# Whose Advantage? Measuring Attention Dynamics across YouTube and Twitter on Controversial Topics

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## Abstract

The ideological asymmetries have been recently observed in contested online spaces, where conservative voices seem to be relatively more pronounced even though liberals are known to have the population advantage on digital platforms. Most prior research, however, focused on either one single platform or one single political topic. Whether an ideological group garners more attention across platforms and/or topics, and how the attention dynamics evolve over time, have not been explored. In this work, we present a quantitative study that links collective attention across two social platforms – YouTube and Twitter, centered on online activities surrounding popular videos of three controversial political topics including Abortion, Gun control, and Black Lives Matter over 16 months. We propose several sets of video-centric metrics to characterize how online attention is accumulated for different ideological groups. We find that neither side is on a winning streak: left-leaning videos are overall more viewed, more engaging, but less tweeted than right-leaning videos. The attention time series unfold quicker for left-leaning videos, but span a longer time for right-leaning videos. Network analysis on the early adopters and tweet cascades show that the information diffusion for left-leaning videos tends to involve centralized actors; while that for right-leaning videos starts earlier in the attention lifecycle. In sum, our findings go beyond the static picture of ideological asymmetries in digital spaces and provide a set of methods to quantify attention dynamics across different social platforms.

## 1 Introduction

Several recent studies have documented the ideological asymmetries between the left-wing and right-wing activism (Brady et al. 2019; Schradie 2019; Freelon, Marwick, and Kreiss 2020; Waller and Anderson 2021). Some highlight the dominance of conservative voices on social media (Brady et al. 2019); others portray the widespread symbolic support for progressive social movements (Jackson, Bailey, and Welles 2020). The term "conservative advantage" is coined to describe the strategic dissemination of right-wing users to spread their messages (Schradie 2019). However, most of the existing research bases on the analysis of a single platform or a single political topic. Relatively little is known about how different ideological groups garner attention across platforms, and whether the group advantage of gaining visibility remains across topics and over time. To answer these questions, this work designs several sets of cross-platform measurements on the collective attention dynamics of two different ideological groups across three controversial political topics.

Online platforms, such as Twitter, YouTube, Reddit, and Facebook, are social-technological artifacts that segregate online attention into silos defined by the underlying software and hardware systems. Video views on YouTube are known to be driven by discussions outside the platform (Rizoiu et al. 2017), and to be part of users' broader information diet (Hosseinmardi et al. 2021). What is not known, however, is how groups of related content comparatively evolve across different social platforms. Collective attention on political content have been studied on one topic, such as the Occupy Movement (Thorson et al. 2013), Gun Control/Rights (Zhang et al. 2019), and Black Lives Matters (De Choudhury et al. 2016; Stewart et al. 2017). Yet, cross-cutting studies that compare different movements are rare. With data from three long-running controversial topics, this work seeks to provide measures across YouTube and Twitter and paint a nuanced picture about the temporal patterns of attention from left to right.

We choose three topics: `Abortion`, `Gun Control`, and `Black Lives Matter` (`BLM`). We rely on video hyperlinks to connect the content from YouTube to Twitter. A motivating example is given in Figure 1. We plot the time series of daily view count for the collected `BLM` videos from YouTube (top panel) and daily volume of tweets mentioning these `BLM` videos from Twitter (bottom panel). Both time series are further disaggregated by video uploaders' political leanings. Visually, the view count dynamics of both left- and right-leaning videos are relatively stable in year 2017, except a sharp spike caused by the "Unite the Right rally"[1] event in Charlottesville, USA. On the bottom panel, the tweet count dynamics of right-leaning videos have many spikes, which can be attributed to the upload of new videos from far-right YouTube political commentators. The measures on YouTube and Twitter present a contrasting story here: if we

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[1]https://en.wikipedia.org/wiki/Unite_the_Right_rally

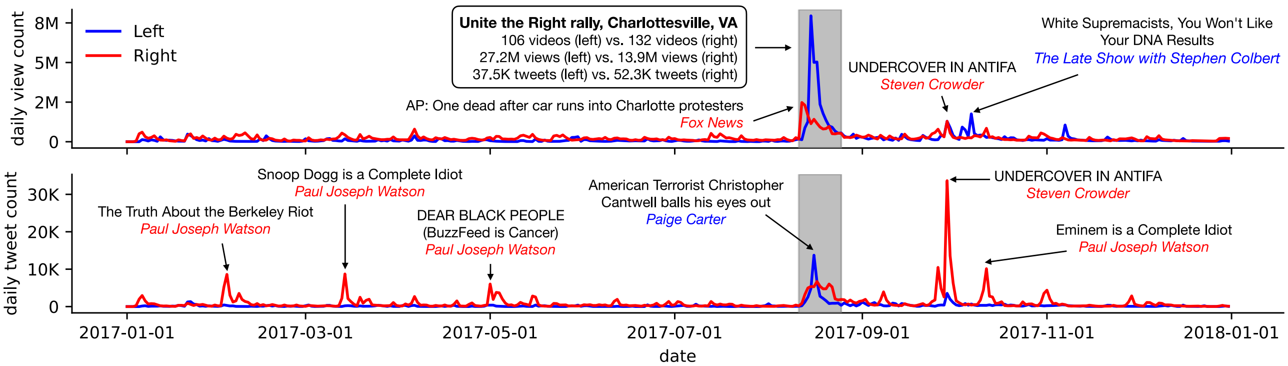



Figure 1: Attention time series (top: daily view count; bottom: daily tweet count) related to `BLM` throughout 2017. The view count dynamics of both left- and right-leaning videos have a handful of sharp peaks, while the tweet count dynamics of right-leaning videos peak more frequently. Notable video releases (with the most views and tweets) are labeled. YouTube channel titles are *italicized* and colored by video leanings. Best viewed in colors.

focus on the two weeks period after the rally, left-leaning videos attracted more attention on YouTube (measured by views, left: 27.2M, right: 13.9M) while right-leaning videos had higher exposure on Twitter (measured by tweets, left: 37.5K, right: 52.3K). This example demonstrates the need for cross-platform analysis – findings on one platform may not generalize to another.

