Fifteen Seconds of Fame: TikTok and the Supply Side of Social Video

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Abstract

TikTok has rapidly developed from a punchline for jokes about "kids these days" into a formidable force in American politics. The speed of this development is unprecedented, even in the rapidly-changing world of digital politics. Through a combination of hashtag and snowball sampling, we identify 11,546 TikTok accounts who primarily post about politics, allowing us to analyze trends in the posting, viewing and commenting behavior on 1,998,642 tiktoks they have uploaded. We test a number of theories about how the unique combination of affordances on TikTok shapes how it is used for political communication. Compared to the dominant platform for political videos (YouTube) we find that a higher percentage of TikTok users upload videos, TikTok view counts are more dominated by virality, and viewership of videos are less dependent on a given accounts' number of followers/subscribers. We discuss how these findings affect the production of content that ultimately determines the experience of TikTok consumers.

Word Count: 7,456

1 Introduction to Politics on TikTok

TikTok has rapidly developed from a punchline for jokes about "kids these days" into a formidable force in American politics. The speed of this development is unprecedented, even in the rapidly-changing world of digital politics (Karpf, 2012). The TikTok app was released the United States in August of 2018; it was the most downloaded App in the Apple App store in the first quarter of 2019, beating out social media heavyweights like Facebook, Instagram and YouTube. The company's 2020 Transparency Report indicates that 104 million videos were removed from the platform worldwide and that this was less than one percent of all videos—putting a floor on the number of videos uploaded in this six-month period at over 10 billion (TikTok, 2019). This is more than double the same figure from the second half of 2019, indicating continuing blistering growth (TikTok, 2020).

In 2020, the *New York Times* ran multiple stories about the political influence of the platform on American politics. "The Political Pundits of TikTok" (Feb 27) details the emergence of sometimes partisan-affiliated "Hype Houses" that produce political content, and included the quote that "TikTok is Cable News for Young People." "TikTok Users, K-Pop Fans Say They Helped Sabotage Trump Rally With False Registrations" (June 21) explained the disappointing size of the audience of President Trump's first post-pandemic-onset rally as the result of a coordinated misinformation campaign conducted by political TikTok users.

This paper presents a large-scale quantitative descriptive analysis of TikTok Politics. Building on Serrano, Papakyriakopoulos, and Hegelich (2020)'s analysis of 3,310 political tiktoks sampled from two hashtags and Literat and Kligler-Vilenchik (2019)'s analysis of 1,651 political tikoks sampled from two other hashtags, our analysis includes 1,998,642 tiktoks from the 11,546 accounts we have encountered and scraped as of October, 6th 2020.[1]

The growth of this ecosystem has been vertiginous. At the end of 2019, the accounts we analyze had uploaded 206,661 total tiktoks; as of October 2020, those accounts have uploaded almost 2 million tiktoks (1,998,642). The viewership numbers are even starker. The one-billionth "play" (TikTok's term for what YouTube calls a "view") for these accounts occurred in September 2019; as of October 2020, their tiktoks have been viewed 25.11 billion times.

[1]We encourage the use of capital-T TikTok to describe the platform and lowercase-t tiktok for each individual post.

These numbers are outlandishly large even compared to more well-known online video platforms. The videos uploaded by the thirty-three channels comprising the well-established "YouTube Right" described in Munger and Phillips (2020) received only 2.9 billion views over the years 2016 and 2017, their period of peak popularity. But consider the dozens of tweets a user might "view" in the course of an hour spent "scrolling the feed" (Settle, 2018).

To explain this difference, we reference research on other social media platforms to theorize about what makes TikTok distinct. TikTok represents the synthesis of three of the most powerful affordances in social media: the *televisual medium* that has always been the most broadly popular and powerful; *algorithmic recommendation* that structures the user's experience to a greater extent than any major social media platform to date; and a *mobile-only* interface designed to take advantage of a smartphone's user-facing camera.

This article presents novel theorization about the effects of those affordances, drawing on knowledge created through the study of other political media. To quantitatively test our theories, we use an analogous sample of political YouTubers as a reference set. Compared to the political YouTubers, we find that a higher percentage of TikTok users upload videos, TikTok view counts are more dominated by virality, and viewership of videos are less dependent on a given accounts' number of followers/subscribers.

In combination, these findings support our argument that a primary difference between TikTok and earlier social media platforms is that it changes the incentives and experience of the producers of tiktoks. The default mode of the platform is that a high percentage of its users are creating videos for an audience of strangers in the hope of going viral.

Although there are admittedly important novelties of TikTok from the perspective of the audience, we advocate that scholars pay equal attention to the supply-side factors that determine *who* makes (and *how* they make) the content that flows throughout the platform.

2 What is TikTok?

TikTok is a social media platform targeted at young, mobile-first users. Chinese company ByteDance owns both TikTok and its China-only cousin Douyin, which was founded in September 2016. TikTok was launched a year later, and kickstarted its growth in the US by acquiring and merging with lip-synching app musical.ly in late 2017. TikTok was the most downloaded app in the US in 2019, and second in the world to WhatsApp.

