, we show that exposure to UFC events until 2020 increased Democratic voting in primaries with Sanders, while after that, exposure to UFC events increased Republican voting in primaries with Trump with all effects concentrated among young men.

Keywords: media exposure, political persuasion, political gender gap, youth voting, podcasts, The Joe Rogan Experience.
JEL codes: D72, D83, J16, L82.

Email addresses: `elliott.ash@gess.ethz.ch` (Elliott Ash), `sergio.galletta@uniroma1.it` (Sergio Galletta), `f.masera@unsw.edu.au` (Federico Masera), `lehan.zhang@gess.ethz.ch` (Lehan Zhang)

1. Introduction

Over the last decade, a new class of talk-native online creators have become first-order players in political communication. Podcasters, streamers and YouTubers now produce hours-long conversational programming, distributed through multi-sided, advertising-supported platforms whose recommendation engines and monetization rules shape both audience formation and advertiser reach (Rochet and Tirole, 2003; Armstrong, 2006; Anderson and Coate, 2005). Digitization has lowered the fixed costs of production and distribution, expanding the feasible variety of cultural goods and enabling niche entry at scale (Waldfogel, 2017). Yet attention remains highly concentrated, consistent with "superstar" dynamics in which small differences in perceived quality, identity, or authenticity translate into very large gaps in audiences and revenue (Rosen, 1981). In this environment, algorithmic discovery and subscriber networks substitute for the scheduling and gatekeeping of traditional newsrooms, changing both what gets produced and how it travels (Gentzkow et al., 2015; Anderson and Waldfogel, 2015).

Despite rapid growth, platform-native talk shows remain under-studied in the media-economics and political-economy literatures relative to legacy outlets. Existing work has primarily focused on ideological slant and persuasion in television news, particularly for "Fox News" (DellaVigna and Kaplan, 2007; Strömberg, 2015; Martin and Yurukoglu, 2017; Ash et al., 2024), with a smaller literature on newspapers (Gerber et al., 2009; Braghieri et al., 2024). More recently, research has turned to political bias and persuasion in online and social media environments (Allcott and Gentzkow, 2017; Zhuravskaya et al., 2020; González-Bailón et al., 2023; Braghieri et al., 2024). But the central facts about platform-native talk media are different: programming is long-form rather than packaged into short segments, production is personality-driven rather than newsroom-driven, and distribution is mediated by platform recommendation and sharing rather than fixed channel bundles. We argue that these features matter for persuasion: even when content is only intermittently political, it may still be persuasive because repeated exposure builds familiarity and trust, and because entertainment and politics are interwoven within the same personality-mediated attachment.

Over the same period, political behavior has undergone a striking demographic shift: the partisan gap between young men and young women has widened dramatically. Using comprehensive administrative voter files, we document that the male–female gap in Republican primary participation has nearly doubled among cohorts entering the electorate after the late 2010s, while gender gaps remain comparatively stable at older ages. This divergence is also highly uneven across space. Many counties experienced sharp increases in youth gender gaps, while others changed little. This broad pattern lines up with evidence from recent work using survey data all around the world (Burn-Murdoch, 2024; Glocalities, 2024; Moon and Kim, 2024; Nennstiel and Hudde, 2025; Mehring et al., 2025; Milosav et al., 2026).

Against this backdrop, this paper studies whether exposure to *The Joe Rogan Experience* (JRE), the largest talk-native show in the U.S., helps explain the recent gender divergence in youth political behavior. JRE is an especially natural case because its audience is both large and heavily skewed toward young men. Using passive digital tracking data from Luth Research, we show that Rogan dominates online political and news consumption among young men. Joe Rogan is the most-consumed political creator for this demographic across audio and video platforms, with young males accounting for nearly 90% of viewing and listening time, and with a substantially younger audience than other large online political channels or cable news programs.

What political content are these young male viewers being exposed to on JRE? Using large language models to annotate transcript texts, we produce measures of the content of Joe Rogan's podcasts. The transcripts show that Rogan's political rhetoric changes dramatically over time. First, the main presidential candidate he speaks positively about shifts from Bernie Sanders (2016 and 2020) to Donald Trump (2024). Second, the dominant political content moves from a left-populist slant to a more right-populist slant, especially in the run-up to the 2024 election cycle.

The political relevance of JRE lies not only in the direction of its political content, but also in the format through which it is delivered. Comparing JRE to cable news programs and platform-native talk shows, we show that platform-native talk shows mix politics with entertainment far more than cable news. JRE is especially distinctive: its political messaging is sparse but salient, embedded in long stretches of non-political conversation, highly populist, and unusually mobile across the left–right axis.

Our paper asks whether the gendered trends in partisanship and online consumption are causally related. Our empirical strategy exploits an unusual but impactful source of exogenous variation in attention to Rogan: the timing and location of Ultimate Fighting Championship (UFC) events. Joe Rogan's role as the most prominent UFC commentator creates geographically concentrated bursts of local attention around event dates. We use UFC events in a staggered Difference-in-Differences to estimate their political effects.

A concern of using this simple Difference-in-Differences model is that these events are scheduled in places and at times that may correlate with changes in political preferences. To address these treatment-timing selection issues, we exploit that any effects that Joe Rogan may have via UFC events should be concentrated among young men. This hypothesis stems from the age and gender distribution of his audience and the malleability of young voters' political preferences. We can therefore use women and older age groups to control for general changes in political preferences after a UFC event and exploit only differential changes among young men.

We first show that UFC events generate a clear first stage on exposure. In Google Trends data, UFC events produce sharp local spikes in searches for Rogan-related content. In digital consumption tracking data, we find that UFC events increase time consuming Joe Rogan content, with effects concentrated among young men.

We then link these exposure shocks to administrative data on voting in political primaries. We find that UFC events have on average no differential effect on the political behavior of young men. This lack of average effect masks large heterogeneous effects that mimic the political slant of the JRE. During the 2016 and 2020 presidential primaries, when Rogan supported Sanders, UFC events are followed by an increase in Democratic primary participation among young men. These effects happen only in primary elections in which Sanders is a candidate. In 2024, in concert with the pro-Trump shift in Rogan's rhetoric, UFC events are followed by a large increase in Republican primary participation among young men. Also in this period we do not observe a corresponding effect in primaries that do not include Trump. These results are consistent with a persuasion mechanism operating through exposure to salient political messaging embedded in a trusted entertainment product.

In line with the identification assumption we estimate an event study and show a lack of pre-trends in political preferences before a UFC event in any of the two relevant periods. We also use NASCAR race and boxing events to estimate a placebo difference-in-difference and observe no political changes after these sporting events.

Our contribution is threefold. First, we bring platform-native talk media into the core empirical agenda of media economics and political economy by studying the largest such show using administrative electoral outcomes and exogenous shocks to exposure. Second, we provide a new explanation for why recent political divergence has been especially pronounced between young men and young women: gendered consumption of political content on podcasts. Third, we complement the social-media persuasion literature with evidence from long-form creator media. In particular, Chmel et al. (2025) show that sustained exposure to independent creators can shift policy views and narratives, even when creators are not primarily political. Our findings add a specific channel through which creator media can shape real political behavior: long-form entertainment that intermittently delivers salient political cues to a sharply skewed audience can generate asymmetric electoral responses that standard models of mass media influence do not capture well.

The remainder of the paper proceeds as follows. Section 2 documents the rise and geography of youth gender divergence in administrative voting behavior, and describes our transcript-based measures of Rogan interest, consumption, and political content. Section 3 presents the UFC-based identification strategy and validates the first stage in both search attention and realized consumption. Section 4 reports the main reduced-form effects, age gradients, event-study dynamics, and robustness checks. Section 5 concludes.

2. Political Divergence and the Joe Rogan Experience

2.1. Voting by Gender and Age

Men and women have long differed in their political preferences. Women in the U.S. and other Western democracies tend to support more liberal parties and policy positions than men (Inglehart and Norris, 2000; Box-Steffensmeier et al., 2004; Abendschön and Steinmetz, 2014). For several decades, this gender gap appeared relatively stable. However, in recent years it has widened sharply, driven entirely by changes among young voters. Survey evidence suggests young women are becoming more liberal, while young men are becoming more conservative. This gender divergence appears across a wide range of countries (Burn-Murdoch, 2024; Glocalities, 2024; Nennstiel and Hudde, 2025; Mehring et al., 2025; Milosav et al., 2026), including the U.S (Moon and Kim, 2024).

We validate these patterns using individual-level voter file data from *L2 Political*. L2 harmonizes state voter registration and voter history records into a standardized dataset. The underlying records include a voter identifier, residential address, and demographics (gender and birth date or birth year). The measure of politics comes from participation in primary elections, 2000-2024.[1]

The population-level administrative voter data give us statistical power to identify gender differences in political behavior among youth, who make up a relatively small share of the electorate. This data captures actual behavior, rather than self-reported preferences from surveys, which are prone to biases that can distort reported preferences. For example, women have a higher social desirability bias, which may lead them to report attitudes that align with perceived norms rather than their true preferences (Krumpal, 2013).

For each age-range a, gender g, and election cycle (2-year interval) t, we construct the share of primary voters that voted in the Republican Party $ShRep_{a,g,t}$. We define the gender gap for that election cycle - age as the simple difference in shares: $GenderGap_{a,t} = ShRep_{a,M,t} - ShRep_{a,F,t}$.

Figure 1 panel (a) displays the gender gap in Republican primary voting by age across election cycles. For many years gender gaps were at around 7.5 p.p. across all age groups. The youngest age group (19-23) shows a widening divergence since 2018 while the slightly older one (24-28) started in 2020. For both groups, the gap increased over time, almost doubling by 2024. In the meantime, the older age groups maintain a relatively stable gap. Panel (b) shows a similar dynamic, but the gender gap is constructed by birth year. This figure additionally reveals that voters born after 1998 enter the electoral system at age 18 with already large gender gaps.

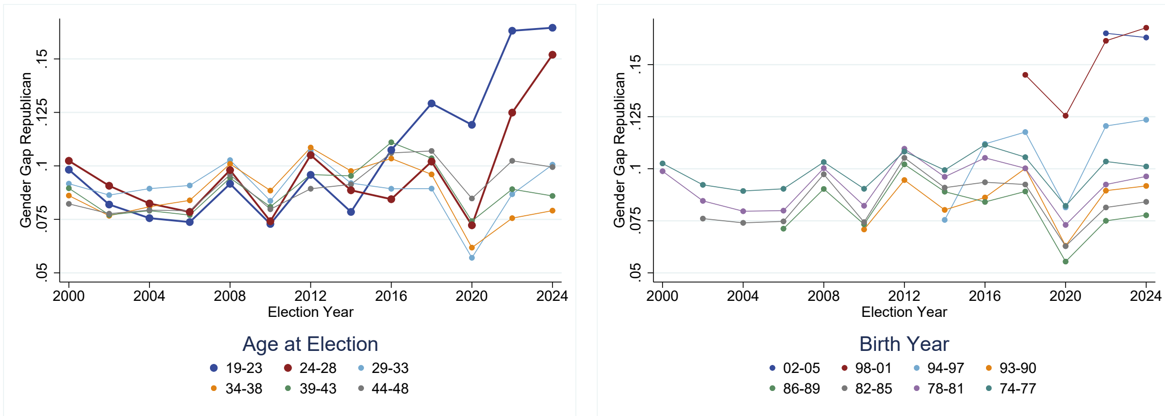
Appendix Figure A.1 provides a further decomposition of these trends by plotting the primary party share by both gender and age. Between 2000 and 2016, two clear patterns appear. First, in line with the gender gap plot, females tend to be more progressive than men. Second, younger voters tend to be more progressive than older voters. Starting in 2018, these stable patterns started to break as the youngest men started to become more conservative relative to the other groups. By 2024, the youngest male group is by far the most conservative group.

These figures show that certain age groups have experienced widening gender gaps while others have not. We call this phenomenon *Gender Divergence*. Gender Divergence can be operationalized in multiple ways, depending on the age groups, outcomes, and comparison benchmarks of interest. For the descriptive analysis in this section, we focus

[1]Data is unavailable for Alabama, Hawaii, Minnesota, Missouri, Montana, North Dakota, Vermont, and Wyoming. We also drop records with missing birth year/date, county FIPS, or gender.

Figure 1: Gender Gap in Political Behavior

(a) Gender Gap by Age　　　　(b) Gender Gap by Birth Year

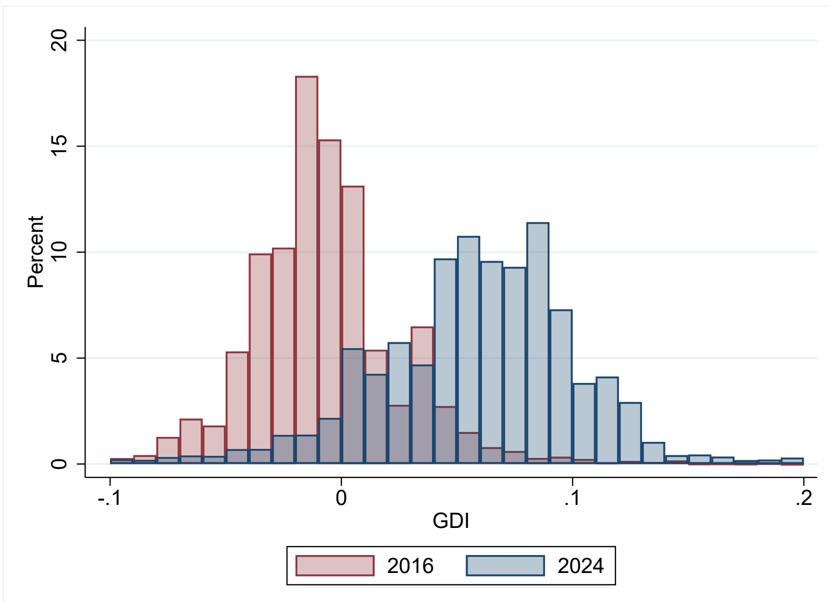


Notes: The figure plots the gender gap in Republican primary participation (male minus female share of two-party primary voters) using L2 voter file data. Panel (a) shows the gap by age group at election (19–23, 24–28, 29–33, 34–38, 39–43, 44–48) over election years. Panel (b) shows the gap by birth-year cohort (1974–1977 through 2002–2005) over election years. The x-axis is election year; the y-axis is the gender gap.

on a simple cohort-based measure. We define the younger group as voters aged 19–28, the age range in which the divergence is most visible, and compare it to voters aged 34–43, a nearby older group whose gender gap remains comparatively stable. The *Gender Divergence Index* (GDI) for election cycle t is the difference between the gender gap in these two groups, formally $GDI_t = GenderGap_{19\text{–}29,t} - GenderGap_{34\text{–}43,t}$.

To illustrate the geography of this divergence, we construct a different GDI measure for each county-election cycle combination. Figure 2 displays the distribution of the Gender Divergence Index across U.S. counties for the 2016 and 2024 primary elections. The histogram reveals substantial heterogeneity in the evolution of gender gaps among young voters across counties. While the GDI has increased considerably over this period, the divergence is far from uniform across the country. The distribution shows that many counties experienced increases in the gender gap (positive GDI values), with the 2024 distribution shifted rightward relative to 2016, indicating a general increase in gender divergence. However, there remains considerable variation, with some counties showing little change. In this paper we aim to explain this part of this variation.

Figure 2: Distribution of Gender Divergence Index by County



Notes: The figure displays histograms of the county-level Gender Divergence Index (GDI) for young voters (ages 19–28) in the 2016 and 2024 primary elections. The GDI measures the difference in the gender gap (male minus female share of Republican primary voters) between the treated age range (19–28) and the control age range (34–43) for each county-election cycle. Histograms are weighted by the number of young two-party primary voters in each county. The x-axis shows GDI values; the y-axis shows the percent of counties (weighted by voter count).

2.2. Interest and Consumption of Joe Rogan

The main measure of consumption of Joe Rogan content comes from passive digital tracking from Luth Research. As a complementary measure we also use Google Trends search data. These data provide different perspectives on Rogan's reach and audience composition.

Luth Research passive consumption tracking. To measure actual consumption behavior, we use Luth Research's passive digital tracking panel, which records time spent consuming online content across major platforms for a large sample of U.S. users. The panel tracks both video consumption (YouTube) and audio consumption (Spotify) with timestamps and content identifiers, allowing us to identify engagement with Joe Rogan channels and podcasts. The data covers the period from January 2023 through October 2025 and include demographic information such as age, gender, and zip code of residence, for each user.