We design a set of metrics from publicly available data on YouTube and Twitter, which include total views, video watch engagement, tweet reactions, the evolution of attention over time, and early adopter networks among tweets and Twitter users. On YouTube, we find that left-leaning videos accumulate more views, are more engaging, and have higher viral potential than right-leaning videos. In contrast, right-leaning videos have higher numbers of total tweets and retweets on Twitter. Statistics on the unfolding speed for views and tweets show that the attention on left-leaning videos attenuates faster, while that on right-leaning videos persists for longer. Note that these observations are not generalized unanimously across topics, e.g., for some metrics, we observe significant differences for `Abortion` and `Gun Control`, but not for `BLM`. These findings expand current wisdom on ideological asymmetries in two ways: the first is exposing the novel facet that left-leaning content attracts more attention in a shorter period of time; the second is the need of contrasting temporal attention statistics between platforms, such as right-leaning tweet cascades tend to start earlier and YouTube views on right-leaning content sustain longer. In sum, our observations paint a richer picture of attention patterns across the political spectrum, provide a basis for further studying political framing and group behavior, and supply fundamental metrics for understanding influences that transcend platforms.

The main contributions of this work include:

- a data curation procedure linking content on YouTube and Twitter for longitudinal topic monitoring.[2]
- several sets of cross-platform metrics that support statistical comparisons for different ideological groups, encompassing the volume and quality of attention, networks of tweets and users, as well as relative temporal evolution.
- adding the temporal and cross-platform dimensions to recent observations on ideological asymmetries. We find that polarized content engages users in distinct ways – more views, more engagement, and faster reactions for videos on the left; comparing to more tweets, more sustained attention for videos on the right.

[2]Our datasets and analysis code are publicly available at https://github.com/picsolab/Measuring-Online-Information-Campaigns

## 2 Related Work

**Online behavior of political groups.** Measurement studies have quantified different aspects of users, contents, and their interactions under political polarization on social media. Conover et al. (2011) presented one of the first profiling studies of polarized political groups on Twitter. There have also been evidences that liberal and conservative groups attract online attention in different manners. Abisheva et al. (2014) focused on a set of influential Twitter users who promoted YouTube videos, and they found that conservatives tweeted more diverse topics than liberals and that conservatives shared new videos faster. Bakshy, Messing, and Adamic (2015) quantified the extent to which Facebook users were exposed to politically opposing contents, and they found that conservatives tended to seek out more cross-partisan content. Lin and Chung (2020) distinguished online behavioral signals, such as linguistic and narrative characteristics, of two ideology groups in response to mass shooting events. Garimella et al. (2018) defined several consumption and production metrics and profiled key user behavior patterns. Ottoni et al. (2018) showed that conservatives used more specific language to discuss political topics and showed more negative emotions in the language. On YouTube, a recent study from Wu and Resnick (2021) found that left-leaning videos attracted more comments from conservatives than right-leaning videos from liberals. However, all of these works are conducted platform-wide, and are not specialized into particular topics or movements.

Online activism, also known as online social movement has been actively studied as a form of digital political campaigns. For example, De Choudhury et al. (2016) presented one of the first studies on the BLM movement, measuring geographical differences in participation, and relationships to offline protests. Stewart et al. (2017) constructed a shared audience network of users who talked about BLM on Twitter and found the existence of superclusters among liberals and conservatives. Zhang and Counts (2015) performed policy decision prediction based on tweet texts analysis on same-sex marriage. In a follow-up work, Zhang and Counts (2016) discussed gender disparity by linking tweet texts to the state-level Abortion policy events. Ertugrul et al. (2019) examined the relation between offline protest events and their social and geographical contexts. Freelon, Marwick, and Kreiss (2020) explained different tactics of liberals and conservatives when approaching audience on social media and articulated the asymmetries of measured behavior between conservatives and liberals. However, all of these works focus on a single controversial topic. In contrast, we examine three political topics and assess consistency of findings across the topics.

**Cross-platform measurement studies.** One early attempt in linking Twitter and YouTube data is from Abisheva et al. (2014), in which the authors found that the features of early adopters on Twitter were predictive for the video view counts on YouTube. Rizoiu et al. (2017) proposed the Hawkes Intensity Process that linked the time series of tweets and views, which led to a metric called *viral potential* for measuring the expected number of views that a video would obtain if mentioned by an average tweet (Rizoiu and Xie 2017). Zannettou et al. (2017) measured the sharing of alternative and mainstream news articles on three different platforms – Twitter, Reddit, and 4chan. This seminal study characterized the role of fringe communities in spreading news. Hosseinmardi et al. (2021) used browsing histories to infer video watch behavior, and quantified the consumption and driver of extreme content with respect to users' information diet. However, all of these works cover a breadth of content sources and categories, but none is focused around social movements or consistent political topics.

This presented work bridges the gap of cross-platform measurement studies on multiple social movements, aiming to provide richer understanding that balances the ideological asymmetry between the left and the right.

## 3 Curating Tweeted Video Datasets

We constructed three new cross-platform datasets by tracking videos on YouTube and posts on Twitter over three controversial topics: Abortion, Gun Control, and BLM. Those topics have been studied extensively by social and political scientists (Zhang and Counts 2016; De Choudhury et al. 2016; Stewart et al. 2017; Garimella et al. 2018). In this section, we first describe the data collection strategy. We then introduce our methods for estimating the political leanings of Twitter users and YouTube videos. Table 1 summarizes the overall statistics of the three topical datasets.

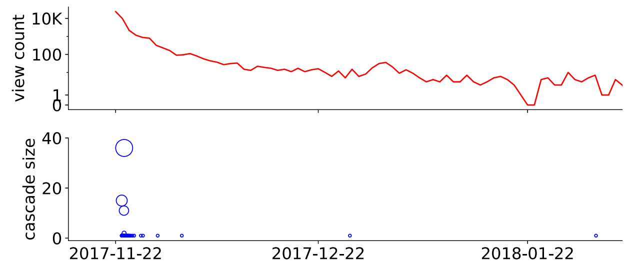



Figure 2: Time series of daily view count (top panel, in log scale) and tweet cascades (bottom panel) for an example video (YouTube video id: PTjMngQwGh8). A tweet cascade is placed at the time of its first tweet, with y-axis and size proportional to the number of tweets in the cascade (see Section 4.3). The viewing dynamic unfolds for months, but tweets only happen sporadically after the first week.