Each tiktok is a 3 to 60 second-long video that loops when finished.[2] The majority of the screen is taken up by the video uploaded by the user. The app offers an extremely wide range of options for customizing these videos, including: video taken with the user's smartphone; photos uploaded from the web; emojis and other text superimposed on the video; and a library of filters and video-distorting effects.

Other users can leave comments on each tiktok, including comment threads which the creator can choose to endorse. The bottom of the screen contains information about the "sound" the tiktok uses, which can either be user-uploaded or chosen from a library of popular sounds.

Upon opening the app, the user encounters a tiktok that starts playing; this is the "For You Page," which plays tiktoks that TikTok's algorithm recommends for that user. To go to the next tiktok, the user swipes up. To see the account which uploaded the current tiktok, swipe right. The user's profile is spare, with a brief bio and the catalogue of that user's previously uploaded tiktoks. The metrics for the account include well-known follower and following numbers, but introduce a new metric that reflects the relative unimportance of "following" on TikTok: the total number of "likes" that user has received across all of their tiktoks. The presence of this metric also discourages users from deleting their old tiktoks, as is now common practice on Twitter and Instagram.

2.1 Who Uses TikTok?

The rapid expansion of TikTok means that there is limited information about the platform's user base. The best hard data comes from the company's August 24, 2020 lawsuit filed against the Trump administration.

In January 2018, TikTok had approximately 11 million Monthly Active Users (MAUs are a standard metric for social media platforms). By June 2020, that number was 92 million MAUs.[3] However, many of these users are unlikely to be politically active; according to internal company data reviewed by the *New York Times*, approximately

[2]The platform also allows users to create tiktoks that are longer than 60 seconds if they use video uploaded from another source. This seems to be a rare practice.

[3]It bears mention that TikTok's global userbase is far larger: it grew from 55 million MAUs to 689 million MAUs in that same time period. These figures do not include any users in China, where Bytedance operates TikTok's sister company Douyin.

a third of their US userbase is under fifteen years old. Among adult users, there is a similar trend of the over-representation of young people.

3 Affordances of TikTok

Social scientists have accumulated a wealth of knowledge about political communication on social media. We apply this knowledge to understand TikTok not as an entirely novel platform but rather as an continuation of earlier developments in social media.

TikTok represents the synthesis of three powerful trends in social media: the *televisual medium* that has always been the most broadly popular and powerful; *algorithmic recommendation* that structures the user's experience to a greater extent than any major social media platform to date; and a *mobile-only* interface designed to take advantage of a smartphone's user-facing camera.

The primary format for the political tiktoks we describe is the vlog, in which the creator's bedroom is visible and they look into the camera and either dance or emote in combination with music or superimposed textual images.[4] This represents an extension of the credibility-via-relatability described by Lewis (2020), Abidin (2018) and other theorists of "influencers" or "micro-celebrities." The point is for the creator to communicate a "mood" or "vibe" that signals to the audience that they should take the creator seriously.

Our clear difficulty in explaining this format in words reflects the relative paucity of information that can be conveyed in the textual medium, or alternatively, the information density of a single tiktok.

For all of our hypothesis, we require a comparison to another platform. There are arguments for several, and ultimately we advocate for comparisons across all of them. For now, we use YouTube videos. The necessary metadata is tractable to collect, and the fact that YouTube and TikTok share the crucial televisual medium allows us to hold that affordance constant while varying the rest. Still, the platforms differ in many ways outside the scope of this analysis, and despite our best efforts, the sampling frames we use for each platform are not identical. Our empirical tests are thus not intended as the final word on TikTok, but the first step towards a necessary cross-platform analysis. In particular, there is a glaring absence of data from Instagram, which would be a useful

[4] One crucial component of TikTok's explosive growth is the global pandemic that hit the US in March 2020. The dominance of the in-home, vlog style of tiktok is related to the inability to leave the home.

recombination of many of the affordances of interest; however, it remains difficult to scrape data from Instagram using the sampling frames we employ.

3.1 Ease of Posting, Algorithmic Rewards

Algorithmic recommendation is perhaps more central to the user's experience of TikTok than any other platform. Like YouTube (and unlike the primary functionality of Facebook and Twitter), the recommendation algorithm on TikTok can draw from the entire universe of tiktoks, not only ones created or shared by an account the user has "followed" or "liked." One feature of any social media feed in environments of content abundance is the necessity of sorting to determine the order in which pieces of content are shown to the consumer, and thus ultimately (given a fixed time period) which pieces of content are viewed at all. TikTok's user interface centers recommendations (on the "For You Page") to a far greater degree than other platforms by rendering its internal architecture more opaque.

This opacity also makes it difficult for researchers to collect data about how the algorithm operates in terms of what kind of content is shown to whom; a major concern about algorithmic curation on YouTube, for example, is that it increases viewership of extremist content and is thus a vector for far-right radicalization (Tufekci, 2018).