Joe Rogan consumption is prevalent in the Luth panel. Among video channels, *PowerfulJRE* (the official Joe Rogan Experience YouTube channel) ranks 16th overall by total hours viewed (Appendix Table A.1). On the audio side, *The Joe Rogan Experience* is the second-most-consumed content producer overall (after Taylor Swift) and by far the most-consumed podcast (Appendix Table A.2).

When focusing on news and politically related channels and creators, Joe Rogan is the most popular personality online (Appendix Table A.3). His audience is heavily gendered, with males accounting for 83.4% of total watch time. When focusing on consumers aged 28 or below, the gender distribution is even more skewed, where young males account for 88.5% of the total watch time. Additionally, Joe Rogan tends to have a much younger audience than other comparable shows. For example, *Meidas Touch*, the largest liberal political channel online is not only gender-balanced but has a median audience age that is 12 years older (47 vs. 35 years old). Overall, this makes Joe Rogan by far the most popular political online channel for young men, with an online audience that is almost five times the size of Fox News for this particular demographic (Appendix Table A.4). Taken all together, this evidence points towards Joe Rogan being a potentially important figure in the formation of political preferences, especially of young men.

Google Trends search interest. The other measure of Joe Rogan interest comes from Google Trends. We work at the quarterly level by designated media market (what

Google calls metro area), constructing an outcome for local search intensity. Google Trends reports an interest index scaled from 0 to 100, where 100 represents the DMA with peak search volume in that quarter. Because this index is normalized within each quarter, we also compute within-quarter DMA rankings to enable comparisons across time periods. Appendix Figure A.2 provides maps showing the Google Trends interest index for "UFC" and "Joe Rogan" across DMAs in Q4 2024. The map shows that interest varies considerably across markets, with some DMAs exhibiting consistently higher search volumes than others. This geographic variation reflects both differences in baseline interest levels and local factors that may drive attention to Rogan's content.

2.3. Political Content in *The Joe Rogan Experience*

We analyze content produced by Joe Rogan using transcripts of JRE from December 2011 to August 2025, retrieved via the Supadata API.[2] For each episode, we collect the full audio transcription of the corresponding YouTube video, along with episode-level metadata including the video title, description, duration, views, and likes.

To create standardized units of analysis, we segment each episode transcript into overlapping text windows. Transcripts are divided into 256-word chunks with a stride of 128 words. This overlapping windowing approach balances semantic coherence of substantively meaningful content, robustness to arbitrary boundary placement, and computational efficiency for large-scale annotation using large language models. We restrict the sample to episodes with transcripts of at least 768 words (corresponding to a minimum of five chunks) to retain all full-length, long-form podcast episodes. The final JRE corpus consists of 466,328 chunks.

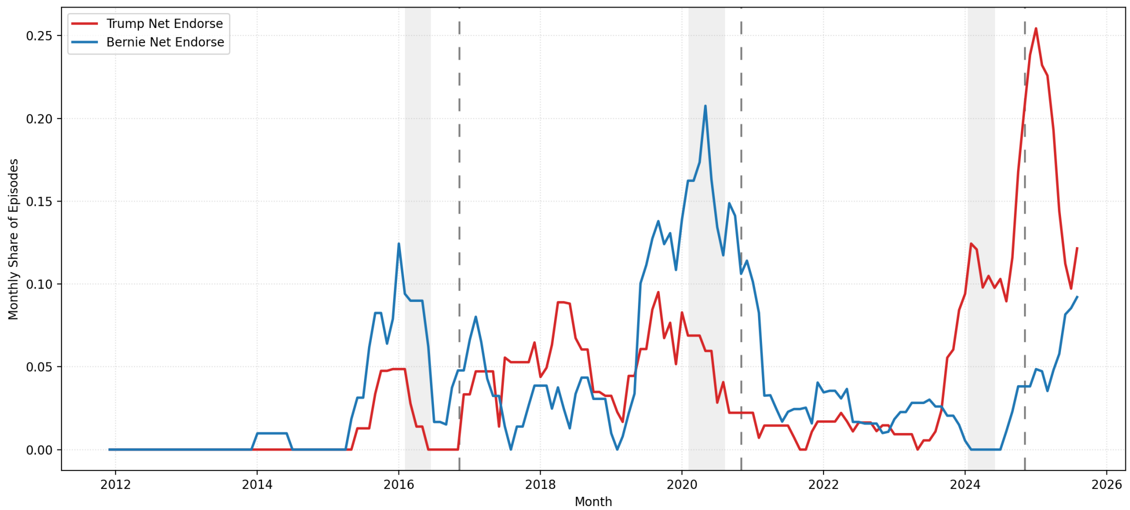
We run text analysis to measure (1) endorsement and opposition towards U.S. presidential candidates Bernie Sanders and Donald Trump, and (2) the prevalence and ideological direction of populist versus non-populist political framing. We use a large language model to annotate transcript segments via structured prompts. Specifically, we use OpenAI's gpt-4.1-mini model through the API.

Candidate Endorsements. The first prompt measures the presence and evaluative direction of candidate-specific political content in transcript segments. It identifies whether Bernie Sanders and Donald Trump are mentioned, and whether the overall

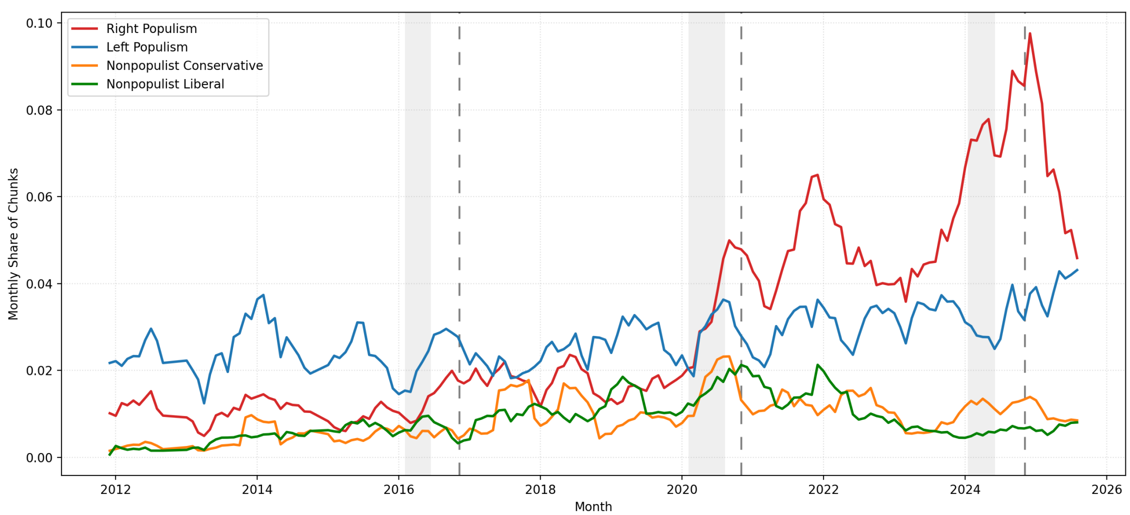
[2] https://publicapis.io/supadata-api

Figure 3: Political content in *The Joe Rogan Experience* over time

(a) Evolution of candidate endorsements in *The Joe Rogan Experience*



(b) Evolution of political framing in *The Joe Rogan Experience*



Notes: Panel (a) shows the six-month moving average of the monthly share of episodes containing net positive endorsements of Bernie Sanders and Donald Trump. Panel (b) shows the six-month moving average of the monthly share of transcript chunks classified as left-populist, right-populist, non-populist liberal, and non-populist conservative political framing. Vertical dashed lines indicate U.S. presidential election months. Grey bars indicate U.S. presidential primary contestation periods.

framing of the segment endorses or opposes each candidate. The full prompt is provided in Appendix B.3.

Figure 3a plots the six-month moving average of the monthly share of podcast episodes containing positive endorsements of Bernie Sanders and Donald Trump.[3] For each month, we compute the proportion of episodes whose transcripts contain net positive evaluative language toward each candidate[4], and smooth the resulting series using a centered six-month moving average. Endorsements of Bernie Sanders are most prevalent during the 2016 and 2020 election cycles, while endorsements of Donald Trump increase sharply during the 2024 cycle, with peaks occurring in the lead-up to each U.S. presidential election. These statistics correspond to anecdotes and intuition that Joe Rogan expressed preference for Bernie Sanders in 2016 and 2020, while preferring Trump in 2024.

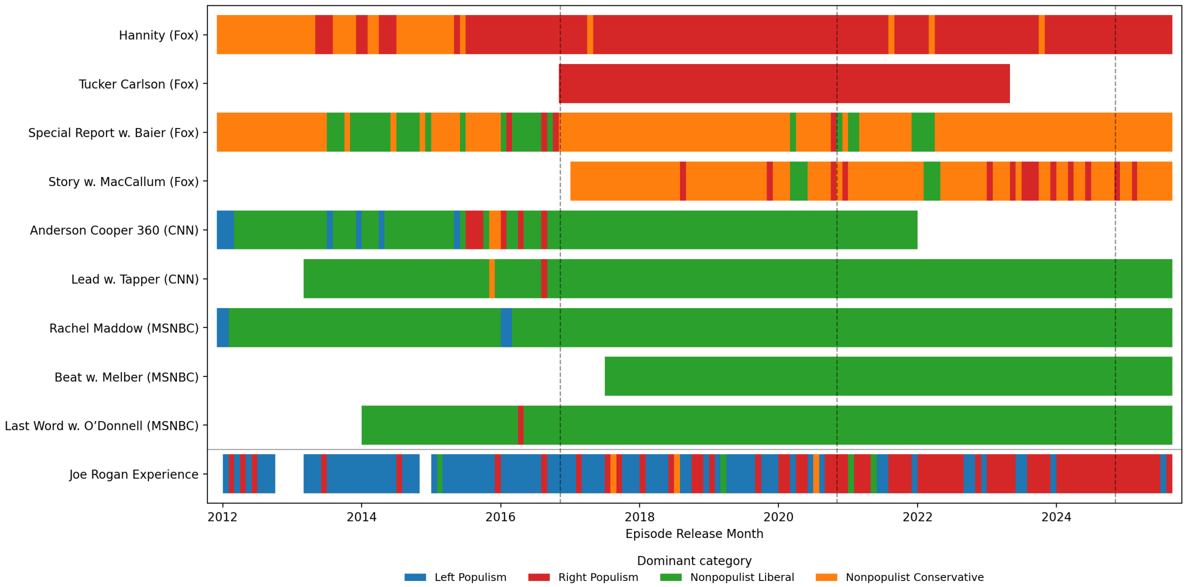
Political framing. The second prompt measures whether a given transcript segment contains political messaging and then classifies its ideological direction. The prompt distinguishes populist messaging from non-populist liberal or conservative partisan messaging, as well as from neutral or non-political content. It identifies the presence of populist rhetoric defined by a moralized "people versus elite" frame and classifies such content as left-wing or right-wing populism based on the primary targets of blame and core grievances. The full prompt is provided in Appendix B.3.

Figure 3b plots the monthly share of transcript segments classified into different political framing categories. For each month, we compute the proportion of transcript segments labeled as left-populist, right-populist, non-populist liberal, or non-populist conservative, based on segment-level annotations. 8% of all segments are categorized into one of these four labels. We observe that JRE is mostly populist when engaging with politics. The most popular populist slant has changed throughout the years. Until 2021 the populist left slant was the most common. Starting in 2021 the populist right rhetoric became the most popular reaching a peak at the 2024 presidential election.

[3] Summary statistics of classification for both endorsements and political framing are in Table A.5.

[4] Each transcript chunk is assigned an endorsement score from 1 to 5 (with 0 for chunks that do not discuss the candidate in endorsement-relevant terms). An episode is coded as containing net positive evaluative language toward a candidate if more of its chunks are classified as positive (score 4–5) than as critical (1–2); neutral/mixed (3) and not-discussed (0) chunks are ignored. Ties count as not net positive, and the two candidates are coded independently.

Figure 4: Variation in main political content over time: Fox, CNN, MSNBC, and JRE



Notes: Each row is a show and runs left to right over the program's coverage period. For every calendar month the bar is colored by the show's dominant political lane—the framing category with the most transcript chunks that month (no smoothing): left populism (blue), right populism (red), non-populist liberal (green), non-populist conservative (orange). White gaps are months without coverage. Cable labels are from the fine-tuned RoBERTa classifier (Appendix B.2; JRE labels are from the `gpt-4.1-mini` populism prompt (Section 2.3). Vertical dashed lines mark the November 2016, 2020, and 2024 U.S. presidential elections. JRE is the only show that repeatedly changes lane; each cable program holds a single lane throughout.

Comparison to cable news. Next, we show how the political content in JRE differs from traditional cable TV programs. We compare JRE to nine prominent cable news programs across Fox News, CNN, and MSNBC. Cable transcripts are processed using the same 256-word chunking strategy as JRE and classified using the same political framing taxonomy. Because the cable corpus is substantially larger, we label a stratified subset with `gpt-4.1-mini` and use these labels to train a RoBERTa classifier for the remaining chunks. Appendix B.2 describes the classifier and validation.

Cable TV programs and JRE differ first in the density of political content. Cable programs are saturated with politics: between roughly one-third and two-thirds of transcript chunks carry partisan or populist framing. On JRE, fewer than one in ten chunks (8.5%) contains slant. Cable delivers a continuous stream of political talk, whereas JRE embeds sparse political messaging within long stretches of comedy, sport, health, and lifestyle conversation.

Where JRE differs most sharply from cable is in the stability of its political framing. Figure 4 plots each show's dominant political lane by month.[5] Cable programs occupy highly stable lanes: Fox opinion programs are dominated by right populism, Fox straight-news programs by non-populist conservatism, and CNN and MSNBC programs by non-populist liberalism. Across the nine cable shows, the most common lane accounts for between 81% and 100% of a program's months. JRE is the salient exception. Its dominant lane alternates between left populism and right populism, without a single lane persisting durably across time. This pattern mirrors the candidate-endorsement and framing series in Figure 3: left populism dominates before 2020, while right populism rises thereafter.

Next we consider and compare the various content sources in their mixing of politics and entertainment. Soft-news formats can draw otherwise inattentive audiences into political topics, while high-choice media environments shape who encounters political information in the first place (Prior, 2007; Baum, 2011). Podcasts extend this dynamic by embedding politics inside long-form, conversational, entertainment-oriented content.

We measure this content mixture by comparing transcripts from the nine cable TV programs with 22 platform-native talk shows, including JRE. Using a BERTopic model fit across both corpora, we classify transcript chunks into broad topical categories and code an episode as mixing politics and entertainment if it contains at least one political chunk and at least one entertainment-oriented chunk. Appendix B.1 describes the topic model and category mapping.

Appendix Figure A.5 shows how this measure has changed over time by content source. By this measure, 43.1% of platform-native talk shows episodes mix politics and entertainment, compared with 16.9% of cable TV episodes. This difference persists over time, with platform-native talk shows on average consistently having twice the rate of content mixing politics and entertainment within episodes. The contrast is not simply that platform-native talk shows are more entertaining in style; rather, cable programs are topically concentrated in politics, while platform-native talk shows more often interleave political and non-political material within the same program.

[5] Figure A.6 reconstructs the same picture episode by episode, assigning each individual episode to its own dominant lane. The cable rows stay near-solid while the JRE row flickers between left and right from one episode to the next. The contrast between stable cable programming and the more volatile JRE format is even sharper at this finer resolution.

3. Empirical Strategy

3.1. Identification using UFC events

We want to estimate how exposure to the Joe Rogan Experience can affect gender differences in electoral behavior among young US voters. A simple comparison of political outcomes between JRE listeners and non-listeners, or between high- and low-JRE audience areas, confound persuasive effects of Rogan exposure with pre-existing differences in the political composition of young men relative to young women. In particular, podcast audiences are highly selective, making it difficult to distinguish persuasion from sorting, especially when the object of interest is gender differences. Young men are substantially more likely than young women to consume JRE, and the men who do so may already differ systematically in political preferences from men who do not. Moreover, counties with higher JRE listening may differ along unobserved dimensions, e.g., cultural, economic, or informational, that shape both media demand and the male–female gap in partisan preferences. A credible design, therefore, requires exogenous variation in Rogan exposure that is orthogonal to local determinants of the youth gender gap.