### 3.1 Finding YouTube Videos and Twitter Posts of Controversial Topics

We are interested in topical YouTube videos and the discussions about them on Twitter. Following the approach used in (Wu, Rizoiu, and Xie 2018), we collected public tweets that mentioned any YouTube URLs via the Twitter filtered streaming API. Our raw Twitter stream spanned 16 months (2017-01-01 to 2018-04-30), and contained more than 1.8 billion tweets. To subsample videos that attracted a reasonable amount of attention before the end of the observation period, we required that the videos must be published in 2017, receive at least 100 tweets and at least 100 views within the first 120 days after upload. We make this filtering choice because (a) analyzing videos with little attention ($<1$ view per day) is bound to generate noises when comparing different groups; (b) characterizing the timing and structure of a video's tweeting cascades requires a non-trivial number of tweets. This yielded 328,557 videos, which were mentioned in 242M tweets by 29.9M users. For each video, we collected its metadata, daily time series of view count and watch time, and all tweets mentioning it.

To identify topic-relevant videos and tweets, we first curated three separate keyword lists for three controversial topics – Abortion, Gun Control, and BLM. We consider a video is potentially relevant if (a) it contains at least one keyword in the video title or description; or (b) it is mentioned in a tweet that contains at least one keyword in the tweet text. Next, we used a mix of manual and semi-automated approaches to annotate the potentially relevant videos. Section A of (Appendix 2022) details the topical keywords, their curation, and our video annotation protocol. In total, we obtained 179 Abortion, 268 Gun Control, and 777 BLM videos, which were mentioned in 970K+ tweets.

Figure 2 shows the daily view count series and tweet cascades for an example video. A notable contrast between the two sources is that YouTube attention data is only available in daily aggregates, i.e., without individual user logs, while tweets have precise timestamp, user information, and relations between tweets and users. Section 4 is dedicated to designing measures for such cross-platform multi-relational

| | YouTube video | | | | Tweet | User | 20% Early Adopters (Twitter user) | | | | (Tweet) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | L | C | R | Total | Total | Total | Lib. | Neu. | Con. | Total | Total |
| Abortion | 58 | 10 | 111 | 179 | 106,776 | 76,337 | 2,534 | 1,708 | 8,202 | 12,444 | 15,843 |
| Gun Control | 81 | 33 | 154 | 268 | 270,543 | 156,145 | 10,987 | 3,371 | 13,591 | 27,949 | 37,264 |
| BLM | 297 | 84 | 396 | 777 | 593,574 | 262,580 | 10,419 | 5,745 | 33,934 | 50,098 | 78,969 |

Table 1: Summary of cross-platform datasets on three controversial topics. L: Left-leaning video; C: Center video; R: Right-leaning video. Lib.: Liberal user; Neu.: Neutral user; Con.: Conservative user. See Section A of (Appendix 2022) for methods of curating tweeted video datasets across YouTube and Twitter, and Section B&C for methods of estimating the political leanings of Twitter users and YouTube videos. The ratios of early adopters are slightly below 20% due to banned and protected users.

temporal data. We bootstrapped the political information about Twitter users and YouTube videos. In particular, we gathered more information about videos' early adopters, defined as the first 20% users who tweeted about each video. We collected the follower lists for all early adopters. Network measures of early adopters are found to indicate future popularity (Romero, Tan, and Ugander 2013). The threshold (first 20%) is chosen to balance the need for data and the burden of collecting network information within practical API limits. After filtering out banned and protected users, we extracted 132K early adopter tweets posted by tens of thousands of users across the three topics (see Table 1).

### 3.2 Estimating Political Leanings of Twitter Users and YouTube Videos

We classified the political leanings of early adopters on Twitter into liberal, neutral, and conservative. Meanwhile, we classified the video leanings into left, center, and right. Twitter users and YouTube videos are related in that left-leaning contents (e.g., `Gun Control` videos) are generally shared by liberal users while right-leaning contents (e.g., `Gun Rights` videos) are shared by conservative users.

We estimated Twitter users' political leanings by first identifying a group of seed users who included political hashtags in their profile descriptions, and then by using a label propagation algorithm (Zhou et al. 2004) to propagate the labels of seed users to other users based on the shared follower network. This is a common approach for classifying user leaning on Twitter (Stewart et al. 2017) and the *follow* relation is found to be the most important in predicting user ideology (Xiao et al. 2020). We performed 10-fold cross-validation to evaluate the classification performance. We observed very high scores in precision, recall, and F-score across all three topics ($> 95\%$ in all metrics). Section B of (Appendix 2022) describes our classification and evaluation methods for Twitter users in more detail.

We estimated YouTube videos' political leanings by first averaging the leaning scores of videos' early adopters on Twitter. We then used an external YouTube media bias dataset (Ledwich and Zaitsev 2020) to label the video leanings and identified optimal classification thresholds. We were able to find 58/10/111 left, center, and right-leaning videos for `Abortion` (analogously, 81/33/154 for `Gun Control` and 297/84/396 for `BLM`). To validate our estimation, we performed one round of manual annotation for videos in `Gun Control`. We used stratified sampling to sample 50 videos based on the video leaning scores. These videos were annotated independently by three authors. The Fleiss' Kappa was 0.69, suggesting a moderate inter-rater agreement. Section C of (Appendix 2022) details our classification and evaluation methods for YouTube videos.

## 4 Measures for Cross-Platform Attention

This section designs several sets of metrics for the cross-platform data, in order to compare content across different political ideologies, and examine whether the differences are consistent across topics, across platforms, and over time.

### 4.1 Aggregate Attention on YouTube and Twitter

We present four metrics for the total video attention on YouTube.

***Total view count*** sums up a video's view count time series until day 120.

***Relative engagement*** is a metric proposed in (Wu, Rizoiu, and Xie 2018) for quantifying the average video watching behavior. Specifically, for each video, we first compute *average watch percentage*, defined as the total watch time divided by total number of views (both at 120 days) and then normalized by the video length (in seconds). The relative engagement score is the percentile ranking of average watch percentage among videos of similar lengths. It is a normalized score between 0 and 1. A higher score means more engaging, e.g., a score of 0.8 suggests that this video is on average watched for longer time than 80% videos of similar length. Note that relative engagement is shown to be stable over time, hence there is no need to examine the temporal variations of watch time, as it would strongly correlate with view counts. In this work, relative engagement is computed based on a publicly available collection of 5.3M YouTube videos (Wu, Rizoiu, and Xie 2018), with details described in Section D of (Appendix 2022).