The present paper cannot speak to this concern. Instead, we highlight the intersection of the recommendation algorithm with another major affordance: TikTok is primarily available as a mobile phone app, explicitly optimized for the front-facing, vertical-orientation camera that feels most natural for its mobile-native target audience. This camera style enhances the user's sense of immersion and social presence (Wang, 2020).

The combination of algorithmic recommendation and mobile-first design produces what we see as the most theoretically relevant aspect of TikTok from a content production standpoint: it lowers the barriers to entry and encourages a high number of viewers to become *posters*.

All social media networks have to solve the problem of the construction of a network. No one wants to post into the void, but others don't want to create a network tie with someone who never posts.

Facebook, LinkedIn and Snapchat aim to become essential for certain forms of social life, relying on users to import their own social networks to the platform. Twitter and Instagram relied on a similar strategy initially, but then developed the hashtag as a way for users with similar interests to find each other and create follower networks (Thorson et al., 2016). As the platforms have matured, this represents a significant barrier to entry for new users (unless they have a specific commercial interest or another source of fame), a particularly acute problem for Twitter's recent growth in the US market. YouTube is distinct in that it has a huge ratio of media producers to consumers, allowing the platform to create different affordances for producers (Caplan and Gillespie, 2020).

TikTok tries to short-circuit this process by guaranteeing an audience for every post. When the user first downloads and opens the app, a tiktok starts playing immediately. The default feed is the "For You Page," which will continue to provide new videos based on the extent to which the user engaged with previous recommendations. Part of this process involves recommending videos with extremely few views.

The tiktok-production also includes a variety of menus with audio and visual effects that enable the user to create novel kinds of videos with minimal effort. This mimics Instagram's strategy for kickstarting early growth: provide users with "filters" that make their photos look cooler. Each tiktok also has a "sound" (discussed in more detail below), allowing the user to participate in popular meme formats.

Our prediction, then, is that more TikTok users will also be *posters*. Empirically, it is difficult to pin down the denominator; it is almost impossible to measure how many people without accounts are watching these videos. One plausible restriction is to only the people who leave comments on other peoples' videos. Each of these has a unique id that can matched to a user profile (or channel); the vast majority never uploads any videos, but we argue that variation in this ratio across platforms is one implication of the theory above.

H1: Among accounts that leave comments, the percentage who also upload videos will be larger on TikTok than YouTube

More insidiously, the centrality of the algorithm disrupts one of the most fundamental laws of political media: audiences have always been *stocks*, not *flows*. Matthew Hindman has done the best work on this topic, first in the context of the blogosphere in Hindman (2008) and then on all web traffic, in Hindman (2018). Two trends in online audiences re-occur, approaching the status of social scientific laws: web traffic is distributed according to a power law, and The behavioral micro-foundation of these "laws" is user habit. The web offers unfathomable consumer choice, ironically heightening our dependence on heuristics and habits. Social networks based on "following" other entities (which are then algorithmically sorted according to the accounts we interact with most often) wear the grooves of user habit ever deeper, but these patterns were discernable in the mid-2000s when readers retraced their steps to visit the same handful of blogs and news websites.

The "For You Page" supplants "following" behavior entirely. Tiktoks simply appear on the screen, granting the platform incredible power in determining the fate of a given tiktok, whether it goes viral or "flops."

The fickleness of virality in contexts with algorithmic recommendation is well-established. Early web-native media companies like Upworthy relied on viral Facebook posts to distribute their articles. Their strategy was to optimize for *shareability*, relying on human endorsements to increase their visibility. They then saw their readership decimated by Facebook's algorithm changes in 2014 (Munger, 2020). Facebook's network-based model could merely change the "rank" a given post would appear in the user's NewsFeed, but TikTok can go farther: at every point in every user's "For You Page," they can choose from any of the trillions of tiktoks on their servers.

We still don't know much about how users interact with the app—how many people use it without following anyone, looking only at the purely algorithmic "For You Page," and how many people use the more traditional "Accounts you Follow" option. One article, citing a private presentation given by TikTok, claimed that 69% of the time users spend on the platform is on the "For You Page," making it the default consumption choice (Stokel-Walker, 2020).

Many of the users of the platform are keenly aware of the metrics of their popularity, and pay close attention to how each of their videos performs. This is an equalizing force for new or unpopular accounts: even without cultivating any following whatsoever, every tiktok is seen by *someone*. If they engage with it at all (a lower bar than retweeting on Twitter, the only other platform where this virality-from-nowhere is possible), it is shown to more people. TikTok thus bundles content production and distribution more tightly than any other non-textual platform.

H2: The relationship between followers and average video views is weaker for TikTok than YouTube.

The combination of the complete opacity of the algorithm and the ease of posting means that there is an unbelievable range of tiktoks that might appear while scrolling the "For You Page." Many of these videos are similar, iterations of the latest trend. Unlike retweets or social endorsements like play counts (already a fickle mapping from quality to success (Salganik, Dodds, and Watts, 2006)), the passive nature of engagement on TikTok gives the app unprecedented discretion over the ultimate popularity of many roughly similar tiktoks.