Our baseline design uses the timing and location of the Ultimate Fighting Championship (UFC) events to generate such variation. The key idea, that we document below, is that UFC events generate geographically and temporally concentrated bursts of attention for Joe Rogan and his online content, particularly among young men. We compile a dataset of UFC events hosted in the United States, including the event date and location. Figure 5 maps the locations of UFC host counties in our data. We geocode event venues to counties and construct indicators for whether a county hosted an event within a pre-specified window before an election.

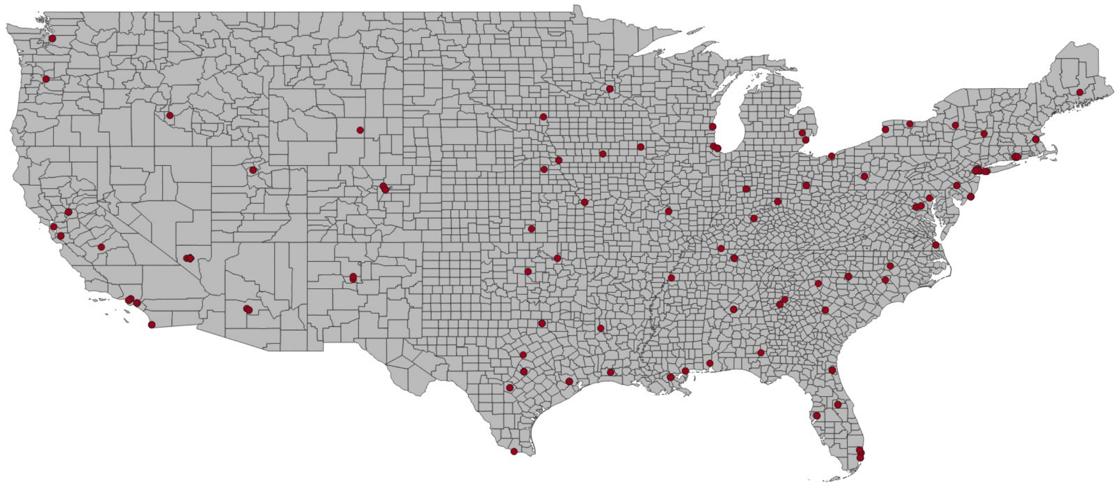
3.2. Estimation Approach

An initial approach to identify the effects of UFC events on political preferences would be to estimate a simple two-way fixed effects Difference-in-Differences framework as follows:

$$Y_{i,s,c,t} = \alpha_c + \alpha_{s,t} + \gamma PostUFC_{s,c,t} + \varepsilon_{i,s,c,t}, \tag{1}$$

where $Y_{i,s,c,t}$ equals one if voter i voted in the Republican primary (versus Democratic) at election t, in state s and county c. County fixed effects α_c absorb time-invariant differences across counties, and election-state fixed effects $\alpha_{s,t}$ absorb shocks common to

Figure 5: Geographic distribution of UFC events (U.S.)



Notes: Each dot marks a city that hosted at least one UFC event in the sample period.

all counties in a given election-state. $\text{PostUFC}_{s,c,t}$ indicates whether the election occurs within 2 years after a UFC event in the county.[6] Because for most people, we observe one primary every 2 years, this corresponds in most cases to the effect of a UFC event on the next primary election. The sample is restricted to Republican or Democratic primary voters since 2000.

A concern of using this simple Difference-in-Differences model to identify the effect of UFC events is that these events are scheduled in places and at times that may correlate with changes in political preferences. For example, UFC may schedule events in cities that are experiencing an economic boom to maximize ticket sales. This, in turn, may be correlated with changes in local political preferences. Because of these selection issues, the parameter γ could confound the political effect of UFC events with other local time-varying characteristics that affect political preferences.

To address these treatment-timing selection issues, we exploit that any effects that Joe Rogan may have via UFC events should be concentrated among young men. This hypothesis is given by the age and gender distribution of his audience and the malleability of young voters' political preferences. To do so, we estimate the following augmented equation:

[6] In Appendix Figure A.3 we show how the effects varies with distance to the UFC event.

$$
\begin{aligned}
Y_{i,s,c,t} = \alpha_c + \alpha_{s,t} + \gamma_1 \text{Male}_i + \gamma_2 \text{Young}_i + \gamma_3 \text{Young}_i \times \text{Male}_i \\
+ \beta_1 PostUFC_{s,c,t} + \beta_2(\text{Male}_i \times PostUFC_{s,c,t}) + \beta_3(\text{Young}_i \times PostUFC_{s,c,t}) \\
+ \beta_4(\text{Young}_i \times \text{Male}_i \times PostUFC_{s,c,t}) + \varepsilon_{i,s,c,t}. \quad (2)
\end{aligned}
$$

Here, Young_i indicates ages 19–28, chosen based on the gender gap statistics shown in Figure 1. Male_i indicates male voters.

In this specification, β_1 controls for general changes in political preferences after a UFC event. If UFC events are scheduled in places that are experiencing an economic boom, and this is correlated with a general increase in Republican primary participation, β_1 will be positive. We further control for selection on unobservables that are either gender (β_2) or age (β_3) specific. For example, UFC could be scheduling events in places where only men are becoming more Republican and this would be captured by β_2.

The parameter of interest β_4 captures the differential change in the political preferences of young men after a UFC event when compared to older men and younger women. This is effectively a quadruple difference that, beyond comparing places with and without a UFC event before and after an event, also exploits the expected differential reaction by age and gender. β_4 captures the causal effect of UFC events on young men under the identifying assumption that, absent the UFC event, young men would not experience differential changes in political preferences.[7]

Our empirical interest in UFC events is that they shift Joe Rogan consumption. A potential exclusion violation comes from UFC events having a direct effect on voting – in particular for Trump, since he is closely associated with UFC and has regularly appeared at those events. This non-JRE channel for UFC persuasion operates in favor of Trump. However, we can distinguish a JRE effect from a direct pro-Trump UFC effect because Joe Rogan endorsed Bernie Sanders in 2016 and 2020. Hence, we allow the effect of UFC events on political preference to be different in elections in which Joe Rogan endorsed Bernie Sanders (for the 2016 and 2020 presidential elections identified by the dummy variable $Sanders_t$) and when he endorsed Donald Trump (for the 2024 presidential election identified by the dummy variable $Trump_t$). If JRE matters more

[7] In Section 4.2 we provide various results in line with this assumption.

than a direct pro-Trump UFC effect, we would see a pro-Bernie effect in 2016 and 2020.[8] In all specifications, standard errors are clustered by county.

3.3. First-Stage Effects of UFC events on Attention to Joe Rogan

Our empirical strategy relies on the premise that local UFC events generate quasi-experimental increases in exposure to Joe Rogan. Before turning to electoral outcomes, we assess this exposure channel directly, in the spirit of a first-stage exercise. We measure attention to Joe Rogan using two complementary measures introduced above: realized consumption in the Luth Research panel and local search attention in Google Trends.

Luth Research passive consumption tracking. We first test whether UFC events translate into higher *realized* Rogan exposure using Luth Research's passive media-consumption data. These data provide a direct measure of viewing and listening, but they cover a shorter window than our electoral outcomes and therefore allow us to study only a subset of UFC events. Within the Luth coverage period (August 2022 through October 2025), UFC held 101 events across 26 U.S. cities, as summarized in Appendix Figure A.4. We link each user to a county via location information and construct a user–day panel in which outcomes measure daily engagement with Rogan content (across Rogan-related YouTube channels and the *Joe Rogan Experience* podcast). We then estimate a user-level difference-in-differences model that mirrors Equation (2) but replaces electoral outcomes with daily Rogan consumption outcomes. Because media consumption is observed at the daily level and attention responses to UFC events should be concentrated shortly after the event, we define exposure over the 150 days following a local UFC event rather than over the multi-year window used for electoral outcomes. We validate this decision in an event study framework in Figure 6.

Table 1 reports that UFC events increase the young-male differential in UFC-related consumption by 0.25 percentage points when measured using channels with names mentioning UFC and by 0.21 percentage points when measured using titles of videos that mention UFC. Most importantly, Columns (3) and (4) show a similar increase in the probability of consuming Rogan content. Also, here the outcome measures whether

[8]To not capture general demographic or gendered trends in these elections, we allow γ_1, γ_2 and γ_3 to be different in "Sanders Endorsed" and "Trump Endorsed" elections. Furthermore, to be sure that any results are not due to selection into treatment reasons that are happening specifically around these important elections we also allow β_1, β_2 and β_3 to be different in "Sanders Endorsed" and "Trump Endorsed" elections.

Table 1: Effect of Local UFC Events on UFC and Rogan Viewing

	UFC		**Rogan**	
	Titles (1)	Channels (2)	Titles (3)	Channels (4)
Post × Young × Male	0.21*	0.25***	0.46***	0.48***
	(0.11)	(0.09)	(0.16)	(0.15)
Observations	4.32M	4.32M	4.32M	4.32M
Average outcome	0.2	0.2	0.8	0.5

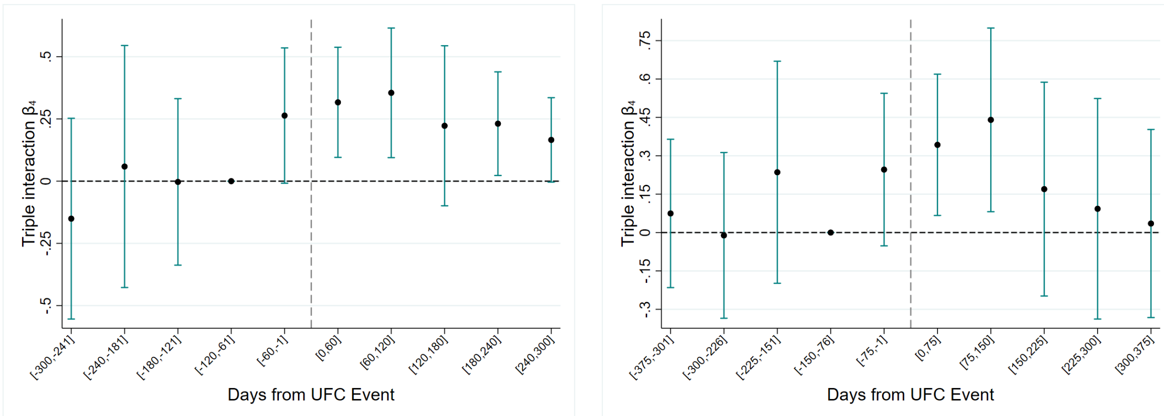
Notes: OLS estimates. The unit of observation is a Luth panel member-day. The sample includes young (ages 18–28) and old (ages 29–100) adults in counties that hosted a UFC event since 2021, excluding Las Vegas. *Post* is a dummy equal to one for days within 150 days after a local UFC event. The table reports the triple-interaction coefficient (Young × Male × Post). Column (1) uses an indicator for any UFC viewing on title-matched content. Column (2) uses an indicator for any UFC viewing on the official channel or related channels. Column (3) uses an indicator for any Rogan viewing via title-matched content. Column (4) uses an indicator for any Rogan viewing via channel-name-matched content. All regressions include date and county fixed effects. Standard errors clustered at the county level are reported in parentheses.

the channel name mentions Joe Rogan or the titles of the episode mention Joe Rogan. Given the popularity of "The Joe Rogan Experience" the vast majority of these come from views and listens of the official podcast. This confirms that the same events used for identification in the electoral analysis also generate the intended first-stage shift in realized Rogan exposure.

Figure 6 reports the dynamic version of this first stage. The pre-event coefficients are close to zero and imprecise, which is consistent with the absence of differential trends in UFC or Rogan consumption before a local UFC event. Immediately after the event, the estimates become positive for both outcomes. UFC-related channel consumption rises in the first post-event bins, as expected, and Rogan consumption also increases among young men relative to the comparison groups. The effect on Rogan consumption is largest during the first 150 days after the event and then attenuates, matching the idea that UFC events create a concentrated attention shock. We also observe a small and statistically insignificant increase just before the UFC events. This is consistent with the UFC being announced and advertised, increasing the interest in Joe Rogan before the actual event.

Figure 6: Effect of UFC events on UFC and Rogan consumption

(a) UFC-related channels (b) Rogan content



Notes: The figure reports event-study estimates around local UFC events using Luth Research passive-consumption data. Panel (a) shows effects on UFC-related channel consumption. Panel (b) shows effects on Rogan consumption. Points denote coefficient estimates and vertical bars denote 95% confidence intervals.

Google Trends search interest. Next, we test whether UFC events raise local search attention to UFC and Joe Rogan. We construct a quarterly DMA-level panel from 2014Q1–2025Q4 for two queries: *"ufc"* and the Joe Rogan *topic* identifier, which captures searches that Google classifies as related to Rogan. The advantage of this data is that it allows use to explore a much longer time frame. On the other hand, the data is aggregated at a higher geographical unit, and we cannot differentiate the search volume by age or gender. Because of this, we estimate a simpler difference-in-differences specification with DMA fixed effects and year-quarter fixed effects. The outcomes are Google's 0–100 search-interest index and the within-quarter DMA rank, where lower rank values indicate higher relative search intensity.

Table 2 shows that UFC events generate a clear contemporaneous increase in search attention. In the event quarter, UFC search interest rises sharply in host DMAs, and Rogan-related search interest also increases. For the ranking outcomes, the negative coefficients indicate that host DMAs move toward the top of the national search distribution. By contrast, the lagged event coefficients are small and statistically indistinguishable from zero, suggesting that the increase is concentrated around the event quarter rather than reflecting persistent differences between host and non-host markets.

Table 2: Effect of UFC events on Google Trends search interest (DMA × quarter)

	UFC		Joe Rogan topic	
	Ranking	Index	Ranking	Index
UFC event	-29.50^{***}	5.08^{***}	-6.48^{***}	1.35^{**}
	(3.82)	(0.66)	(2.19)	(0.54)
UFC event $(t-1)$	-0.07	-0.29	-3.26	0.73
	(2.03)	(0.31)	(2.24)	(0.45)
Observations	10,032	10,032	10,032	10,032
DMA FE	Yes	Yes	Yes	Yes
Time FE (year × quarter)	Yes	Yes	Yes	Yes
SE clustered by	DMA	DMA	DMA	DMA
Las Vegas excluded	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. For ranking outcomes, negative coefficients indicate moving up in the national distribution (higher relative interest). UFC event indicates an event in the current quarter; UFC event $(t-1)$ indicates a UFC event in the previous quarter.

4. Results

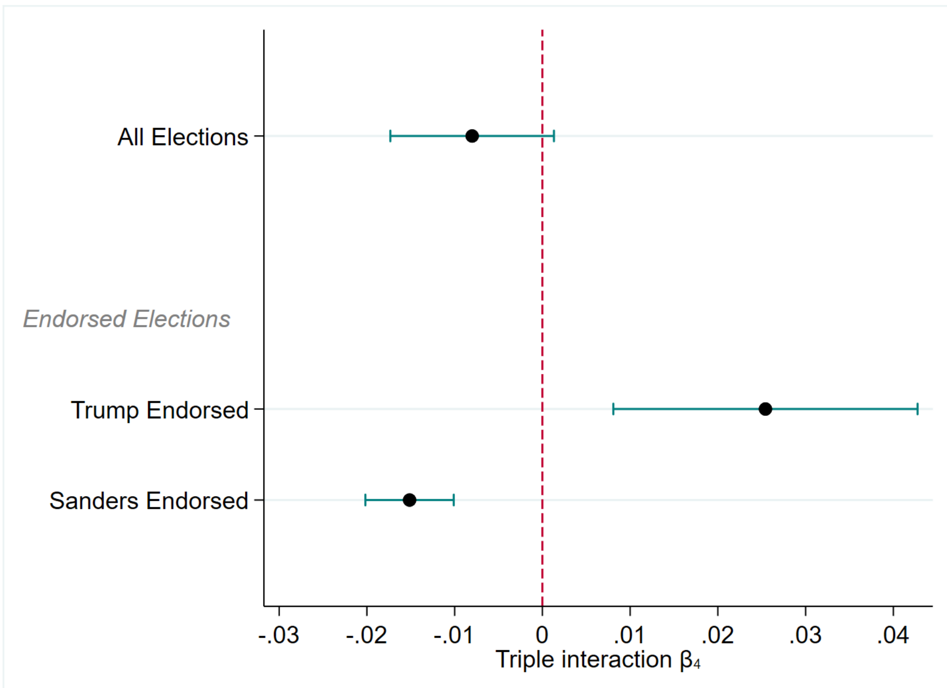
4.1. Main Results

We now ask whether the same local UFC shocks that increase attention to Joe Rogan also affect political behavior. The outcome is Republican primary participation among two-party primary voters. The coefficient of interest is the triple interaction between post-UFC exposure, an indicator for male voters, and an indicator for the young age group, ages 19–28. It therefore asks whether local UFC exposure changes the male–female gap in Republican primary participation among young voters relative to the corresponding change among all other age groups in the estimation sample.