***Fraction of likes*** measures the video reaction – provided by YouTube as the total counts of likes and dislikes and collected via the thumb-up and thumb-down icon on the video page. A relatively lower fraction of likes indicates a more diverse audience reaction to the video content. Note that the majority of videos receive a lot more likes than dislikes.[3]

***Viral potential*** is a positive number, representing the *expected* number of views that a YouTube video will obtain

[3]YouTube announced that the dislike count will no longer be available to the public on Nov 10, 2021. https://blog.youtube/news-and-events/update-to-youtube/

if mentioned by an *average* tweet on Twitter (Rizoiu and Xie 2017). More specifically, it is the area under the impulse response function of an integral equation known as Hawkes Intensity Process (HIP) (Rizoiu et al. 2017), which is learned for each video by using the first 120 days of tweeting and viewing history. We choose this quantity rather than simply dividing the number of views by the number of tweets, because the model takes into account views that are yet to unfold due to its sustained circulation via sharing and tweeting. A self-contained summary about HIP and viral potential computation is given in Section E of (Appendix 2022).

On Twitter, tweets can be categorized into four types: original tweets, retweets, quotes, and replies. This leads to five counting metrics: the total number of ***tweets, original tweets, retweets, quoted tweets***, and ***replies***.

### 4.2 Views and Tweets over Time

***Viewing half-life*** is computed as the number of days to achieve half of its total views at day 120.
***Tweeting half-life*** is computed as the number of days to achieve half of its total tweets at day 120.
***Tweeting lifetime*** is time gap between the first and the last tweets. We do not measure lifetime on viewing because the view count of a video rarely becomes zero even towards the end of the measurement period, but tweets tend to exhaust much sooner.
***Tweeting inter-arrival time*** is the average time difference between every two consecutive tweets about each video.
***Accumulation of views and tweets.*** In addition to the summary metrics above, we also compare the attention accumulation on the left- and right-leaning content on a daily basis. On each day $t$, we compute the fraction of the total views that each video has achieved. This leads to two sets of samples $\{v_i^{(L)}\}_{i=1}^n$ and $\{v_j^{(R)}\}_{j=1}^m$, where $n$ is the number of left-leaning videos and $m$ is the number of right-leaning videos. We then compute the normalized Mann-Whitney U (MWU) statistic (Mann and Whitney 1947),

$$\bar{U}_t = \frac{1}{nm}\sum_i\sum_j\{I[v_i^{(L)} > v_j^{(R)}] + 0.5\, I[v_i^{(L)} = v_j^{(R)}]\}$$

Here $I[\cdot]$ is the indicator function that takes value 1 when the argument is true, 0 otherwise. The U statistic intuitively corresponds to the fraction of sample pairs $(v_i^{(L)}, v_j^{(R)})$ where the sample from left-leaning distribution is larger, accounting for ties. If the distributions of $v^{(L)}$ and $v^{(R)}$ are indistinguishable, then $\bar{U}$ would be around 0.5. We compute the statistic $\bar{U}_t$ on tweets in the same fashion, and both statistics are computed for each day. These two series of statistics allows us to quantify the differences between left- and right-leaning content, and compare the trends on the accumulation of views and tweets over time.

### 4.3 Videos' Tweet Cascades

***Cascade size.*** We define that a *cascade* consists of a root tweet and all of its retweets, replies, and quotes. It is well-known that the vast majority of cascades in online diffusion networks are very small and only a very small fraction of cascades would become very big (Goel, Watts, and Goldstein 2012). Based on the number of tweets in a cascade, we divide the cascades into isolated (only root tweet), small (2-4 tweets), and large ($\geq$ 5 tweets) groups. For videos of each leaning on each topic, we compute the fractions of isolated/small/large cascades and the fraction of tweets in each cascade group. These metrics quantify the structure of online diffusion and allow us to compare behavior on controversial political topics with what was known about tweeted videos in general.
***Cascade start time*** is the percentage of accumulated views of the video when the root tweet of the cascade is posted. It measures how much view attention is accumulated on YouTube before the infusion on Twitter starts. We choose to describe cascade timing relative to the accumulation of view, rather than in absolute number of days since upload, because (a) such relative time more directly correlates the amount of cascades with respect to the views they can potentially drive (rather than through another variable, days); and (b) the percentage of views provides more granularity, since many videos have all views and tweets unfold within a few days after upload.

### 4.4 Networks among Early Adopters on Twitter

For each video, we obtain its follower network among the early adopters. If there exists a following relationship between a pair of users, a directed edge is established. This results in one network for each shared video. We compute a set of metrics per video, and then compare their distributions on each topic for left- and right-leaning videos. We describe two key metrics here, and discuss four additional metrics in Section H of (Appendix 2022).
***Gini coefficient of indegree centrality.*** We calculate the indegree centrality for each node in the network. To have a video-level metric, we use the Gini coefficient, which ranges from 0 to 1 and measures the distribution inequality. Specifically, the Gini coefficient of indegree centrality quantifies the degree of inequality of the indegree distribution. A higher value indicates that a few early adopters are followed more by other early adopters, and a lower value indicates that the indegree distribution is more equal.
***Gini coefficient of closeness centrality*** captures the dispersion in inverse of average shortest path length from one early adopter to all other early adopters of a given video. Higher coefficient implies that a few early adopters can reach the rest of the early adopters within a few hops.

## 5 Observations on Cross-Platform Attention

We report the results on all metrics described in Section 4, in mirroring subsections to aid navigation. Many results in this section are presented as violin plots. The outlines are kernel density estimates for the left-leaning (blue) and right-leaning (red) videos, respectively. The center dashed line is the median, whereas the two outer lines denote the interquartile range. To compare the distributions of each metric for the left- and right-leaning videos, we adopt the one-sided Mann–Whitney U test. We summarize our results in Table 2 at the end of this paper.