That is, every tiktok has a chance to go viral—mimicking the logic of variable rewards that BF Skinner found to be the most effective schedule for operant conditioning. This insight has long been used by designers of machine gambling devices to optimize their slot machines for addiction (Schüll, 2014), and has more recently been applied to video game "loot boxes" (where rewards for achievements take the form of a random prize), which have also been shown to have an addictive quality (Drummond and Sauer, 2018).

Although there is no conclusive evidence that posting tiktoks is addictive, the company seems to admit that watching them may be. The app shows a "public service announcement" from the account *tiktoktips* when a user has been scrolling the "For You Page" for over 90 minutes.

There does exist something of a cargo cult of "the algorithm." It is commonplace for tiktoks to be captioned that the user has been "shadowbanned" (their content is not being shown to others), and the phrase "don't let this flop" evinces the anxiety and desire for viewership that accompanies each upload.

The importance of the algorithm can be estimated from the variance in the viewership numbers for tiktoks created by a single user. The old model of the web, based on audience habits, implies that audiences are largely stable across time; a newspaper based on subscriptions is an antiquated and strong example, but the principle for follower- or subscriber-based social media is similar.

Specifically, we predict that the inequality for TikTok views will be larger than for YouTube. Ignoring the full distribution, the prediction is about the behavior of the *most viral* tiktok per account.

H3: The inequality of viewership for a single accounts' videos will be higher on TikTok than on YouTube.

4 Data

4.1 TikTok API

Unlike social media platforms like Twitter and YouTube, TikTok does not provide an official API to share data on TikTok users and their behavior. However, their mobile application uses an internal API to retrieve data when in use. To access this private API, queries simulating browsing traffic can retrieve any information that is available to a normal user: video content, video descriptions, audio files, comments and engagement numbers like such as the number of likes and views. This API offers several different endpoints, but we focus here on the two endpoints that return the full population for a given query: User and Comments.

Given a user id, the User endpoint provides data on each tiktok produced by this user. This user history as accessed through the User endpoint is a complete snapshot of the account. Only tiktoks removed by the user are not returned by the API. The Comment endpoint functions analogously, returning all of the comments left on a certain tiktok given its tiktok id.

These two endpoints can be combined to deploy a snowball sampling procedure that is made credible by the fact that they each return the entire population. In contrast, the Hashtag endpoint returns up to 2,000 tiktoks using a given hashtag but lacks any information on sampling criteria. In addition to the absence of sample bias, these two endpoints represent efficient methods to quickly obtain large amount of data.

4.2 Snowball Sampling

The objective of this paper is to understand how the affordances of TikTok structure the dynamics of political discussion on the platform: how many people create political videos, how densely attention is concentrated across those videos, and how important follower networks are for the structure of that attention. In the absence of a comprehensive list of all political tiktok accounts (and acknowledging that such a list is likely impossible), we use snowball sampling to iteratively discover new political accounts. We adopt here a broad definition of political content, which includes both normative stances on society ("reducing wealth redistribution inequality", "abortion is a crime" or "LTGBTQ+ rights must be protected") as well as comments on daily politics (with topics such as the "2020 US election", "BlackLivesMatter" (BLM) or "policies mitigating the COVID-19 pandemic"). Religious groups are one big community on TikTok an they frequently mentioned keywords vaguely related to politics, but religious content unrelated to politics was coded as non-political. We define a TikTok account as political if at least 70% of produced content of the given user is political. Any threshold here is of course somewhat arbitrary but we chose this line because it focuses on people that reliably produce political content and excludes accounts that just occasionally post content that could be considered as political. For instance, following the BLM demonstrations in the summer 2020, many users produced content supporting or opposing the demonstrations during the summer and turned back to their usual non-political content afterwards. Using a 70% threshold helps to exclude these users from the sample.

We first identified 865 accounts focused on political topics through the use of the Hashtag endpoint, searching for standard terms in 2020 US politics like "#politics", "#MAGA", and "#democrats." After collecting the 272,546 tiktoks produced by this initial sample, we use two criteria to identify potentially political accounts. Accounts who were either (1) frequently mentioned - within duets or with a direct address in the video description - in this initial sample; or (2) frequently commenting on this videos in this initial sample, were 'qualified' for data collection. The assumption here is that accounts mentioned by or interacting a lot with political contents are likely to be political themselves. One advantage of this approach is that we capture content producers as well as content consumers "active" enough to leave a comment. Using this method, we could identify more than 200,000 distinct accounts.

Once "potentially political" accounts were collected, we selected the most active accounts and labeled ,100 additional accounts[5]. Combined with the original set of accounts, we obtained a sample of 1,999 accounts, which was big enough to train a classifier and generalise our hand-coding to the 200,000 potentially political accounts.