Figure 7 reports the main reduced-form estimates. Pooling all elections, the coefficient is small and statistically indistinguishable from zero, around -0.8 percentage points. This result shows that, on average, UFC events do not shift political preferences.

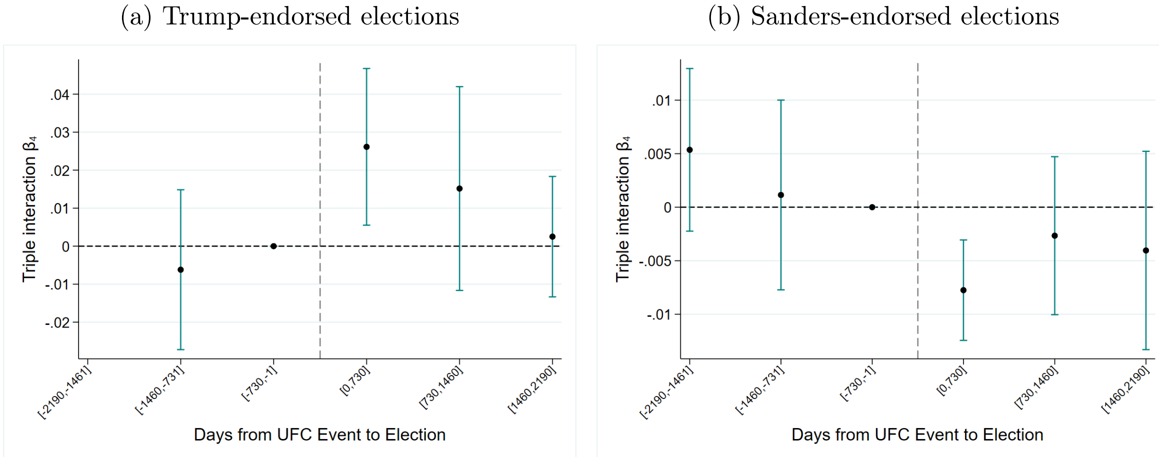
To see the effect of Joe Rogan's shifting political support, we separate elections by endorsement context. In Trump-endorsed elections, UFC exposure increases the young male–female gap in Republican primary participation by about 2.5 percentage points relative to the corresponding gap among all other ages. Instead, in Sanders-endorsed elections, the coefficient is negative, about -1.5 percentage points, implying a relative reduction in the young male–female Republican primary gap. The same local exposure

Figure 7: Effect of UFC events on primary election voting



Notes: The figure reports estimates of the triple interaction between post-UFC exposure, an indicator for male voters, and an indicator for young voters ages 19–28. The outcome is Republican primary participation among two-party primary voters. Estimates are reported for all elections, Trump-endorsed elections, and Sanders-endorsed elections. Positive estimates indicate a widening of the young male–female Republican primary gap relative to all other age groups. Points denote coefficient estimates and horizontal bars denote 95% confidence intervals.

Figure 8: Dynamic effects of UFC events on primary election voting



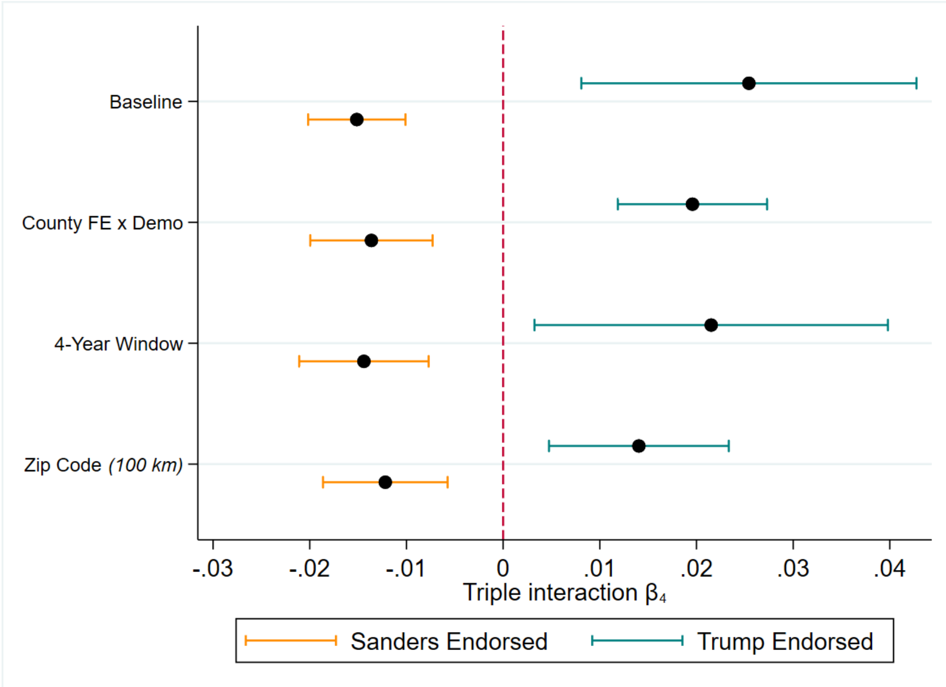
Notes: The figure reports event-study estimates of the triple interaction between UFC exposure, male voters, and young voters ages 19–28. The horizontal axis indexes the number of days between the UFC event and the election. The omitted category is the 730 days immediately before the UFC event and is normalized to zero. Panel (a) focuses on Trump-endorsed elections; panel (c) focuses on Sanders-endorsed elections. Points denote coefficient estimates and vertical bars denote 95% confidence intervals.

shock therefore pulls voting in opposite partisan directions depending on the political content associated with Rogan at the time. Importantly, the sign reversal is difficult to reconcile with a generic UFC or local-event channel, but is consistent with content-mediated persuasion.

Next, we check whether treated counties were already on different trajectories before UFC exposure. In the event-study specification in Figure 8, we replace the single post-UFC indicator with event-time bins. Across Trump-endorsed, and Sanders-endorsed specifications, the lead coefficients are close to zero and do not display a systematic pre-trend.[9] The post-event coefficient estimates are consistent with the main evidence. In Trump-endorsed elections, the first two-year post-event bin is positive, about 2.5 percentage points. In Sanders-endorsed elections, the corresponding coefficient is negative, about 0.8 percentage points. Later post-event effect are smaller and not statistically significant. The timing evidence therefore supports the interpretation that the main estimates are driven by changes following UFC exposure rather than by pre-existing trends in UFC host counties.

[9]UFC events have been announced only until August 2026 so we do not have enough observations to estimate a long pre-trends in the Trump-endorsed event study.

Figure 9: Robustness of UFC effects on primary election voting



Notes: The figure reports robustness checks for the triple-interaction estimate. Each row re-estimates the effect separately for Trump-endorsed and Sanders-endorsed elections under an alternative specification: the baseline model, richer county-by-demographic fixed effects, a four-year exposure window, and a zip-code-based exposure definition. Positive estimates indicate a widening of the young male–female Republican primary gap relative to all other age groups. Points denote coefficient estimates and horizontal bars denote 95% confidence intervals.

4.2. Specification and identification checks

This section reports some supporting results testing the robustness of our main results. First, we show robustness to specification checks. Second, we look at identification.

A natural concern is that the sign reversal reflects an arbitrary exposure window, county-level assignment, or differential demographic trends in UFC-hosting places. Figure 9 reports estimates that address these concerns directly. The Trump-endorsed coefficient remains positive across when adding richer county-by-demographic fixed effects, we use a longer four-year exposure window, and we implement a zip-code-based exposure definition. Similarly, the Sanders-endorsed coefficient remains negative across the same exercises.

Next, we provide additional evidence for our identification assumptions based on a series of placebo checks, reported in Figure 10. We first estimate the effects of UFC events on elections in which Joe Rogan did not explicitly endorse any candidate. We find no effect, even though these elections occurred during the same period as the elections in which Joe Rogan endorsed Trump (first estimate) or Sanders (second estimate). These results work against a partisan persuasion channel, where Rogan is endorsing either all Democrats or all Republicans. The specific candidate matters. Additionally, confirms that with the estimated coefficients we are not capturing some time-period specific effect but they only appear in elections directly endorsed by Joe Rogan.

In the third placebo estimate, we test whether we observe any UFC effect in other presidential primaries before the Rogan endorsement period. Again, there is no effect.

To provide further evidence that the estimated effects are not driven by pre-existing trends in age and gender specific political preferences, we estimate whether having a UFC event after the Trump-endorsed primary (fourth estimate) or the Sanders-endorsed primary (fifth estimate) is able to predict primary participation. This additional pre-trend analysis show no effect.

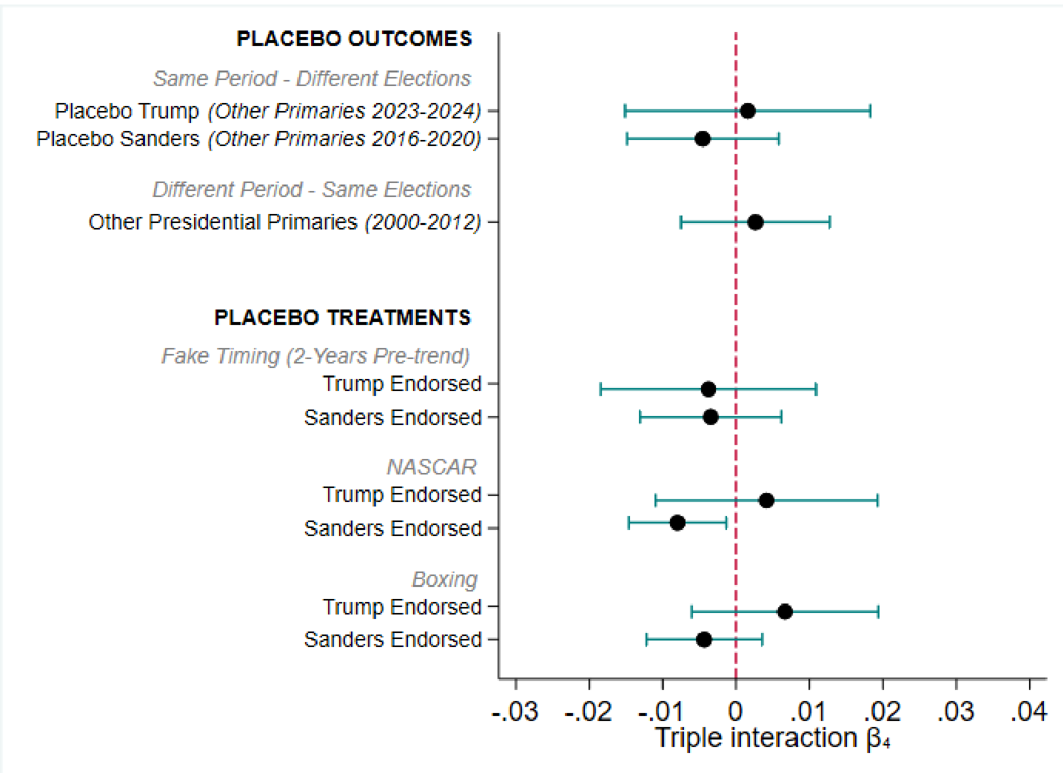
Finally, we test whether any large sporting or fighting event, rather than UFC events specifically, generates the observed response. We look at NASCAR events, or boxing events, and we see that the estimates are small and do not display the Trump-positive/Sanders-negative sign reversal. These falsification exercises therefore suggest that the main results are not driven by generic sports exposure, local event demand, or pre-existing political trends in event-hosting counties.

Finally, if UFC events matter because they raise local attention to Rogan, the largest responses should occur closest to the event location. Therefore we perform a distance-gradient exercise to further check our the exposure interpretation. Appendix Figure A.3's estimates broadly follow this pattern. In Trump-endorsed elections, the positive estimates are largest within roughly 150 kilometers of the event and become smaller farther away. In Sanders-endorsed elections, the negative estimate is concentrated in the closest distance band and fades with distance. In sum, these patterns are hard to reconcile with a purely national shock coinciding with UFC events, but they are natural if local events generate stronger local exposure to Rogan.

5. Conclusion

What happens to those who most experience Joe Rogan? Our results indicate that platform-native, long-form podcasts can matter for electoral behavior in ways that are sizable yet demographically uneven. We show that UFC events serve as an exogenous

Figure 10: Placebo checks



Notes: The figure reports placebo outcome and placebo treatment checks for the triple-interaction estimate. Placebo outcomes use elections in which the Rogan-content channel predicts no effect. Placebo treatments use fake UFC timing and alternative sporting events, including NASCAR and boxing. Points denote coefficient estimates and horizontal bars denote 95% confidence intervals.

shock to Joe Rogan exposure. These events lead to local increases in Rogan-related attention in Google Trends and raise realized consumption in passive tracking data, with effects concentrated among young men. The exposure shocks are followed by changes in primary partisanship that widen the gender gap among young voters. In 2016 and 2020, when Rogan endorsed Bernie Sanders, UFC events shifted young men into Democratic primaries. Starting in 2021, when Joe Rogan rhetoric became more rightwing and there were increasing endorsements of Trump, UFC exposure shifted young men into Republican primary participation. There has been little corresponding change for young women or for older cohorts.

These findings suggest that the podcast ecosystem can operate as a politically consequential information channel, not only because of its reach but also because of its audience composition. Rogan's audience is overwhelmingly male and disproportionately young, and the estimated electoral effects closely mirror this demographic gradient. In that sense, the results point to a structural asymmetry. Even modest persuasive effects at the individual level can translate into large aggregate consequences when exposure is highly concentrated within a specific demographic group. This mechanism offers a plausible explanation for why recent political divergence has been especially pronounced between young men and young women, while remaining comparatively stable at older ages.

More broadly, the paper highlights how new media formats differ from traditional political communication. Long-form, personality-driven podcasts blur the line between entertainment and political messaging, operate largely outside established journalistic norms, and are weakly constrained by platform moderation or equal-time considerations (Chmel et al., 2025). They can therefore expose audiences to politics through content they seek out for entertainment, lifestyle, comedy, sports, health, or everyday conversation, rather than through outlets they recognize as political news. These cues also arrive through a trusted, perceived authentic and credible, recurring parasocial relationship (Ferchaud et al., 2018; Kim and Patterson, 2025; Rasheed et al., 2025). This may make them feel less like adversarial partisan messaging than equivalent claims delivered by a cable TV program anchor. In JRE, this format is especially consequential because the political signal is not fixed: exposure tracks Rogan's evolving cues, from more left-populist content around the Sanders endorsements in 2016 and 2020 to more right-populist content after 2021. When such content is delivered through channels with sharply skewed audiences, it can generate asymmetric political responses that standard models of mass media influence do not capture well. These dynamics may become increasingly important as political communication continues to shift away from broadcast and toward decentralized, platform-native media.

References

Abendschön, S. and S. Steinmetz (2014): "The gender gap in voting revisited: Women's party preferences in a European context," *Social Politics*, 21, 315–344.

Allcott, H. and M. Gentzkow (2017): "Social media and fake news in the 2016 election," *Journal of Economic Perspectives*, 31, 211–36.

Anderson, S. P. and S. Coate (2005): "Market Provision of Broadcasting: A Welfare Analysis," *Review of Economic Studies*, 72, 947–972.

Anderson, S. P. and J. Waldfogel (2015): "Media Market Structure and Optimal Variety," in *Handbook of Media Economics, Vol. 1A*, ed. by S. Anderson, J. Waldfogel, and D. Stromberg, Elsevier, 139–177.

Armstrong, M. (2006): "Competition in Two-Sided Markets," *RAND Journal of Economics*, 37, 668–691.