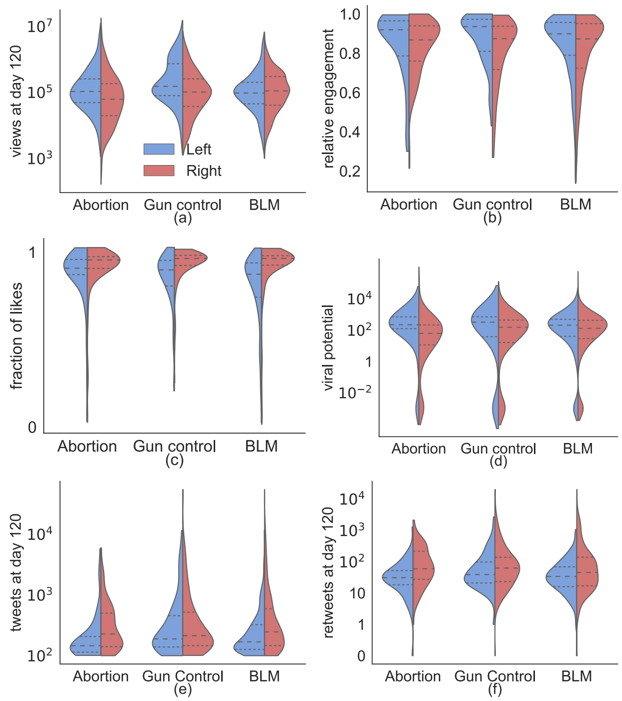



Figure 3: Violin plots comparing the left-leaning (blue) and right-leaning (red) videos in (a) total number of views at 120 days after upload, (b) relative engagement, (c) fraction of likes, (d) viral potential, (e) total number of tweets, and (f) total number of retweets at 120 days after the video upload. Left-leaning videos are more viewed, more engaging, having more diverse reactions, and more viral than right-leaning videos across all three topics (except views in `BLM`). In `Abortion` and `BLM`, right-leaning videos are significantly more tweeted, especially with more retweets.

### 5.1 Aggregate Attention on YouTube and Twitter

**Total view count.** Figure 3(a) shows the distribution of video views at day 120 after upload. Using the view count at the same day removes the effects of video age, so that the videos published for longer time are not taking an unfair advantage. In `Abortion` and `Gun Control`, the median, as well as $25^{th}$ and $75^{th}$ percentile of views of left-leaning videos are higher than that of right-leaning videos. The median views for left-leaning videos are 107,346 for `Abortion` and 153,482 for `Gun Control`, versus 62,780 and 103,373 for right-leaning ones. The differences in view distribution are statistically significant ($p < 0.01$, Table 2 row 1). For `BLM`, right-leaning videos have higher median and $75^{th}$ of views, but the effect is not significant.

**Relative engagement.** From Figure 3(b), we can see that videos in all three topics are highly engaging, with mean relative engagement at 0.834 for `Abortion`, 0.824 for `Gun Control`, and 0.831 for `BLM`. This is because our data processing procedure requires videos to have at least 100 tweets and 100 views, which tends to select videos with significant amount of interests. Left-leaning videos are significantly more engaging than their right-leaning counterparts across all three topics ($p < 0.05$, Table 2 row 2).

**Fraction of likes.** Figure 3(c) presents the proportion of likes in videos' reactions. Left-leaning videos across all topics have significantly smaller fraction of likes than right-leaning videos ($p < 0.001$, Table 2 row 3). This may be explained by the observation that there are far more cross-partisan talks on left-leaning videos (Wu and Resnick 2021).

**Viral potential.** Figure 3(d) shows the distributions of viral potential. We find that the left-leaning videos have significantly higher viral scores than the right-leaning videos across all three topics ($p < 0.05$, Table 2 row 4), meaning that given the same amount of tweets exposing the video on Twitter, an average left-leaning video can effectively attracts more views than an average right-leaning video. The difference is most notable in `Abortion`: a typical left-leaning video receives 224 views from an average tweet, whereas a typical right-leaning video receives only 63 views.

**Tweet counts.** Figure 3(e) and (f) show the distributions of total tweets and retweets. Contrasting to the observation that left-leaning videos are more viewed, here we find that right-leaning videos are significantly more tweeted, especially with more retweets and more replies ($p < 0.001$, Table 2 row 5-7) in `Abortion` and `BLM`. On the other hand, we do not observe a significant difference in original tweets and quotes, except for `BLM` where right-leaning videos have prevailing volume across all tweet types.

To examine the robustness of presented results in this section, we bootstrapped videos for each topic and for each ideological group. Specifically, for each group, we created $1,000$ bootstrapped sets of videos that are of the same size as the original group (shown in Table 1). Next, we computed the mean of proposed metrics (shown in Figure 3) for each bootstrapped set. Lastly, we used the *independent t-test* to check the statistical significance between left- and right-leaning groups. The results of the *t-tests* support all reported relations in Table 2 row 1-6 with $p < 0.001$.

### 5.2 Views and Tweets over Time

We measure how quickly left- and right-leaning videos attract views and tweets. We find that left-leaning videos are reacted on YouTube and Twitter quicker across all topics.

**Viewing half-life** and **Tweeting half-life.** We notice that there are significant differences in the attention consumption patterns: right-leaning videos have more prolonged attention spans on YouTube across all topics ($p < 0.01$, Table 2 row 10). Right-leaning videos also have longer attention spans on Twitter for `Abortion` and `Gun Control` ($p < 0.05$, Table 2 row 11). For example, Figure 4(a) shows that right-leaning videos for `Abortion` have the longest attention span – taking 9 days for 75% videos to achieve viewing half-life, while left-leaning videos only take 3 days. Comparing Figure 4(a) to Figure 4(b), we find that attention spans on Twitter are shorter than that on YouTube. In `Abortion`, left-leaning videos take 2 days for 75% of videos to reach tweeting half-life (vs. 3 days for views) and right-leaning videos take 5 days for 75% of videos to reach tweeting half-life (vs. 9 days for views).

**Tweeting lifetime** and **Tweeting inter-arrival time.** Figure 4 (c) and (d) shows the distributions of tweeting lifetime

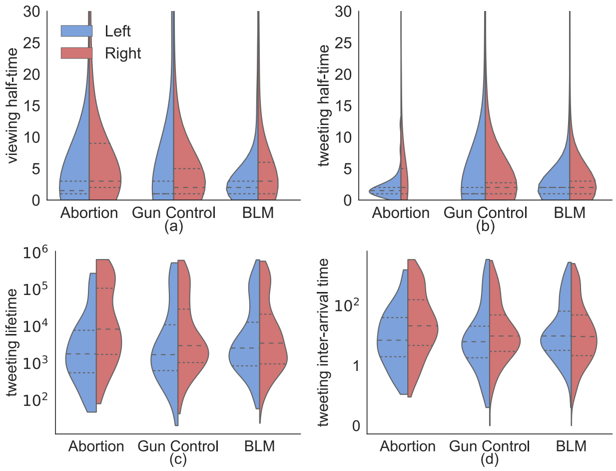



Figure 4: The number of days to receive 50% (a) views and (b) tweets. The time gaps (in minutes) between tweets measured as (c) tweeting lifetime and (d) tweeting inter-arrival time. Left-leaning videos are mentioned more quickly on Twitter and have shorter circulation duration for all metrics in `Abortion` and `Gun Control`.