We then classified the content they produced and eventually confirmed their focus on politics. To do so, we trained a neural network to predict whether a tiktok is political based on its description. Neural networks are powerful predicting tools, especially for text classification tasks (Chang and Masterson, 2020). We used a simple network with one hidden layer with 100 units trained on a document-term matrix (vocabulary 15,000). Neural networks can efficiently model large amount of high-dimensional data. Hence, we do not need to preprocess the text (no vocabulary pruning, no stemming, no lemmatizing), which increases the amount of information provided to the model and the reproducibility of the classification. This is especially useful in cases like short-form social media, where much of the "text" is not intended to function like standard written English.

As mentioned earlier, our training sample is made up by 1,999 hand-coded accounts (1,182 political and 817 non-political). In total, these accounts produced 934,226 tiktoks (406,315 political and 527,911 non-political). Because we use text-classification, we discarded videos with less than 3-word descriptions - 28% - and used the resulting 672,660 videos (345,856 political and 326,804 non-political) to train a neural network. 80% of the accounts were used for training, while 20% were kept aside for validation

[5]Most of the accounts were coded by at least by two different coders. Inter-Coder Reliability was 0.87.

purposes. Although the prediction happens at the tiktok level, we split and validate at the measurement level (user): for each user we average the individual predictions and consider the resulting average political probability of a user. Users with an average political probability higher than 50% were labeled as political and retained in the final dataset. The model achieved a prediction accuracy of 74% at the individual level and 83% at the user level (recall is 81% and precision is 87%).

Using the classifier, we predicted the 22,000 000 potentially political tiktoks and identified 11,597 political accounts, which produced 2,026,506 videos.

4.3 YouTube Dataset

In order to understand how TikTok is used in light of the structure of the platform, we use an analogous dataset from YouTube as a benchmark. YouTube shares many affordances of Tiktok: it is a televisual medium, which use algorithmic recommendation to help its users navigate the content. The most noticeable difference lies in the length of the videos (longer on YouTube) and the prevalence of channel subscription (unlike for TikTok, it is very common to pre-select content producers on Youtube by subscribing to their channel). So, in the space of affordances of interest for our analysis, these platforms are the most similar, and there is a wealth of academic experience collecting and modelling YouTube data from which we can draw.

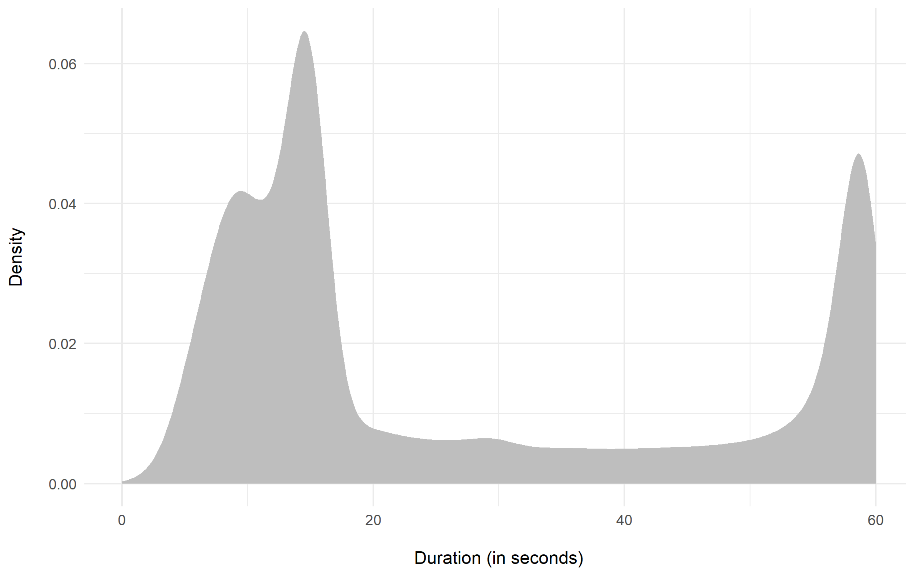
The YouTube dataset was constructed as part of a parallel project attempting to identify the universe of large political YouTube accounts. This effort was far less novel, and the presence of prior research allowed us to begin the process with a large collection of accounts. The final dataset combines the channels identified by REDACTED with an analogous snowball sampling based on the transcripts of the videos (if other accounts are mentioned) and the accounts recommended by the YouTube algorithm.

The YouTube dataset consists of 1,712 political channels (2,000 for TikTok), which produced an average of 700 videos each. Data was collected in May 2020 and entails both account-specific metrics (number of subscribers, number of videos, total number of views) as well as video-specific metrics (views and comments). In total, it includes just over about 1,000,000 YouTube videos with a total of more than 300,000,000 comments.[6]

Although our sampling frames for the two platforms are thus broadly similar, they are not identical — and even if the process we followed were the same, the way that

[6]Interestingly, the videos in the two datasets gathered a similar amount of comments (400 comments/video for YouTube and 350 comments/video for TikTok).