Ash, E., S. Galletta, M. Pinna, and C. S. Warshaw (2024): "From viewers to voters: Tracing Fox News' impact on American democracy," *Journal of Public Economics*, 240, 105256.

Baum, M. A. (2011): "Soft news goes to war: Public opinion and American foreign policy in the new media age," .

Box-Steffensmeier, J. M., S. De Boef, and T.-M. Lin (2004): "The dynamics of the partisan gender gap," *American Political Science Review*, 98, 515–528.

Braghieri, L., S. Eichmeyer, R. Levy, M. Mobius, J. Steinhardt, and R. Zhong (2024): "Article Level Slant and Polarization of News Consumption on Social Media," *Available at SSRN 4932600*.

Burn-Murdoch, J. (2024): "A new global gender divide is emerging," Financial Times column.

Chmel, K., E. Kim, J. Marshall, T. Fisher-Love, and N. Lubin (2025): "How social media creators shape mass politics: A field experiment during the 2024 US elections," *arXiv preprint arXiv:2512.15401*.

DellaVigna, S. and E. Kaplan (2007): "The Fox News effect: Media bias and voting," *The Quarterly Journal of Economics*, 122, 1187–1234.

Ferchaud, A., J. Grzeslo, S. Orme, and J. LaGroue (2018): "Parasocial attributes and YouTube personalities: Exploring content trends across the most subscribed YouTube channels," *Computers in Human Behavior*, 80, 88–96.

Gentzkow, M., J. M. Shapiro, and D. F. Stone (2015): "Media Bias in the Marketplace: Theory," in *Handbook of Media Economics, Vol. 1A*, ed. by S. Anderson, J. Waldfogel, and D. Stromberg, Elsevier, 623–645.

Gerber, A. S., D. Karlan, and D. Bergan (2009): "Does the media matter? A field experiment measuring the effect of newspapers on voting behavior and political opinions," *American Economic Journal: Applied Economics*, 1, 35–52.

Glocalities (2024): "Growing despair and polarization between young women & men impacts elections," https://www.motivaction.nl/en/actualities/downloads/growing-despair-and-polarization-between-young-women-men-impacts-elections.

González-Bailón, S., D. Lazer, P. Barberá, M. Zhang, H. Allcott, T. Brown, A. Crespo-Tenorio, D. Freelon, M. Gentzkow, A. M. Guess, et al. (2023): "Asymmetric ideological segregation in exposure to political news on Facebook," *Science*, 381, 392–398.

Grootendorst, M. (2022): "BERTopic: Neural topic modeling with a class-based TF-IDF procedure," *arXiv preprint arXiv:2203.05794*.

Inglehart, R. and P. Norris (2000): "The developmental theory of the gender gap: Women's and men's voting behavior in global perspective," *International Political Science Review*, 21, 441–463.

Kim, E. and S. Patterson (2025): "The American viewer: Political consequences of entertainment media," *American Political Science Review*, 119, 917–931.

Krumpal, I. (2013): "Determinants of social desirability bias in sensitive surveys: a literature review," *Quality & quantity*, 47, 2025–2047.

Martin, G. J. and A. Yurukoglu (2017): "Bias in cable news: Persuasion and polarization," *American Economic Review*, 107, 2565–99.

McInnes, L., J. Healy, S. Astels, et al. (2017): "hdbscan: Hierarchical density based clustering." *J. Open Source Softw.*, 2, 205.

McInnes, L., J. Healy, and J. Melville (2018): "Umap: Uniform manifold approximation and projection for dimension reduction," *arXiv preprint arXiv:1802.03426*.

Mehring, K., G. Off, and K. Wojnicka (2025): "The populist radical right, the gender gap and protective masculinity across European countries," *European Journal of Politics and Gender*, 1, 1–42.

Milosav, Đ., Z. Dickson, S. B. Hobolt, H. Klüver, T. Kuhn, and T. Rodon (2026): "The youth gender gap in support for the far right," *Journal of European Public Policy*, 33, 444–468.

Moon, P. W. and H. J. Kim (2024): "The Growing Gender Divide: Changing Perceptions of Gender Equality among the Youth in the United States," *International Area Studies Review*, 27, 1–20.

Nennstiel, R. and A. Hudde (2025): "Is there a growing gender divide among young adults in regard to ideological left–right self-placement? Evidence from 32 European countries," *European Sociological Review*, jcaf021.

Prior, M. (2007): *Post-broadcast democracy: How media choice increases inequality in political involvement and polarizes elections*, Cambridge University Press.

Rasheed, H., L. Cuddy, B. Molokach, J. Nam, S. Feuerstein, L. Holbert, and D. Young (2025): "From Punchlines to Politics: The Joe Rogan Experience as a Case Study of the Politicization of Apolitical Spaces in the US," .

Reimers, N. and I. Gurevych (2019): "Sentence-bert: Sentence embeddings using siamese bert-networks," in *Proceedings of the 2019 conference on empirical methods in natural language processing and the 9th international joint conference on natural language processing (EMNLP-IJCNLP)*, 3982–3992.

Rochet, J.-C. and J. Tirole (2003): "Platform Competition in Two-Sided Markets," *Journal of the European Economic Association*, 1, 990–1029.

Rosen, S. (1981): "The Economics of Superstars," *American Economic Review*, 71, 845–858.

Song, K., X. Tan, T. Qin, J. Lu, and T.-Y. Liu (2020): "Mpnet: Masked and permuted pre-training for language understanding," *Advances in neural information processing systems*, 33, 16857–16867.

Strömberg, D. (2015): "Media and politics," *Annual Review of economics*, 7, 173–205.

Waldfogel, J. (2017): *Digital Renaissance: What Data and Economics Tell Us About the Future of Popular Culture*, Princeton University Press.

Zhuravskaya, E., M. Petrova, and R. Enikolopov (2020): "Political Effects of the Internet and Social Media," *Annual Review of Economics*, 12, 415–438.

Appendix A. Appendix

A. Figures and Tables

Figure A.1: Share Republican Vote Share by Age and Gender

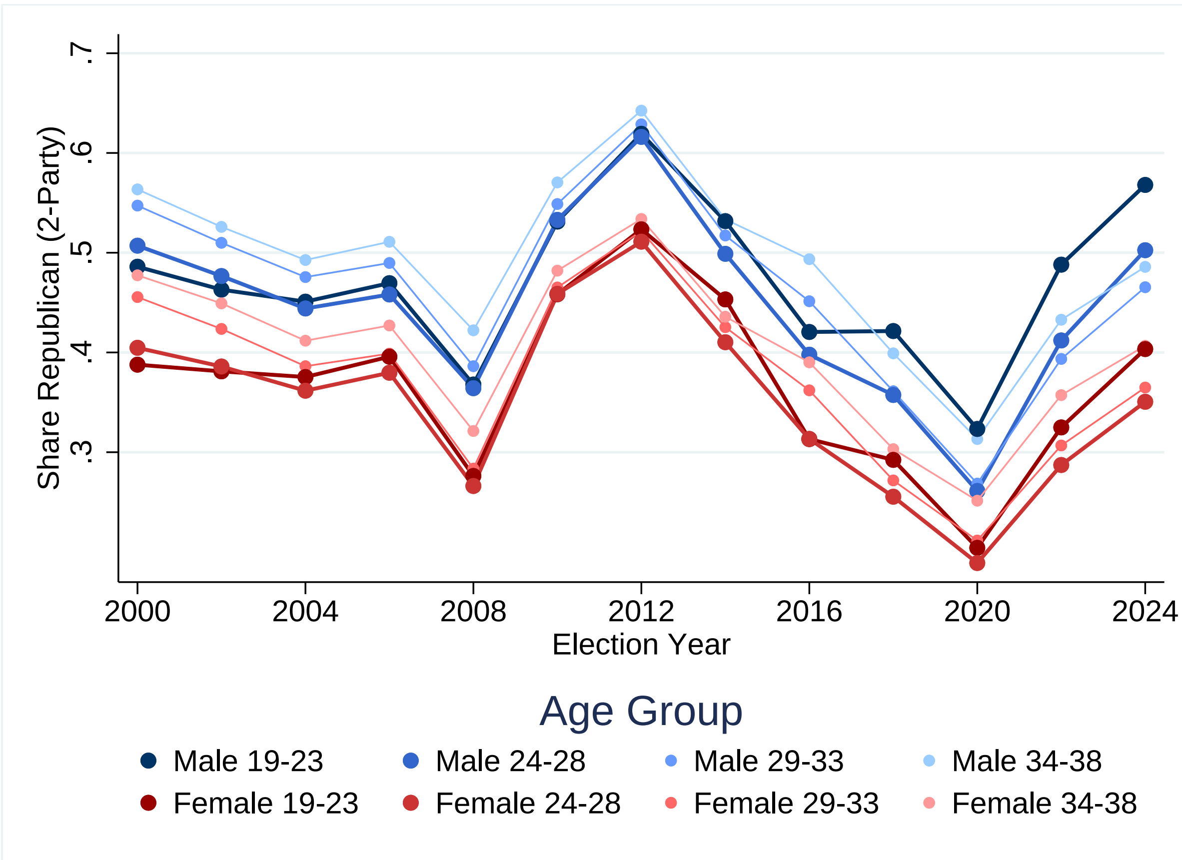


Figure A.2: Google Trends Index Maps: Q4 2024

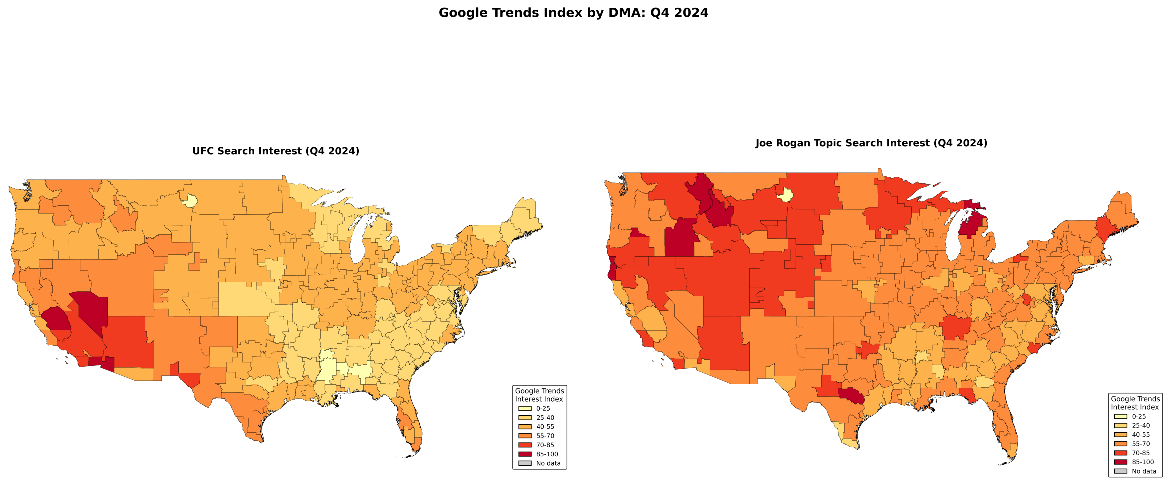
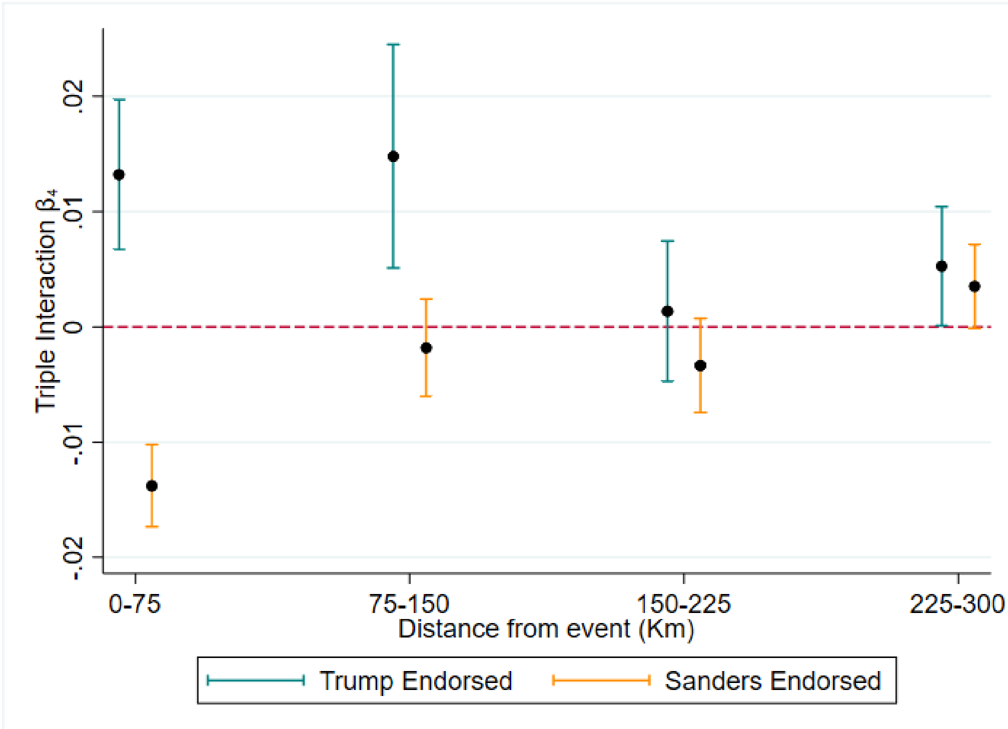


Figure A.3: Distance decay of UFC exposure effects



Notes: The figure reports how the estimated effect of UFC exposure on the youth gender gap varies with distance from the UFC event location. Treatment is assigned using distance bands around UFC host locations. Points denote coefficient estimates and vertical bars denote 95% confidence intervals.

Table A.1: Top Video Channels by Hours Viewed

Rank	Channel	Description	Hours Viewed	%Male	%Young	%Young Male
Overall			*6.45M*	*47%*	*28%*	*16%*
1	Ms Rachel	Toddler educational videos	26,468	15%	31%	5%
2	Markiplier	Gaming, comedy YouTuber	24,441	51%	74%	38%
3	Law& Crime Network	Court trials, true crime	23,492	29%	15%	6%
4	Explore With Us	True crime documentaries	23,240	27%	21%	7%
5	MeidasTouch	Liberal political commentary	20,184	46%	2%	2%
6	A&E	Reality TV, documentaries	19,654	31%	18%	8%
7	penguinz0	Gaming, comedy commentary	18,170	78%	74%	59%
8	CoryxKenshin	Gaming YouTuber	17,428	54%	67%	41%
9	Bailey Sarian	True crime, beauty content	15,649	5%	24%	2%
10	SML	Comedy sketches	15,499	77%	68%	59%
...						
16	**PowerfulJRE**	**Joe Rogan podcast**	**12,720**	**78%**	**16%**	**14%**

Notes: This table presents the top channels by hours viewed using Luth Research passive media consumption tracking data. The unit of observation is a channel. Hours Viewed represents total hours of content consumed across all users. Demographics (%Male, %Young, %Young Male) are computed as the share of total hours viewed by each demographic group. Young users are defined as ages 19–28. The overall row reports aggregate statistics across all channels.

Table A.2: Top Podcast Channels by Hours Viewed

Podcast	Description	Hours	%Male Listened	%Young	%Young Male
Overall		*0.36M*	*40%*	*24%*	*11%*
Joe Rogan	**Long-form interviews**	**15,802**	**87%**	**18%**	**16%**
Distractible	Comedy, Markiplier	8,352	53%	82%	45%
Morbid	True crime	8,178	11%	23%	2%
Crime Junkie	True crime	6,380	6%	15%	2%
Rotten Mango	True crime	4,049	12%	62%	9%
Last Podcast On The Left	True crime, comedy	3,882	61%	19%	15%
Small Town Murder	True crime, comedy	3,323	19%	3%	1%
Dateline NBC	True crime, news	3,219	12%	5%	0%
Serial Killers	True crime	2,996	22%	24%	6%
And That's Why We Drink	True crime, paranormal	2,676	7%	25%	5%

Notes: This table presents the top 10 podcasts by total hours listened in the Luth Research passive media consumption tracking data. Demographics (%Male, %Young, %Young Male) are computed as the share of total hours listened accounted for by each demographic group. Young users are defined as ages 19–28.