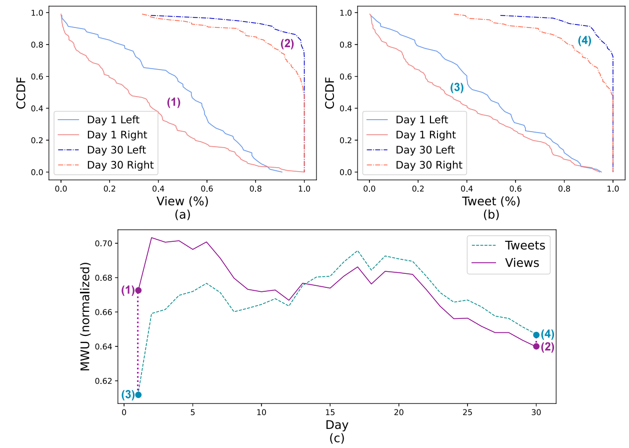



Figure 5: The distribution of accumulated views and tweets in `Abortion` videos on the first day of video upload and at $30^{th}$ day: (a) percentage of views achieved, (b) percentage of tweets achieved, (c) MWU statistic values for each day from the first day to day 30. The area marked with (1,2,3,4) in (a) and (b) are shown in (c) as a normalized MWU statistic. For example, (1) shows difference between left- and right-leaning videos in terms of view accumulation. This difference is measured using MWU test and shown in (c) where (1) is marked. The difference between left- and right-leaning videos, in both views and tweets accumulation, tend to become smaller in later days. Section F of (Appendix 2022) includes the same set of plots for `Gun Control` and `BLM`.

and inter-arrival time. The results are mixed across topics. For `Abortion` and `Gun Control`, the MWU test results show that left-leaning videos have significantly less scores in both metrics than right-leaning videos ($p < 0.05$, Table 2 row 12-13). But for `BLM`, both metrics show similar distributions between left- and right-leaning videos.

These results suggest that left-leaning videos have shorter circulation duration and are mentioned more quickly (except `BLM`). The most notable difference is in `Abortion` where the median of tweeting lifetime and inter-arrival time for right-leaning videos are more than three times of those for left-leaning videos. For instance, the median tweeting lifetime is 1811.6 minutes for left-leaning videos, while the median is 8453.8 minutes for right-leaning videos.

**Accumulation of views and tweets.** We examine how much views and tweets are accumulated each day. Figure 5(a) and (b) show the Complementary Cumulative Distribution Function (CCDF) of views and tweets percentages accumulated for the first day (video published date) and $30^{th}$ day for `Abortion` videos. We observe that left-leaning videos tend to achieve views/tweets faster than right-leaning videos, which is consistent with Figure 4. For example, after day 1, 56.9% left-leaning videos have achieved viewing half-life, but only 26.1% right-leaning videos achieved the same. For tweet accumulation, after 1 day, the gap of tweeting half-life between left- and right- leaning videos is 11.4% (46.6% and 35.1%, respectively). By day 30, only 3 left-leaning videos have not accumulated 80% of views.

Figure 5(c) compares the normalized MWU statistic values of left- and right-leaning videos in views $\bar{U}_v$ and tweets $\bar{U}_t$ on each of the 120 days since upload. It shows that the difference between left- and right-leaning videos is larger in the beginning and decreases towards 0.5 over time. At the $120^{th}$ day (as the observation period ends), both will be 0.5 by definition, we thus truncate the plot at day 30. We also observe that the differences in views is larger than that of tweets across left- and right- leaning videos initially, whereas the discrepancy between views and tweets narrows as videos get older. This is because more videos have already fully achieved all the views and tweets.

## 5.3 Videos' Tweet Cascades

**Cascade size.** Goel, Watts, and Goldstein (2012) found that one-node-cascades (isolated cascades) account for 96% of all cascades in their *Twitter Videos* dataset. Figure 6(a) shows that the proportions of isolated cascades in our datasets are lower, measured at 91.5%, 91.2%, and 91.9% respectively for `Abortion`, `Gun Control`, and `BLM`. Notwithstanding a confounder that the dynamics on Twitter has changed significantly since (Goel, Watts, and Goldstein 2012), this may still suggest that tweets on controversial topics are less isolated than tweets of videos about any topics. Figure 6(b) shows the volume of tweets involved in each cascade group. It is interesting to find that most tweets belong to either isolated cascades or large cascades. Aggregated over left and right-leaning videos in `Abortion`, `Gun Control`, and `BLM`, 47%, 43.4%, and 47.3% of tweets are isolated, whereas 44.7%, 48.4%, and 44.3% are in large cascades of size 5 and above, dominated by a handful of cascades over 1,000 tweets.

**Cascade start time.** We compare when tweet cascades start in the process of view accumulation, grouped by differ-

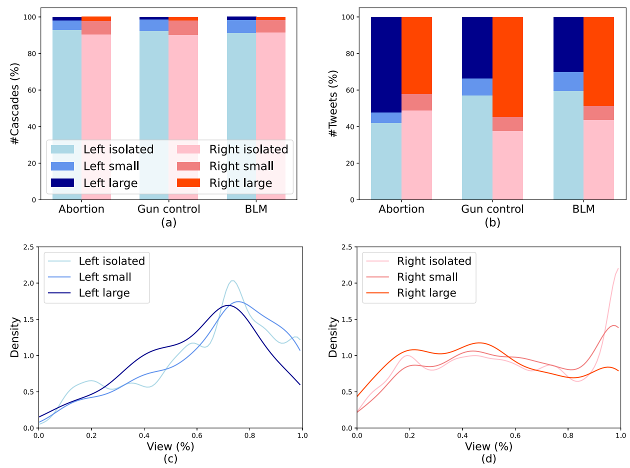
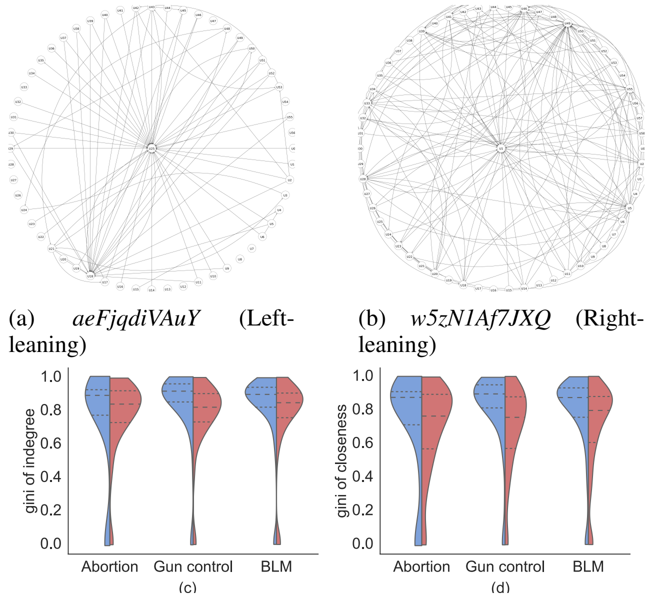