Figure 1: TikTok Duration



process interacted with each platform would be different. As a result, the results are presented alongside bootstrapped samples for each platform, providing evidence that our empirical tests are robust to the construction of the sample.

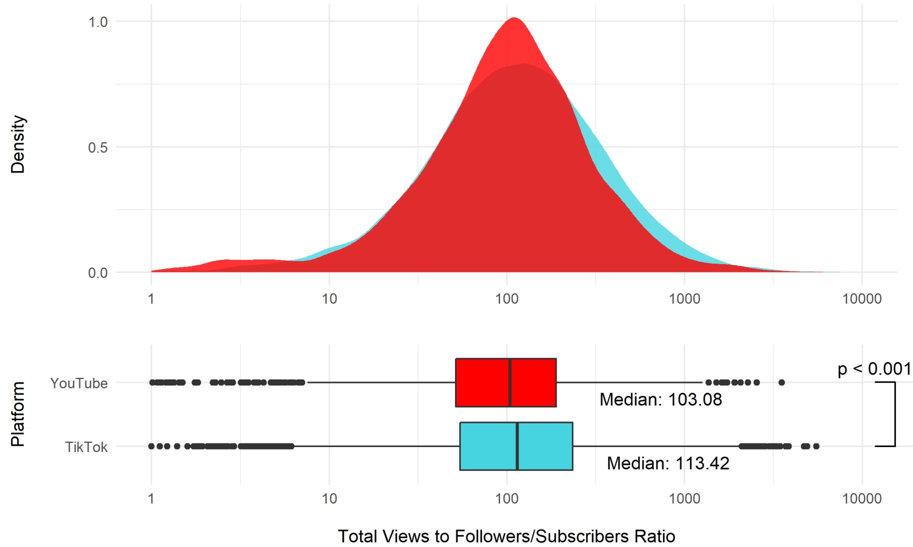
5 Results

5.1 Description

One key feature of our data that has not, to our knowledge, been demonstrated elsewhere is the distribution of the duration of tiktoks. Formally constrained to be one minute or less, the empirical distribution displays a striking bi-modality, suggesting that there are at least two distinct genres of political tiktok in terms of their narrative structure. Figure 1 shows that the majority (57.55% of tiktoks are between 5 and 20 seconds long, peaking at 15 seconds long. There are very few tiktoks between 18 and 55 seconds long, but there is another significant cluster at the very top of the distribution, peaking at 58 seconds long.

These results give important context for thinking about how tiktoks differ from YouTube videos that cannot be found in the formal constraints of each. However, there are related data point that we do not have access to: the duration a viewer has to spend on a given tiktok or YouTube video before the platform records this as a "view,"

Figure 2: Higher Views to Followers Ratio on TikTok

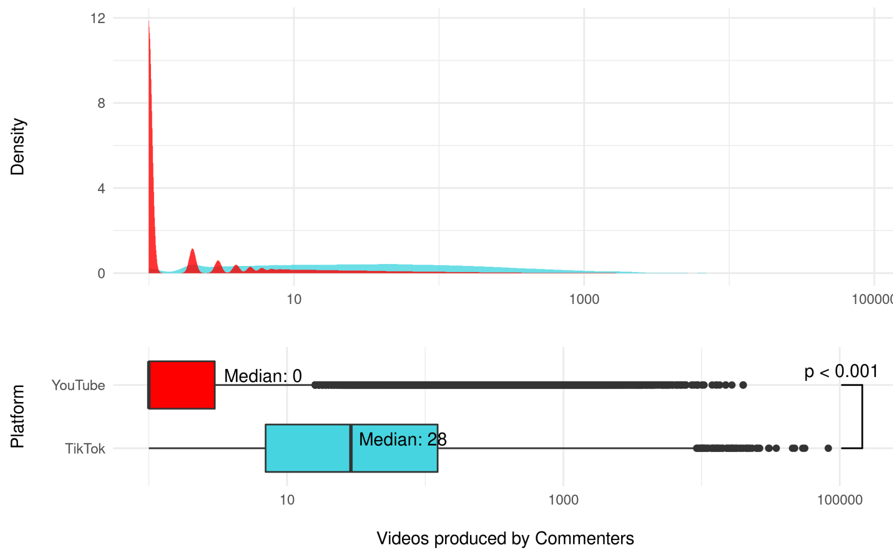


and the way the platforms treat repeat viewership of a given video. The latter is an especially important facet of TikTok, given the possibility of looping a single video over and over again. We thus use the number of views per video reported by the platforms' APIs in our analysis, but highlight this potential limitation.

Figure 2 displays evidence that serves as a face validity check of our data: the ratio of views to followers is higher on TikTok than YouTube. We present all of the following results in the same format: the data for YouTube are shown in red and TikTok in blue, with the shade of each color matching the color of the respective company's logo. Here, each observation is an account that uploads videos. The statistic of interest is the ratio of the total number of views on all videos uploaded by an account to the number of followers/subscribers that account had at the time we scraped the data.