Table A.3: Top Political/News Channels (Combined)

Rank	Creator	Description	Hours Viewed	%Male	%Young	%Young Male
Overall			*112,846*	*64%*	*12%*	*9%*
1	**Joe Rogan**	**Long-form interviews**	**28,522**	**83%**	**17%**	**15%**
2	MeidasTouch	Liberal political commentary	20,184	46%	2%	2%
3	MSNBC	Liberal news	10,809	54%	7%	4%
4	Fox News	Conservative news	10,213	67%	10%	9%
5	NBC News	Mainstream news	8,932	58%	10%	7%
6	Brian Tyler Cohen	Liberal commentary	8,059	56%	6%	3%
7	Forbes Breaking News	Business/political news	7,283	65%	8%	6%
8	Asmongold TV	Gaming, commentary	6,884	86%	37%	33%
9	ABC News	Mainstream news	6,286	50%	12%	8%
10	CNN	Liberal-leaning news	5,674	61%	13%	9%

Notes: This table presents the top 10 news and political content creators ranked by total hours viewed across all users in the Luth Research passive media consumption tracking dataset. The sample includes all users in the Luth panel. Hours Viewed represents the total hours of content consumed from each creator across all channels and podcasts associated with that creator. Demographics (%Male, %Young, %Young Male) are computed as the share of total hours viewed by each demographic group. Young users are defined as ages 19–28.

Table A.4: Top Political/News Channels (Combined - Young People)

Rank	Channel	Description	Hours Viewed	%Male	Avg. Length per Viewer
1	**Joe Rogan**	**Long-form interviews**	**4,907**	**88%**	**2.2 h**
2	H3 Podcast	Political commentary	3,085	18%	4.2 h
3	Asmongold TV	Gaming, commentary	2,576	89%	1.6 h
4	Fox News	Conservative news	1,001	89%	0.4 h
5	NBC News	Mainstream news	866	74%	0.3 h
6	MSNBC	Liberal news	757	50%	0.4 h
7	CNN	Liberal-leaning news	748	67%	0.3 h
8	ABC News	Mainstream news	745	66%	0.2 h
9	Forbes Breaking News	Business/political news	582	80%	0.3 h
10	LiveNOW from FOX	Conservative news	567	71%	0.4 h

Notes: This table presents the top 10 news and political content creators by hours viewed among young users (ages 19–28) in the Luth Research passive media consumption tracking data. The unit of observation is a creator. The sample is restricted to young users aged 19–28. Hours Viewed represents total hours of content consumed across all channels/podcasts associated with each creator. %Male (Hours) is the percentage of viewing hours accounted for by male users. Avg. Length per Viewer is the average hours of content consumed per unique viewer.

Figure A.4: UFC Events and Luth Data

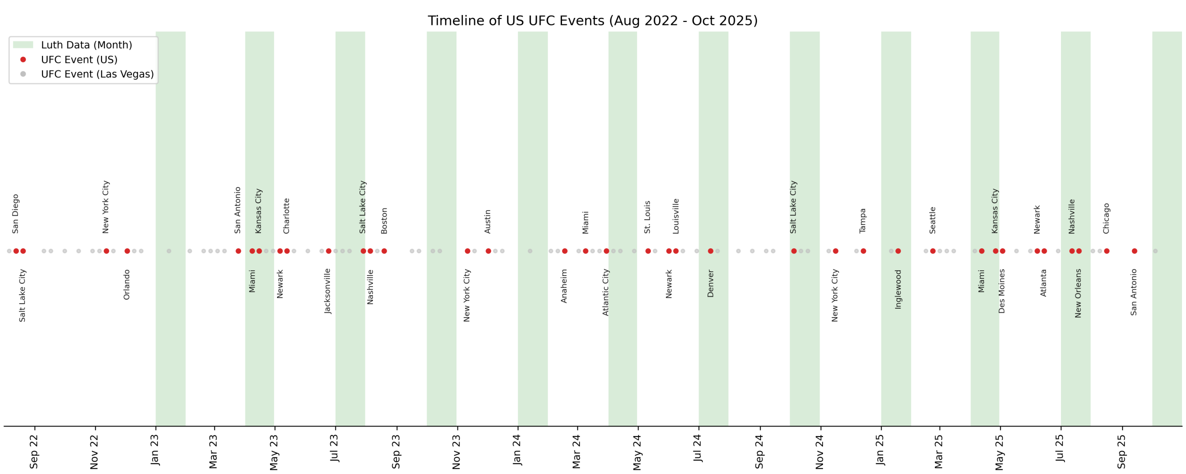


Table A.5: Distribution of endorsement/mention scores and political-content labels in JRE

Panel A. Candidate Endorsement and Mention Scores

	Individual chunks (%)			Episodes (%)		
Measure	1–2	3	4–5	1–2	3	4–5
Trump endorsement	1.70	1.43	0.36	5.79	24.87	16.38
Bernie endorsement	0.11	0.13	0.10	2.20	4.87	5.61
Trump mention	96.39	0.12	3.44	51.55	0.78	47.67
Bernie mention	99.60	0.00	0.35	86.93	0.14	12.93

Notes. 1–2 = critical/low, 3 = neutral/mixed, 4–5 = positive/high. For endorsements the three buckets do not sum to 100%; the remainder is score 0 (subject not discussed in endorsement terms). Mention buckets sum to 100% (score 1 = essentially not mentioned). Values are percentages. Chunk-level shares use all dated chunks as the denominator; episode-level shares use all episodes. An episode's score is the maximum score across its chunks.

Panel B. Political Framing labels

Category	Individual chunks (%)	Episodes (%)
Right populism	3.46	0.39
Left populism	2.87	0.61
Nonpopulist conservative	1.00	0.11
Nonpopulist liberal	0.98	0.06
Unclear / balanced	19.80	13.62
No politics	71.89	85.21
Total	100.00	100.00

Notes. The four populism/ideology categories (rows 1–4) are those plotted; *unclear/balanced* and *no politics* are shown for completeness. Categories are mutually exclusive and sum to 100%. Values are percentages. Chunk-level shares use all dated chunks as the denominator; episode-level shares use all episodes. An episode's score is the most frequent chunk label.

Table A.6: Cable Shows and Platform-native Talk Shows Corpus

Show	Channel	Coverage	Chunks	Genre
Panel A. Cable news (N = 9)				
Hannity	Fox News	2011-12–2025-08	98,614	Conservative political talk
Tucker Carlson Tonight	Fox News	2016-11–2023-04	53,941	Conservative talk / current affairs

continued on next page

Table A.6 continued

Show	Channel	Coverage	Chunks	Genre
The Story with Martha MacCallum	Fox News	2017-01–2025-08	81,282	News / talk
Special Report with Bret Baier	Fox News	2011-12–2025-08	106,863	News & political commentary
The Lead with Jake Tapper	CNN	2013-03–2025-08	79,267	News broadcast
Anderson Cooper 360°	CNN	2011-12–2021-12	61,238	Television news program
The Rachel Maddow Show	MSNBC	2011-12–2025-08	61,826	News discussion / commentary
The Last Word with Lawrence O'Donnell	MSNBC	2014-01–2025-08	57,499	News & political commentary
The Beat with Ari Melber	MSNBC	2017-07–2025-08	43,515	News & politics, legal focus
Panel B. Platform-native Talk Shows (N = 22)				
The Joe Rogan Experience	**PowerfulJRE**	**2011-12–2025-08***	**466,328**	**Comedy / long-form interview**
The Ben Shapiro Show	The Daily Wire	2015-09–2024-09	213,215	Conservative political talk
Pod Save America	Crooked Media	2017-01–2026-01	124,285	Progressive political talk
This Past Weekend w/ Theo Von	Independent	2010-09–2025-12	86,410	Comedy / storytelling interview
Lex Fridman Podcast	Independent	2018-08–2025-08	85,944	Science, tech & politics interviews
The Jordan B. Peterson Podcast	The Daily Wire	2016-12–2024-09	81,530	Psychology, religion, cultural-political
Huberman Lab	Scicomm Media	2021-01–2026-01	59,314	Neuroscience, health & science
We Are Change	Independent YouTube	2011-05–2025-10	48,702	Conspiracy / activist alt-media
Call Her Daddy	SiriusXM, orig. Barstool	2018-10–2024-09	33,274	Sex / relationships advice, comedy

continued on next page

Table A.6 continued

Show	Channel	Coverage	Chunks	Genre
Anthony Brian Logan	Independent	2018-02–2025-10	33,100	Conservative political / culture commentary
Stay Free with Russell Brand	Independent	2014-06–2025-09	31,660	Politics, contrarian / conspiracy talk
Louder with Crowder	TheBlaze, Rumble	2014-12–2025-08	30,086	Conservative commentary, comedy
The Mel Robbins Podcast	Independent, 143 Studios	2017-02–2025-12	26,661	Self-help, motivational
The Charlie Kirk Show	Salem / Turning Point USA	2023-11–2026-01	22,913	Conservative talk radio
No Lie with Brian Tyler Cohen	Independent YouTube	2020-07–2026-01	14,675	Progressive political commentary
Mark Dice	Independent YouTube	2009-12–2025-09	12,894	Conservative commentary, conspiracy
Real Time with Bill Maher	HBO	2011-01–2025-09	12,006	Political talk show, panel, satire
The Amazing Lucas	Independent	2018-08–2025-09	6,486	Right-leaning political / culture commentary
Taylor Lorenz	Independent	2024-02–2025-09	4,335	Internet culture, tech, media criticism
Ms. Rachel (Songs for Littles)	Independent	2020-04–2025-10	2,262	Children’s educational music

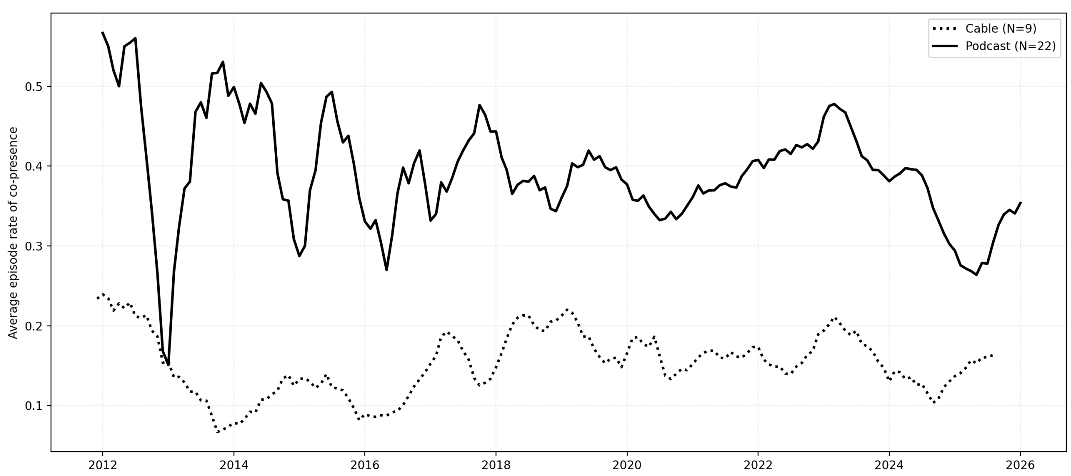
Notes: Coverage is the first–last calendar month with at least one analysed chunk. Chunks are transcript segments assigned to a BERTopic cluster. Genre descriptions are from each shows Wikipedia page.

Table A.7: Composition of transcript chunks by political-framing category: cable news versus *The Joe Rogan Experience*

Show	Network	Non-pol.	Left pop.	Right pop.	Nonpop. lib.	Nonpop. cons.	N
Hannity	Fox	31.4	1.7	42.4	2.2	22.3	98,614
Tucker Carlson Tonight	Fox	37.7	3.1	41.4	2.6	15.3	53,941
Special Report w. Baier	Fox	61.3	1.8	8.1	10.7	18.1	106,863
The Story w. MacCallum	Fox	54.0	1.8	14.1	9.0	21.2	81,282
Anderson Cooper 360	CNN	67.5	3.2	3.3	22.7	3.3	61,238
The Lead w. Tapper	CNN	63.1	2.8	3.3	25.9	4.9	79,267
The Rachel Maddow Show	MSNBC	47.1	8.1	2.3	40.2	2.2	61,826
The Beat w. Melber	MSNBC	37.1	8.2	2.9	50.1	1.8	43,515
The Last Word w. O'Donnell	MSNBC	35.9	8.3	2.4	51.0	2.4	57,499
All cable (pooled)		49.4	3.8	14.4	20.6	11.8	644,045
Joe Rogan Experience	—	**92.0**	2.7	3.4	0.9	1.0	461,955

Notes: Cells are the percentage of a show's transcript chunks in each framing category (rows sum to 100 up to rounding). "Non-pol." combines chunks with no codeable political stance (for JRE, the LLM's `no_politics` and `unclear_or_balanced` labels; for cable, the classifier's `neither` class). Cable labels are from the fine-tuned RoBERTa classifier (Appendix B.2) and exclude advertising chunks (162,632 chunks, 20.2% of raw cable chunks, removed by the ad filter), matching the main analysis. JRE labels are from the `gpt-4.1-mini` populism prompt over the full corpus (Section 2.3); N is labelled chunks.

Figure A.5: Episode-level co-presence of politics and entertainment – platform-native talk shows vs. cable TV

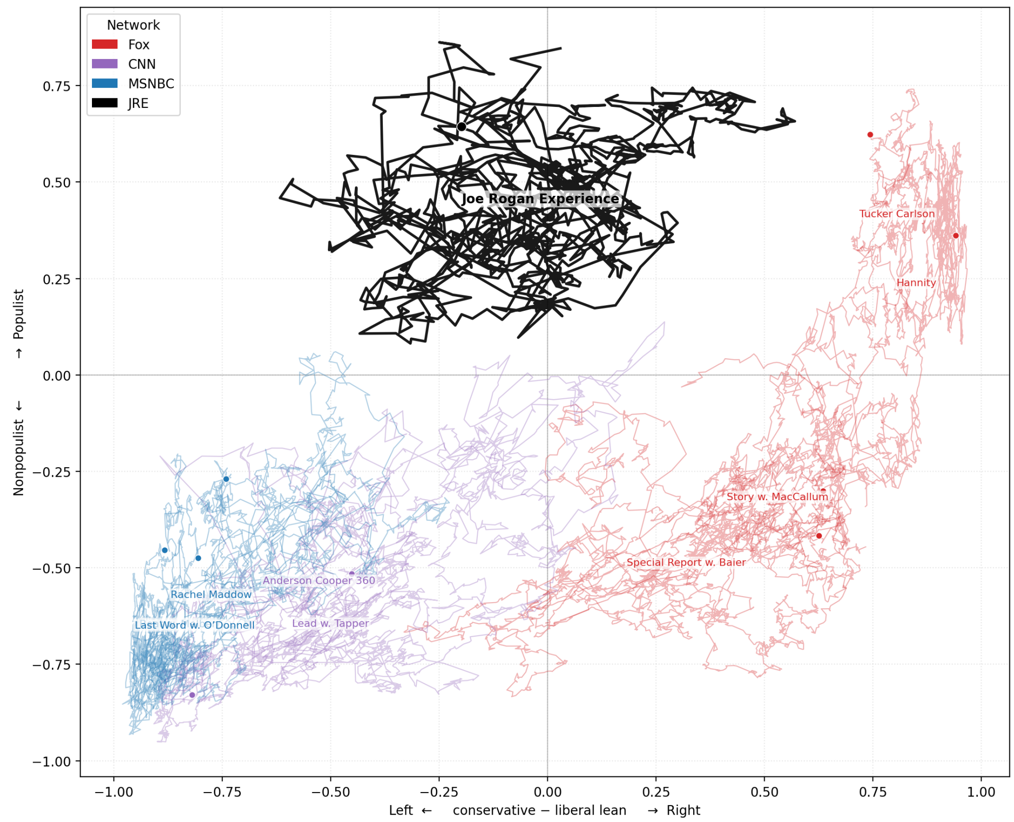


Notes: This graph plots the average episode-level rate of co-presence of politics and entertainment over time, pooled across shows with a six-month moving average. The dotted line is the pooled average of cable shows ($N = 9$) and the solid line is the pooled average of talk-native podcasts and YouTube shows ($N = 22$). An episode is counted as having co-presence if it contains at least one politics chunk and at least one entertainment chunk, excluding advertising and host-filler chunks.