Figure 6: Comparing the left- and right-leaning videos in (a) proportions of cascade sizes – isolated (1 tweet), small (2-4 tweets) and large (5+ tweets); (b) volume of tweets in each cascade type. (c) and (d) show the density of cascade start time in relation to accumulated view percentage for `Abortion` videos. Because the left-leaning videos accumulate views quicker (90% of left-leaning videos reach viewing half-life within 3 days after upload while 59.4% of right-leaning videos do), more left-leaning tweet cascades are shown to start after viewing half-life. Section G of (Appendix 2022) includes the same set of plots for `Gun Control` and `BLM`.




(a) *aeFjqdiVAuY* (Left-leaning) (b) *w5zN1Af7JXQ* (Right-leaning)

Figure 7: Follower networks of early adopters for (a) a left-leaning and (b) a right-leaning video with similar network size in `Abortion`. We compare the left- and right-leaning videos in (c) Gini coefficient of indegree centrality, and (d) Gini coefficient of closeness centrality.

ent cascade sizes. Figure 6(c) and (d) show the distribution of cascade start times of left- and right-leaning videos in `Abortion` relative to percentages of views. For right-leaning videos, there is a peak of isolated cascades started at the end of the videos' viewing lifetime. We also observe that for left-leaning videos, the peaks for isolated, small and large cascades are concentrated near 70% of view accumulation while peaks for right-leaning videos are more distributed over different stages of view accumulation. Moreover, in all topics, more right-leaning tweet cascades start before viewing half-life regardless of cascades size. For example, 41% of right-leaning isolated cascades started before viewing half-life while 25% of left-leaning isolated cascades started before viewing half-life in `Abortion`. This is consistent with the observation that views of right-leaning videos unfold much slower (See Figure 4(a) and Figure 5(a)), allowing tweet cascades to start at earlier stages of view accumulation process. The difference in cascade start time is significant between left- and right-leaning videos in all topics for isolated and small cascades ($p < 0.001$, Table 2 row 14-15) and is significant for `Abortion` and `Gun Control` for large cascades ($p < 0.001$, Table 2 row 16).

## 5.4 Networks among Early Adopters on Twitter

Figure 7(c) and (d) show the distributions of the Gini coefficient of indegree centrality and the Gini coefficient of closeness centrality. Gini coef. of indegree centrality of left-leaning videos' networks is significantly larger in `Gun Control` and `BLM` ($p < 0.001$, Table 2 row 17). For Gini coefficient of closeness centrality, the MWU test results indicate that left-leaning videos' networks have significantly greater Gini index than those of right-leaning videos' networks across all topics ($p < 0.05$, Table 2 row 18).

This suggests that the networks of early adopters for left-leaning videos have more users serving as hubs, i.e., who are followed by more early adopters and have shorter path to other early adopters. This also suggests that in the networks of early adopters for right-leaning videos, users are more equally facilitating dissemination of political information which is consistent with the findings shown in (Conover et al. 2012). As an example of this, we present the follower networks of early adopters of one left-leaning video and one right-leaning video in `Abortion` in Figure 7(a,b). To have a fair comparison we sample two videos having similar network size (57 and 59 for left and right-leaning videos, respectively). The left-leaning video has Gini coef. of indegree centrality: 0.918, Gini coef. of closeness centrality: 0.90. The right-leaning video has Gini coef. of indegree centrality: 0.748, Gini coef. of closeness centrality: 0.536. It can be observed that the sharing of this left-leaning video relies more on central users who are followed by more early adopters and have shorter path to others. On the other hand, in the follower network of the early adopters of this right-leaning video, indegree and closeness centrality distributions are more equal.

Apart from the reported metrics, we have also performed preliminary examination on the correlation and trends between two and more metrics. An example on linking relative engagement to the view and tweet counts is presented in Section I of (Appendix 2022). We have not seen consistent and salient patterns that are not already captured by individual measures.

## 6 Conclusion and Discussion

This work presents a quantitative study that links collective attention towards online videos across YouTube and Twitter over three political topics: `Abortion`, `Gun Control`, and `BLM`. For each topic, we curated a cross-platform datatset that contained hundreds of videos and hundreds of thousands of tweets spanning 16 months. The extracted videos all have a non-trivial amount of views and tweets. The key contributions include several sets of video-centric metrics for comparing attention consumption patterns between left-leaning and right-leaning videos across two platforms. We find that left-leaning videos are more viewed and more engaging, while right-leaning videos are more tweeted and have longer attention spans. We also found that the follower networks of early adopters on left-leaning videos are of higher centrality, whereas tweet cascades for right-leaning videos start earlier in the attention lifecycle. This study enriches the current understanding of ideological asymmetries by adding a set of temporal and cross-platform analyses.

**Limitations.** Extensive discussions about social data biases are presented in (Olteanu et al. 2019). The biases can be introduced due to the choice of social platforms, data (un)availability, sampling methods, etc. Here we discuss three limitations in our data collection process.

A recent study found that Twitter filtered streaming API subsamples high-volume data streams that consist of more than 1% of all tweets (Wu, Rizoiu, and Xie 2020). The authors proposed a method of using Twitter rate limit messages to quantify the data loss. Based on this method, we find our 16-month Twitter stream has a sampling rate of 79.4 % – we collected 1,802,230,572 out of 2,270,223,254 estimated total tweets. Under a Bernoulli process assumption, the chance of collecting a video tweeted more than once in our tweet stream is 95.8%. Since most missing videos are tweeted sporadically, the sampling loss from Twitter APIs is small, which minimally affects the measures on tweeting activities, including attention volumes, timing, and cascade sizes. Confidence intervals for simple measures such as volume can be derived (Wu, Rizoiu, and Xie 2020).