To account for outliers, we calculate the difference in medians of this statistic between TikTok (median = 113) and YouTube (median = 103) accounts. A Wilcoxon rank sum test indicates this difference is statistically significant and substantively meaningful, $W = 8375238, p < 0.001, r = 0.04, CI_{95\%}[0.02, 0.06]$. The distributions of the ratios are both roughly normally distributed, with the TikTok distribution shifted upwards, indicating that the total views to followers ratio is indeed higher on TikTok (although bootstrapped means for this metric shows a slight overlap between the 5th and 95th percentile of both distributions: 9).

Figure 3: More Commenters Also Create Videos on TikTok



5.2 Hypothesis Testing

We now use these datasets to test the theories we propose above. We calculate differences in statistical significance using non-parametric unpaired two-sample Wilcoxon rank sum tests for group differences and Fisher's 1925 z-test for correlation coefficient differences, implemented via the R package `cocor` (Diedenhofen and Musch, 2015). In addition, we used bootstrapping to investigate the sample sensitivity of our results. The bootstrapped results are obtained in the following way: for each platform we sample 20% of the posts for 500 iterations and for each iteration we take the mean of the metric of interest. We then compare the 5th and 95th percentile of the distributions for each platform, considering a result as robust if these "confidence intervals" do not overlap.

Figure 3 displays evidence supporting H1: among accounts that leave comments, the percentage who also upload videos is larger on TikTok than YouTube. Here, each observation is an account that left any positive number of comments on one of the videos in our data. Due to API cap restraints, we only collect information about the *number* of videos uploaded by these commenters, not their content.

The statistic of interest is the distribution of the number of videos uploaded by these commenters. These distributions are visibly distinct, with a much higher percentage of YouTube commenters never uploading a video. To give an intuition using an arbitrary threshold: on YouTube 18.47% of commenters created at least 5 videos compared to 78.05% of commenters on TikTok.

Figure 4: Bootstrapped Mean Commenter Videos per Platform

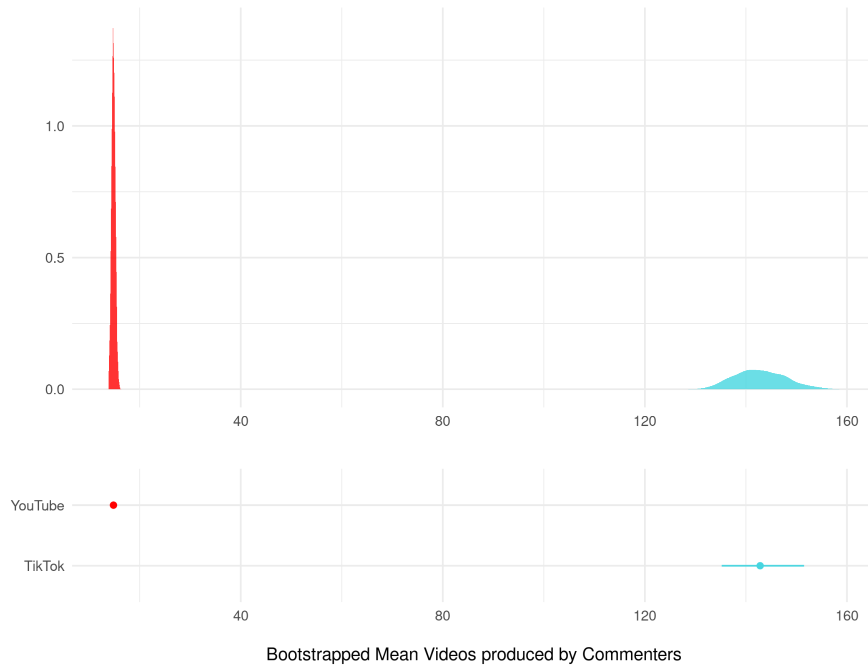


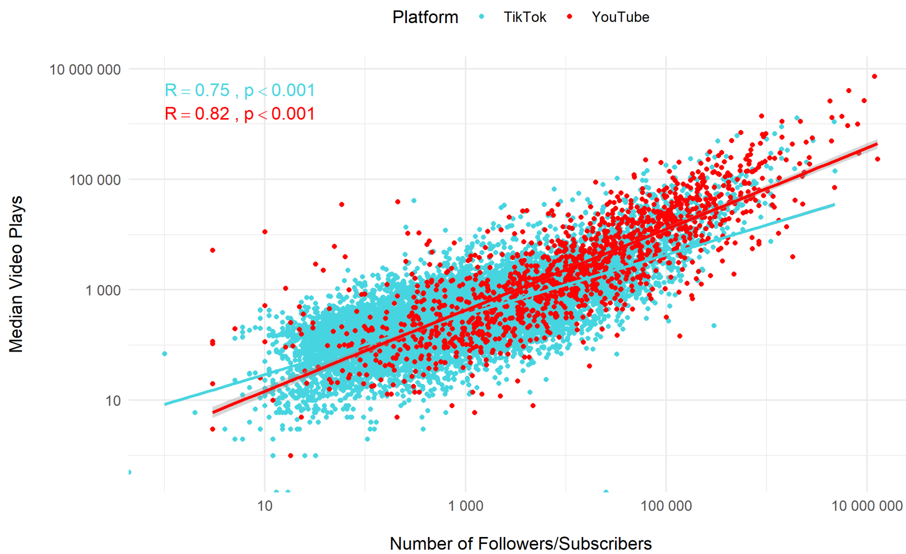
Figure 4 shows the bootstrapped means distribution of produced videos by commenters per platform. The huge gap between the two distributions and a non-overlapping 5th and 95th percentile confirm the previously noted pattern that commenters produce more videos on TikTok compared to YouTube.