Figure A.6: Dominant political lane at the episode level: cable versus *The Joe Rogan Experience*

Notes: Each row is a show and runs left to right over the program's coverage period. Each thin vertical bar is a single episode, placed at its release date and colored by that episode's dominant lane (no monthly aggregation, no smoothing): left populism (blue), right populism (red), non-populist liberal (green), non-populist conservative (orange). White gaps are time periods without coverage. Cable labels are from the fine-tuned RoBERTa classifier (Appendix B.2; JRE labels are from the `gpt-4.1-mini` populism prompt (Section 2.3). Vertical dashed lines mark the November 2016, 2020, and 2024 U.S. presidential elections. JRE is the only show that repeatedly changes lane; each cable program holds a single lane throughout.

Figure A.7: Trajectories through political space: cable versus *The Joe Rogan Experience*



Notes: Each line traces a show's path over time through a two-dimensional political space; a dot marks its most recent point and the show's label sits at the centroid of its path. The horizontal axis is liberal–conservative lean, (right pop. + non-pop. cons.) − (left pop. + non-pop. lib.); the vertical axis is populist content, (left pop. + right pop.) − (non-pop. lib. + non-pop. cons.), each computed from the show's framing composition (normalized to sum to one and smoothed over time using a 3-month MA). Cable programs cluster tightly in network-specific corners; JRE (black) sits high in the populist band and sweeps across the entire left–right axis.

B. Content Analysis Appendix

B.1. BERTopic Model for Mixing Politics With Entertainment

This appendix describes the topic model behind the politics–entertainment co-presence measure reported in Section ??. Our aim is to place cable news and platform-native talk shows on a single measurement scale, so that the quantity "how much political content is mixed with non-political content" is defined identically for both media regimes and is driven by subject matter rather than by show, network, or format labels.

We pool the transcripts of all 31 shows—nine cable news programs and 22 podcasts and online talk shows, listed with their coverage and genre in Appendix Table A.6—into a single corpus of roughly 2.08 million transcript chunks. Where a show is available from more than one transcript source, we keep a single copy of each segment. The model is fit once over this pooled corpus, so cable and podcast chunks are embedded, clustered, and labelled by exactly the same procedure.

We embed every chunk with the `all-mpnet-base-v2` sentence-transformer (768 dimensions) (Reimers and Gurevych, 2019; Song et al., 2020) and fit a single BERTopic model (Grootendorst, 2022) over the corpus. BERTopic reduces the embeddings with UMAP (McInnes et al., 2018) (10 components, 15 neighbours, cosine distance) and clusters the reduced vectors with HDBSCAN (McInnes et al., 2017) (Euclidean distance, minimum cluster size tuned to yield approximately 128 topics); topic keywords are extracted with a class-based TF–IDF over an English-stopword-filtered count vectorizer. So that topic discovery is not dominated by any single outlet or period, the model is fit on a sample balanced across (source $\times$ show $\times$ year) cells; once fit, every non-advertising chunk in the full corpus is assigned to its nearest topic via the trained model. The procedure returns 145 interpretable topics.

Each of the 145 topics is labelled by GPT-5 from its top keywords and representative chunks, and mapped to one of 12 broad categories: U.S. politics, the culture war, foreign affairs, and crime/law; science and technology, health and wellness, sports and combat, entertainment and the arts, everyday lifestyle, and conspiracy/paranormal; and two non-substantive categories, advertising and a residual host-filler category. Table B.8 reports the full mapping, the number of topics and chunks in each category, and representative topics.

The 12 broad categories collapse into three macro-buckets. The politics bucket combines U.S. politics, the culture war, foreign affairs, and crime/law (97 topics; 665,320 chunks). The entertainment bucket combines science and technology, health and wellness, sports and combat, entertainment and the arts, everyday lifestyle, and conspiracy/paranormal (33 topics; 293,850 chunks). The remaining two categories—advertising reads and host filler (the latter also absorbing the chunks HDBSCAN leaves unclustered as "outliers")—form an excluded bucket and enter neither side of the metric.

We then classify each episode for co-presence: an episode is coded as mixing politics and entertainment if it contains at least one politics chunk and at least one entertainment chunk. The statistics in Table B.9 and Figure A.5 are the share of a segment's episodes meeting this condition, pooled within the cable and podcast segments and smoothed with a centered six-month moving average.

Table B.8: BERTopic broad categories and politics–entertainment macro-buckets

Broad category	Bucket	Topics	Chunks	%	Representative topics
Politics macro-bucket (97 topics; 665,320 chunks)					
politics_us	Politics	62	471,785	22.7	Biden & presidential politics; US elections & campaigns; border & immigration
foreign_affairs	Politics	12	98,564	4.7	Russia–Ukraine war; Israel–Hamas & Gaza; North Korea talks
culture_war	Politics	18	80,187	3.9	Trans women in sport; platform moderation & free speech; race & CRT
crime_law	Politics	5	14,784	0.7	Drug policy & DUIs; financial fraud; high-profile trials
Entertainment macro-bucket (33 topics; 293,850 chunks)					
everyday_lifestyle	Entertainment	7	70,816	3.4	Religion & meaning; hunting & outdoors; sex & dating advice
science_tech	Entertainment	10	69,748	3.4	Physics & cosmology; AI & deep learning; psychedelics
entertainment_arts	Entertainment	9	68,586	3.3	Stand-up comedy; kids' songs; Hollywood & the Oscars
sports_combat	Entertainment	1	40,731	2.0	MMA & kickboxing fight analysis
health_wellness	Entertainment	2	27,895	1.3	Diet, supplements & gut health; injuries & training
conspiracy_paranormal	Entertainment	4	16,074	0.8	UFOs & Area 51; Atlantis & ancient cataclysms; JFK
Excluded (15 topics; 1,122,493 chunks)					
host_filler	Excluded	4	1,100,214	52.9	Filler banter; production credits / outros; BERTopic outliers
ads	Excluded	11	22,279	1.1	Mattress, apparel & home-security sponsor reads
Total		**145**	**2,081,663**	**100.0**	

Notes: The model produced 145 topics over 2.08 million non-advertising chunks. GPT-5 labelled each topic and mapped it to one of 12 broad categories. "Politics" and "Entertainment" chunks form the numerator and denominator of the co-presence metric. "Excluded" categories—ads and host filler, which absorbs the BERTopic outlier cluster—are dropped from both.

Table B.9: Broad-category composition of each show, as the percentage of the show's transcript chunks assigned to each category.

Show	Politics categories				Entertainment categories						Aggregate	
	US politics	Culture war	Foreign aff.	Crime & law	Science & tech	Health	Conspiracy	Sports	Entertain. arts	Lifestyle	**Politics**	**Entertain.**
Panel A. Cable news												
Special Report (Baier)	53.1	1.5	8.2	0.4	0.1	0.1	0.0	0.0	0.4	0.1	**63.2**	**0.8**
Hannity	52.9	2.1	4.3	0.7	0.2	0.3	0.3	0.0	0.6	0.3	**59.9**	**1.6**
The Story (MacCallum)	49.3	1.5	8.7	0.5	0.2	0.0	0.1	0.0	0.5	0.1	**60.0**	**0.9**
The Lead (Tapper)	49.9	1.8	5.6	0.6	0.1	0.0	0.1	0.0	0.3	0.1	**57.8**	**0.6**
The Rachel Maddow Show	51.3	1.7	6.9	0.4	0.1	0.1	0.0	0.0	0.7	0.1	**60.3**	**1.0**
Anderson Cooper 360°	20.1	5.1	8.5	0.3	0.3	0.1	0.1	0.0	1.3	0.2	**34.0**	**2.0**
The Last Word (O'Donnell)	48.0	2.1	3.7	0.6	0.2	0.0	0.0	0.0	0.6	0.2	**54.4**	**1.0**
Tucker Carlson Tonight	44.9	2.6	11.0	0.8	0.4	0.1	0.1	0.0	0.4	0.1	**59.3**	**1.2**
The Beat (Melber)	17.7	6.7	13.1	1.6	1.7	1.6	1.1	0.0	8.6	0.3	**39.1**	**13.5**
Panel B. Podcasts / online talk shows												
Joe Rogan Experience	6.3	3.2	1.8	1.6	3.7	2.6	3.3	8.6	9.6	5.6	**12.9**	**33.5**
The Ben Shapiro Show	26.6	7.0	5.9	0.3	0.4	0.2	0.1	0.0	0.7	1.9	**39.8**	**3.1**
Pod Save America[a]	10.9	3.3	0.6	1.0	2.0	12.9	0.1	0.2	1.8	0.9	**15.7**	**17.9**
Pod Save America[a]	29.0	2.2	2.6	0.2	0.1	0.3	0.0	0.0	0.2	0.2	**34.0**	**0.8**
This Past Weekend (Theo Von)	17.8	4.9	9.9	0.5	1.6	0.5	0.7	0.5	1.3	1.5	**33.0**	**6.1**
Lex Fridman Podcast[a]	3.9	1.3	3.6	0.6	21.4	0.6	0.6	3.0	0.8	6.6	**9.4**	**33.1**
Lex Fridman Podcast[a]	4.0	1.4	4.6	0.7	21.7	0.6	1.1	3.3	1.6	1.8	**10.5**	**30.0**
The Jordan B. Peterson Podcast	5.9	6.2	3.5	0.1	2.8	0.4	0.1	0.1	0.5	27.8	**15.6**	**31.7**
Huberman Lab	4.7	5.8	1.2	0.6	1.3	0.3	0.2	2.5	12.8	2.5	**12.3**	**19.6**
We Are Change	23.9	3.6	3.5	0.1	0.5	0.2	0.1	0.0	2.2	0.1	**31.1**	**3.0**
Call Her Daddy	0.3	0.5	0.0	0.0	0.0	0.1	0.0	0.0	0.3	28.6	**1.0**	**29.0**
Anthony Brian Logan	21.5	14.0	2.5	1.7	0.3	0.1	0.2	0.1	1.2	0.1	**39.9**	**2.0**
Stay Free (Russell Brand)	10.5	7.3	5.9	0.3	12.2	0.2	0.5	1.0	2.5	3.0	**24.1**	**19.4**
Louder with Crowder	20.6	6.3	7.5	1.0	1.1	0.5	0.6	0.0	1.9	0.9	**35.4**	**5.0**
The Mel Robbins Podcast	0.9	3.1	0.5	0.2	0.4	0.4	0.2	2.9	20.8	1.9	**4.7**	**26.6**
The Charlie Kirk Show	2.5	1.6	10.9	1.6	14.4	0.2	1.7	1.8	1.6	2.1	**16.5**	**21.9**
No Lie (Brian Tyler Cohen)	11.5	15.4	1.0	0.9	0.2	0.7	0.1	2.7	5.1	0.7	**28.8**	**9.4**
Mark Dice	1.8	3.3	0.3	0.2	0.3	0.3	0.1	6.2	18.5	3.4	**5.6**	**28.7**
Real Time (Bill Maher)	4.8	2.0	1.9	0.1	22.6	0.0	1.6	3.6	2.6	2.1	**8.8**	**32.6**
The Amazing Lucas	4.5	35.5	0.9	0.1	0.5	0.4	0.0	0.0	3.4	0.2	**40.9**	**4.5**
Power User (Taylor Lorenz)	8.8	5.6	3.5	0.7	2.4	0.1	1.6	0.6	0.9	2.4	**18.6**	**8.0**
Ms. Rachel	14.9	1.4	0.5	0.1	0.0	0.1	0.0	0.0	33.6	0.0	**17.0**	**33.7**

Notes. Each cell is the percentage of a show's BERTopic chunks assigned to that broad category, out of *all* of the show's chunks; advertising and host-filler chunks are part of the base but omitted as columns, so a row's ten content cells sum to less than 100%. The **Politics** aggregate sums US politics, culture war, foreign affairs, and crime & law; **Entertainment** sums science & tech, health, conspiracy, sports, entertainment arts, and lifestyle. Rows are ordered by analysed chunk count within each panel. [a]Pod Save America and the Lex Fridman Podcast each appear twice because they were scraped into two independent source corpora.

B.2. Cable News Political-Framing Classifier

We label the political framing of JRE chunk by chunk with gpt-4.1-mini (Section 2.3). The pooled cable corpus is twice the size of the JRE corpus, so applying the same LLM prompt to every cable chunk would be costly and slow. We instead use the LLM to label a training sample and fine-tune a smaller encoder model to label the remainder. The training sample combines (i) a stratified random draw of cable chunks (about 4,000 per program), (ii) an active-learning batch targeting chunks where the model is least certain, and (iii) our previously LLM-labeled chunks from the JRE and pilot corpora, for a total of 81,201 labeled chunks (64,869 train / 8,210 validation / 8,122 test), split so that chunks from the same episode never cross the train–test boundary. All training labels are produced by the same gpt-4.1-mini prompt used for JRE, so the classifier inherits a single, consistent labeling standard across both corpora.

The classifier is a multitask fine-tune of roberta-base with a shared encoder and two classification heads: an ideology head (non-political, liberal, conservative) and a populism head (populist vs. non-populist), the latter masked on chunks the ideology head assigns to "non-political." The two heads compose into the four political lanes used in the main text plus a residual non-political category. We train for four epochs (learning rate 2×10^{-5}, batch size 16, maximum sequence length 512) and select the checkpoint with the highest validation macro-F1.

On the 8,122-chunk held-out test set, the ideology head reaches 79.6% accuracy (macro-F1 0.77) and the populism head 84.5% accuracy (macro-F1 0.84). Collapsing the two heads into the five-way scheme used in the main text—non-political, non-populist liberal, left populism, non-populist conservative, right populism—yields 75.4% accuracy and a macro-F1 of 0.67; per-class F1 scores appear in Table B.10. Performance is strongest on the non-political and right-populist categories and weakest on non-populist conservatism, which the LLM and human coders also confuse most often with right populism.

Because the training labels are themselves model-generated, we benchmark the classifier against an independent sample of 50 chunks hand-annotated by the authors into the five-way scheme. Table B.11 compares the fine-tuned classifier with three LLMs—including its own `gpt-4.1-mini` teacher—against this human gold standard. The classifier agrees with the human coders on 68.8% of chunks (Cohen's $\kappa = 0.61$), higher than the gpt-4.1-mini teacher (52.1%, $\kappa = 0.41$), the GPT-5 flagship model (58.3%, $\kappa = 0.47$), and GPT-5-nano (45.8%, $\kappa = 0.33$). This ordering is consistent with a distilled student averaging out the idiosyncratic, chunk-level noise in its teacher's labels while preserving the systematic signal; the sample is small ($n = 50$), but it indicates that substituting the classifier for the LLM on the cable corpus does not degrade—and may modestly improve—agreement with human judgment. On the larger 1,200-chunk pilot set (no human labels), the classifier and the `gpt-4.1-mini` teacher agree on 81.5% of chunks ($\kappa = 0.76$), confirming that the classifier faithfully reproduces the LLM standard at scale.

Table B.10: Held-out per-class performance of the cable framing classifier

	Non-political	Non-pop. liberal	Left populism	Non-pop. conservative	Right populism
F1	0.84	0.67	0.61	0.51	0.71

Notes: Per-class F1 on the 8,122-chunk held-out test set under the five-way scheme. Overall accuracy 0.754, macro-F1 0.667. Training and evaluation labels are from `gpt-4.1-mini`.

Table B.11: Agreement with human annotation: classifier versus LLMs

Labeler	Agreement	Cohen's κ	Macro-F1
RoBERTa classifier (ours)	68.8%	0.61	0.68
GPT-5 (flagship)	58.3%	0.47	0.54
`gpt-4.1-mini` (teacher)	52.1%	0.41	0.53
GPT-5-nano	45.8%	0.33	0.45

Notes: Agreement, Cohen's κ, and macro-F1 against 50 chunks hand-annotated by the authors into the five-way scheme. The classifier is trained on `gpt-4.1-mini` labels yet agrees with human coders more closely than any LLM, including its own teacher.