In this paper, we present various measurements focused on YouTube videos, which are the main entities that link the two platforms. YouTube viewers are unknowable (via publicly available data) and Twitter users are hard to track consistently over time. Therefore, we track videos which attract views and tweets. All the presented metrics are video-centric and we do not assume that the viewers or tweeters of the videos represent specific groups of users. We believe that each set of videos (`Abortion`, `Gun Control`, and `BLM`) represent YouTube videos that are relevant to the topic, curated by keyword queries and semi-manual coding. The number of videos belonging to each topic is not large but we attempted to include all relevant videos shared on Twitter which have non-trivial activities. Thus our results intend to explain attention gathering behavior of topic-relevant videos. Nevertheless, it is unclear that our observations about ideological asymmetries can generalize to videos with less attention and/or videos about other topics. We leave this generalization validation as future work.

One data integrity limitation is the time gap between tweet collection in 2017–2018 and early adopters' follower networks collected in early 2020. Our data collection is limited by the Twitter search API quota, which restrains collecting tweets and Twitter user followers simultaneously. The tweeted videos stream has on average 3.7M tweets in each day. Collecting the follower network for all these tweets far exceeds the capacity of Twitter API, focusing on the early-adopter network is a practical trade-off between still having informative results and making data collection feasible. A related issue comes from unavailable YouTube videos and Twitter users since content publicly available in 2017 may be deleted, banned, or protected in 2020. We found that between 17% to 19% candidate videos become unavailable in our dataset.

**Practical implications and future work.** We believe this work adds a new dimension to the understanding of online political behavior and discourse – cross platform links. Further examination in this direction could bear theoretical and empirical fruits. The measurements presented in this work are mostly quantitative. One direction of future work is to complement qualitative analysis. For example, to gain deeper insight into our observations about how the user attention to left-leaning YouTube videos was driven by a group of elite early adopters, one can examine typical diffusion networks from both left- and right-leaning groups and study the diffusion process of the video spreading. One could also examine the framing of left- and right-leaning content in both video descriptions and tweets about them. For example, Lin and Chung (2020) used mixed-methods approaches to identify the primary framing and rhetorics in online conversations related to gun control, which can be expanded to enrich the quantitative analyses, such as investigating the linguistic features of YouTube descriptions and tweet cascades, and their relationships to the changes in collective attitudes. Finally, understanding the collective attention across multiple social platforms is important for content producers, who could devise better strategies in promoting their content in another domain.

## Ethical Statement

All data that we obtained was publicly available at the time of data collection. We discarded deleted, protected, and private content at the time of analysis. In our released dataset, we anonymized user identities. Therefore, the analyses reported in this work do not compromise any user privacy.

## Acknowledgments

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| row | crossref | metric | definition | significance | | |
|---|---|---|---|---|---|---|
| | | | | Abortion | Gun Control | BLM |
| | | **YouTube and Twitter aggregate attention metrics (Section 5.1)** | | | | |
| 1 | fig. 3a | view_$x$ | Total number of views at day $x$ | **L** > R** | **L** > R*** | × |
| 2 | fig. 3b | relative_engagement | Rank percentile of watch percentage among videos of similar lengths | **L** > R* | **L** > R*** | **L** > R** |
| 3 | fig. 3c | fraction of likes | Number of likes divided by total number of reactions | L < **R***** | L < **R***** | L < **R***** |
| 4 | fig. 3d | viral_potential | Number of views potentially excited by one tweet | **L** > R*** | **L** > R** | **L** > R* |
| 5 | fig. 3e | tweet_$x$ | Total number of tweets at day $x$ | L < **R***** | × | L < **R***** |
| 6 | fig. 3f | retweet_$x$ | Total number of retweets at day $x$ | L < **R***** | × | L < **R***** |
| 7 | – | reply_$x$ | Total number of replies at day $x$ | L < **R***** | × | L < **R***** |
| 8 | – | original_tweet_$x$ | Total number of original tweets at day $x$ | × | × | L < **R***** |
| 9 | – | quote_$x$ | Total number of quotes at day $x$ | × | × | L < **R***** |
| | | **Temporal metrics of views and tweets (Section 5.2)** | | | | |
| 10 | fig. 4a | viewing half-life | Number of days to reach 50% views | L < **R***** | L < **R**** | L < **R***** |
| 11 | fig. 4b | tweeting half-life | Number of days to reach 50% tweets | L < **R**** | L < **R*** | × |
| 12 | fig. 4c | tweeting lifetime | Time gap between the first and the last tweets in minutes | L < **R***** | L < **R*** | × |
| 13 | fig. 4d | tweeting inter-arrival time | Average time gap between every two consecutive tweets in minutes | L < **R**** | L < **R*** | × |
| | | | **Tweet cascades measures (Section 5.3)** | | | |
| | | <u>cascade start time</u> | Percentage of accumulated views of the video when the root of the cascade is tweeted | | | |
| 14 | fig. 6c,d | (isolated cascades) | | **L** > R*** | **L** > R*** | **L** > R*** |
| 15 | fig. 6c,d | (small cascades) | | **L** > R*** | **L** > R*** | **L** > R*** |
| 16 | fig. 6c,d | (large cascades) | | **L** > R*** | **L** > R*** | × |
| | | **Network metrics of early adopters (Section 5.4)** | | | | |
| 17 | fig. 7c | Gini_indegree | Gini coefficient of indegree centrality | × | **L** > R*** | **L** > R*** |
| 18 | fig. 7d | Gini_closeness | Gini coefficient of closeness centrality | **L** > R* | **L** > R*** | **L** > R*** |
| 19 | – | Gini_betweenness | Gini coefficient of betweenness centrality | × | **L** > R* | × |
| 20 | – | network_density | Density of early adopters' follower network | × | × | **L** > R*** |
| 21 | – | max_indegree | Max indegree value in early adopters' follower network | L < **R**** | × | × |
| 22 | – | global_efficiency | Average efficiency over all pairs of distinct early adopters | L < **R*** | L < **R**** | × |

Table 2: Summary of all metrics and comparison across political leanings. **L** > R* means that the metric of a randomly selected left-leaning video is significantly larger than that of a randomly selected right-leaning video. Significance is measured by one-sided Mann–Whitney U test. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. The significantly larger leaning is boldfaced. "×" sign indicates non-significant relation. Sample size: `Abortion` (L: 58; R: 111), `Gun Control` (L: 81; R: 154), `BLM` (L: 297; R: 396). See the corresponding cross-referenced figures and discussions in Section 5 for more details, "–" sign means the metric is not presented in a figure.

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