B.3. LLM Annotation Task Prompts

Presidential Candidate Mention-Endorsement Prompt

```
I will provide you with a partial transcript from a YouTube video.

Your task is to determine whether the transcript mentions and, if so, whether it
↪  endorses or opposes U.S. politicians Bernie Sanders and Donald Trump.

GENERAL RULES:
    - The transcript is a snippet of a larger conversation.
    - There may be multiple speakers or quoted viewpoints.
    - Do NOT attribute statements to individual speakers.
```

```
    - Judge the OVERALL framing or ‘‘net effect’’ of the snippet.
    - Base all judgments ONLY on explicit or strongly implied content in the text.

Consistency Rule (MANDATORY):
    - If a candidate’s Mention score is 2 or lower, the Endorsement score MUST be 0
    ↪  for that candidate.

--------------------------------
STEP 1: Candidate Mention
--------------------------------
For each candidate, assess whether the transcript clearly references the candidate.

Count a mention ONLY if there is a clear reference by:
    - First and/or last name
    - Unambiguous title (e.g., ‘‘President Trump’’ or "Senator Sanders")
    - Widely recognized nickname (e.g., ‘‘The Donald,’’ ‘‘The Don,’’ "DJT", "Orange Man",
    ↪  ‘‘Bernie’’)
    - Contextual clues that leave no reasonable doubt about the identity being
    ↪  referenced (e.g., ‘‘the 2020 Democratic presidential candidate from Vermont’’
    ↪  or "Feel the Bern" for Bernie Sanders; ‘‘the 45th President of the United
    ↪  States’’ for Donald Trump).

Do NOT infer a mention from vague references (e.g., ‘‘the president,’’ ‘‘a Democrat’’).
Do NOT consider it a mention if the transcript contains a similar name to the
↪  candidate but it is spelled differently.

Mention scale (1-5):
    5 = Definitely mentioned, clear and direct
    4 = Probably mentioned, strong but slightly indirect
    3 = Unclear or insufficient evidence
    2 = Probably not mentioned
    1 = Definitely not mentioned

Tie-breaking rule:
Use score 3 ONLY when the available text does not allow a confident directional
↪  judgment.
If there is clear evidence favoring a higher or lower score, do NOT default to 3.

Provide:
    - A VERY brief explanation (maximum 2 sentences, no more than 35 words) that
    ↪  clearly states WHO AND WHAT is being discussed.
```

```
    - 1-2 direct quotes or concise paraphrases supporting the score

--------------------------------
STEP 2: Candidate Evaluation
--------------------------------
For each candidate, assess the OVERALL evaluative stance of the snippet toward that
↪  candidate. Before scoring, internally decide: ‘‘Does this snippet make the
↪  candidate look better or worse overall?’’

Important:
    - A candidate can be mentioned WITHOUT being endorsed.
    - Criticism or attack counts as opposition.
    - Mentioning a candidate in order to criticize them is NOT neutral.
    - When assigning endorsement scores, prioritize moral or evaluative language over
    ↪  policy description alone.
    - If the Mention score is 2 or lower, Endorsement MUST be 0.

Endorsement scale (0-5):
    5 = Definitely yes, strong positive support or praise
    4 = Probably yes, mild or implicit positive support
    3 = Neutral, descriptive or mixed with no clear stance
    2 = Probably no, negative criticism
    1 = Definitely no, strong negative criticism
    0 = Candidate not mentioned at all

Tie-breaking rule:
Use score 3 ONLY when the available text does not allow a confident directional
↪  judgment.
If there is clear evidence favoring a higher or lower score, do NOT default to 3.

Provide:
    - A VERY brief explanation (maximum 2 sentences, no more than 35 words) that
    ↪  clearly states WHO is being endorsed or opposed.
    - 1-2 direct quotes or concise paraphrases supporting the score


--------------------------------
WORKED EXAMPLES
--------------------------------
Example 1: Clear Mention + Negative Endorsement
```

```
Transcript snippet:
    ‘‘Trump keeps claiming the election was rigged, even though courts rejected those
    ↪ claims over and over.’’
Donald Trump
    Mention: 5
        Explanation: Donald Trump is explicitly named and discussed in relation to
        ↪ election claims.
        Evidence: ‘‘Trump keeps claiming the election was rigged’’
    Endorsement: 1
        Explanation: The snippet criticizes Donald Trump by portraying his claims as
        ↪ false and rejected.
        Evidence: ‘‘courts rejected those claims over and over’’
All other candidates
    Mention: 1
    Endorsement: 0


Example 2: Unclear Reference (No Explicit Mention)
Transcript snippet:
    ‘‘The current president has done more damage to the economy than anyone expected.’’
Donald Trump
    Mention: 3
        Explanation: ‘‘The current president’’ could refer to Trump but is not
        ↪ explicit.
        Evidence: ‘‘The current president’’
    Endorsement: 3
Bernie Sanders
    Mention: 1
    Endorsement: 0


Example 3: Clear Mention + Positive Endorsement
Transcript snippet:
    ‘‘Bernie Sanders has been consistent for decades, fighting for working people when
    ↪ no one else would.’’
Bernie Sanders
    Mention: 5
        Explanation: Bernie Sanders is explicitly named and praised.
        Evidence: ‘‘Bernie Sanders has been consistent for decades’’
    Endorsement: 5
```

```
        Explanation: The snippet strongly praises Sanders' consistency and advocacy.
        Evidence: ‘‘fighting for working people when no one else would’’
Donald Trump
    Mention: 1
    Endorsement: 0


Example 4: Mixed or Quoted Viewpoints → Net Effect
Transcript snippet:
    ‘‘Some people say Donald Trump is unqualified, but others argue he's very skilled
     ↪  when it comes to business and the economy.’’
Donald Trump
    Mention: 5
        Explanation: Donald Trump is explicitly named and evaluated.
        Evidence: ‘‘Donald Trump is unqualified’’; ‘‘he's very skilled when it comes to
         ↪  business and the economy’’
    Endorsement: 4
        Explanation: The snippet presents mixed evaluations but leans toward
         ↪  endorsement because the economy is a huge factor.
        Evidence: Both negative and positive claims are included.
Bernie Sanders
    Mention: 1
    Endorsement: 0



Here is the transcript: ${transcript}

Respond in strictly valid JSON with this structure:
{
  "bernie_sanders": {
    "mention": {
      "score": integer 1-5,
      "explanation": "Short explanation based only on the text.",
      "evidence": ["Quote/paraphrase 1", "Quote/paraphrase 2"]
    },
    "endorsement": {
      "score": integer 0-5,
      "explanation": "Short explanation based only on the text.",
      "evidence": ["Quote/paraphrase 1", "Quote/paraphrase 2"]
```

```
    }
  },
  "donald_trump": {
    "mention": {
      "score": integer 1-5,
      "explanation": "Short explanation based only on the text.",
      "evidence": ["Quote/paraphrase 1", "Quote/paraphrase 2"]
    },
    "endorsement": {
      "score": integer 0-5,
      "explanation": "Short explanation based only on the text.",
      "evidence": ["Quote/paraphrase 1", "Quote/paraphrase 2"]
    }
  },
}
```

Populism framing prompt

```
    I will provide you with a partial transcript from a YouTube video.

Your task is to determine whether the speaker in this snippet is engaging in (1) POPULIST political messaging in the modern (21st-century) United States, and if so whether it is LEFT-populist or RIGHT-populist; or (2) non-populist partisan messaging; or (3) neutral/no politics.

IMPORTANT CONTEXT RULES:
    - The transcript is a snippet of a larger conversation.
    - There may be multiple speakers or quoted viewpoints.
    - Do NOT attribute statements to individual speakers.
    - Judge the OVERALL framing or ‘‘net effect’’ of the snippet.
    - Base all judgments ONLY on explicit or strongly implied content in the text.
    - Do NOT classify based solely on the presence of political ideas, labels, or buzzwords.

CRITICAL STANCE DISTINCTION:
    If the transcript discusses a political ideology, policy, group, or narrative, first determine whether the speaker is:
        (a) endorsing/advancing it,
        (b) criticizing/attacking it, or
        (c) neutrally describing it.
```

```
    If the speaker criticizes or attacks an ideology/narrative, the label should
    ↪  generally reflect the OPPOSING direction (e.g., attacking ‘‘MAGA’’ tends toward
    ↪  left/nonpopulist_liberal; attacking ‘‘socialists/left’’ tends toward
    ↪  right/nonpopulist_conservative), unless the speaker clearly rejects both.

MULTIPLE SPEAKERS RULE:
A partial transcript may include multiple speakers or quoted viewpoints.
Classify the OVERALL DIRECTIONAL FRAMING of the snippet as a whole, considering:
    - Which viewpoints are presented as correct, reasonable, or persuasive
    - Which viewpoints are mocked, criticized, dismissed, or undermined
    - Whether one direction clearly dominates the framing

============================================================
CORE CONCEPT: WHAT COUNTS AS POPULISM (US, 21st century)
============================================================
Populism is not simply ‘‘being partisan’’ or ‘‘being angry.’’

For this task, populism requires BOTH of the following:

(1) PEOPLE vs ELITE FRAME

    The snippet must frame politics as a conflict between: ‘‘the people’’ (e.g.,
    ↪  ordinary people, working people, regular Americans, the public)
    and
    ‘‘the elite’’ (e.g., establishment, corporations, billionaires, media, bureaucrats,
    ↪  experts (scientists, lawyers, doctors), political class)

(2) MORALIZED ANTI-ESTABLISHMENT CLAIM

    The elite must be portrayed as: corrupt, rigged, bought, illegitimate,
    or
    betraying the people or as controlling institutions against the people’s
    ↪  interests

If a snippet is partisan but lacks this people-vs-elite moral frame, it is
↪  NON-POPULIST partisan.

============================================================
RIGHT vs LEFT POPULISM (MODERN U.S. CUES)
============================================================
```

```
Use the following guidance to distinguish RIGHT-populism from LEFT-populism.
Focus on:
  (1) the PRIMARY TARGET OF BLAME,
  (2) the CORE GRIEVANCE being advanced,
  (3) when present, the implied or stated PROPOSED RESOLUTION and
  (4) common rhetorical cues/examples used to express these

A proposed resolution is NOT required, but may help resolve ambiguous cases.

-----------------------------------------------------------
RIGHT-POPULISM (MAGA-style) often includes:
-----------------------------------------------------------

PRIMARY TARGET OF BLAME:
  - Cultural elites (media, universities, Hollywood)
  - Political or bureaucratic institutions (‘‘the establishment,’’ ‘‘deep state’’,
  ↪  "democrats", DOJ/FBI)
  - Experts or technocrats (scientists, public health officials)
  - Global or transnational actors (‘‘globalists,’’ UN, WEF)

CORE GRIEVANCES:
  - Loss of cultural status or national identity
  - Betrayal of ‘‘real Americans’’ by elites
  - Illegitimate or rigged institutions (elections, courts, DOJ/FBI)
  - Imposed social or cultural change (‘‘wokeness,’’ DEI, gender ideology)
  - Lawlessness, crime, or chaos tolerated by elites
  - Elite overreach through expertise (e.g., COVID rules, climate mandates)
  - Claims of urban crime and chaos

PROPOSED RESOLUTION (WHEN PRESENT):
  - Exclusion or removal (deportations, bans, border closure)
  - Punishment or purge of elites or institutions
  - Rejection, defunding, or bypassing of institutions
  - Restoration of authority or ‘‘law and order’’

COMMON RHETORICAL CUES:
  - ‘‘real Americans’’ vs ‘‘coastal elites’’ or ‘‘mainstream media’’
  - nationalism, nativism, or anti-immigration emphasis
  - culture-war framing (‘‘cancel culture,’’ ‘‘CRT,’’ ‘‘trans agenda’’)
```

```
  - anti-globalism / anti-UN / anti-WEF
  - pro-gun rights framed as defense against elite tyranny
  - exaggerated claims of urban crime or societal collapse
  - skepticism of science/experts framed as elite overreach (e.g., COVID measures, climate action)
  - foreigner/immigrant "invasion"

KEY DIAGNOSTIC:
  The elite is primarily cultural, institutional, or global, and the grievance
  centers on culture, sovereignty, legitimacy, or authority.

-----------------------------------------------------------
LEFT-POPULISM (Bernie-style) often includes:
-----------------------------------------------------------

PRIMARY TARGET OF BLAME:
  - Billionaires, corporations, Wall Street, monopolies
  - Wealthy donors or corporate-funded politicians
  - Economic elites exercising outsized power

CORE GRIEVANCES:
  - Economic exploitation or inequality
  - A “rigged economy” favoring the wealthy
  - Corporate or donor capture of democracy
  - Inability of ordinary people to afford basic needs
  - Concentration of wealth and power

PROPOSED RESOLUTION (WHEN PRESENT):
  - Redistribution of wealth or resources
  - Expansion of public goods or services
  - Regulation or breakup of corporations and monopolies
  - Institutional reform (e.g., campaign finance reform)
  - Collective empowerment (unions, worker power)

COMMON RHETORICAL CUES:
  - “working class” or “regular people” vs “billionaires” or “oligarchs”
  - “corporate greed,” “bought politicians”
  - focus on wages, healthcare costs, housing, monopoly power
  - pro-labor or union framing
  - critiques of both parties as serving wealth
```

```
KEY DIAGNOSTIC:
  The elite is primarily economic, and the grievance centers on exploitation,
  inequality, or concentrated wealth.

===========================================================
NON-POPULIST PARTISAN ANCHORS (WHEN POPULISM IS ABSENT)
===========================================================

When a snippet contains directional political content but does NOT meet the
people-vs-elite + moralized anti-establishment criteria for populism,
use the following anchors to distinguish non-populist alignment.

NON-POPULIST LIBERAL (ANCHORS):
  - Defense of institutions (courts, elections, agencies)
  - Emphasis on expertise, norms, pluralism, or democratic process
  - Rights-based or inclusion-based arguments without elite corruption claims
  - Criticism of right-wing movements framed as dangerous, illiberal, or
  ↪  anti-democratic,
    rather than as elite conspiracies or systemic betrayal

NON-POPULIST CONSERVATIVE (ANCHORS):
  - Defense of markets, police, military, or constitutional order
  - Emphasis on tradition, stability, rule of law, or fiscal restraint
  - Cultural criticism framed as social decline or bad policy,
    rather than elite betrayal or systemic illegitimacy
  - Pro-authority or law-and-order arguments that do NOT delegitimize institutions

===========================================================
DECISION PROCESS (do this in order)
===========================================================
Step 1: Is there meaningful political content at all?
        If no → no_politics

Step 2: If political content exists, is the speaker’s stance clearly directional?
        If the stance is descriptive, balanced, mixed, explicitly anti-all-sides,
        or lacks sufficient context → unclear_or_balanced

Step 3: If the stance is directional, does the message include BOTH:
        (a) a PEOPLE vs ELITE frame, and
```

```
        (b) a MORALIZED anti-establishment claim
        (i.e., elites are portrayed as corrupt, rigged, illegitimate, betraying the
        ↪  people,
        or controlling institutions against the public)?

        If no → classify as nonpopulist_liberal or nonpopulist_conservative.

Step 4: If Step 3 is satisfied,
        classify as LEFT-populism or RIGHT-populism using the left/right cues.

===========================================================
LABELS
===========================================================
- no_politics:
  No meaningful political content or political signaling.

- unclear_or_balanced:
  Political content is present, but the speaker's stance is descriptive, balanced,
  ↪  internally mixed,
  explicitly rejects all sides, or lacks sufficient context to infer a dominant
  ↪  direction.

- left_populism:
  Clear people-vs-elite + anti-establishment moral framing, oriented toward
  ↪  class/worker vs billionaires/corporations/oligarchy.

- right_populism:
  Clear people-vs-elite + anti-establishment moral framing, oriented toward
  ↪  nationalist/culture-war/institution-skeptic frames (MAGA-style).

- nonpopulist_liberal:
  Liberal/Democratic-aligned stance without the core populist people-vs-elite moral
  ↪  frame.

- nonpopulist_conservative:
  Conservative/Republican-aligned stance without the core populist people-vs-elite
  ↪  moral frame.


OUTPUT REQUIREMENTS:
```

```
Provide:
  - A VERY brief explanation (maximum 2 sentences, no more than 35 words) that
  ↪  clearly states WHO is being criticized or endorsed AND whether it is populist
  ↪  or not.
  - 1-2 direct quotes or concise paraphrases as evidence.

Here is the transcript:
${transcript}

Respond in strictly valid JSON:
{
  "populism_label": {
    "label": "left_populism|right_populism|nonpopulist_liberal|nonpopulist_conservat
    ↪  ive|unclear_or_balanced|no_politics",
    "explanation": "Short explanation based only on the text.",
    "evidence": ["Quote/paraphrase 1", "Quote/paraphrase 2"]
  }
}
```