Figure 5 displays evidence in support of H2: the relationship between followers and video views is weaker for TikTok. Here, each observation is an account that uploads videos. We run a log-log regression of the number of followers/subscribers each of these accounts had at the time we scraped the data on the median of the number of views on all videos uploaded by that account. In all cases, the subscriber/follower account is able to account for the majority of the variance in views. For YouTube, the R^2 is higher than for TikTok.

Reviewing the results in greater detail, we can observe that on TikTok a 1 percent increase in followers is associated with a 0.54 percent increase in median video plays per account on TikTok (b = 0.54, r = 0.75, $R^2 = 0.56$). In comparison, we can observe that on YouTube a 1 percent increase in subscribers is associated with a 0.73 percent increase in median video plays per account, showing that a follower yields more average video plays on YouTube than on TikTok (b = 0.73, r = 0.82, $R^2 = 0.67$).

Next, in order to test whether the higher correlation between followers/subscribers

Figure 5: Subscriber Count Explains More of the Variance in YouTube Views

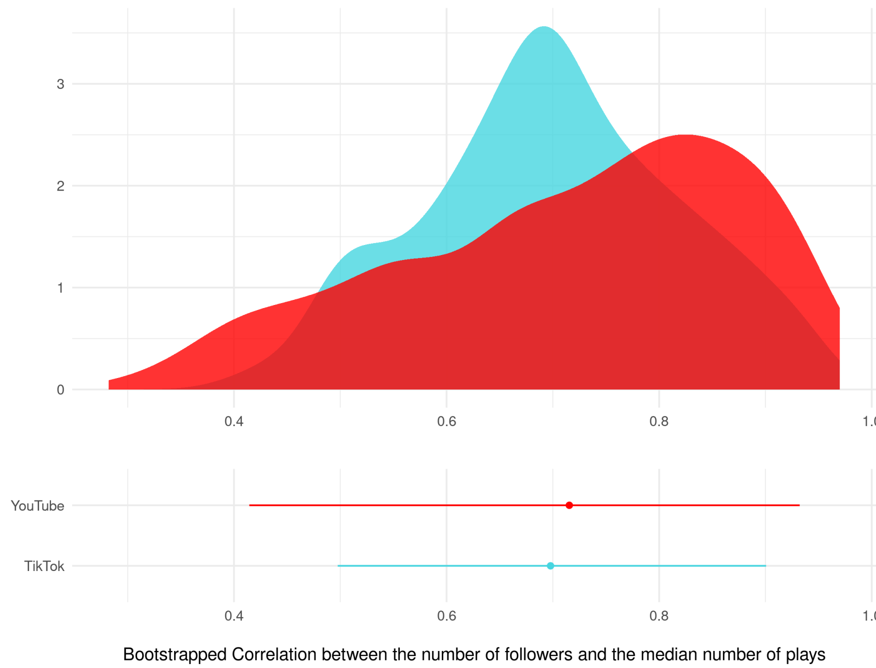


and average video plays on TikTok is statistically significantly, we use Fisher's 1925 z-test for correlation coefficient differences, implemented via the R package `cocor` (Diedenhofen and Musch, 2015). This is indeed what we find: the difference between the two correlations is statistically significant ($z = 6.55, p < .001, r_{MedianDiff} = 0.07, CI_{95\%}[0.05, 0.09]$). This confirms the relationship expected by H3, albeit the correlation difference is somewhat small (varying between r = 0.05 and 0.09).

In order to test whether this small difference is potentially an artifact of our sample, we calculate the bootstrapped results. Figure 5 shows that the mean correlation for YouTube is higher, as shown before. However, the 5th and 95th percentiles of both platforms overlap, which means this difference is not robust to permutations of our sample.

Finally, Figure 7 displays evidence that agrees with H3: the ratio of viewership for a single accounts' most popular video to their average video viewership is higher on TikTok than YouTube. Each observation is again an account that uploads videos. The statistic of interest is the ratio of the number of views on their most popular video to the median number of views their videos get. The distributions are similar in shape, but shifted upward for TikTok. The median value of the peak-median ratio is 64 for TikTok, meaning that the median accounts' most popular video has 64 as many views as their average (median) video. For YouTube, that number is only 40. A Wilcoxon rank sum test indicates the differences between the Peak-Median Play Ratio on the two platforms

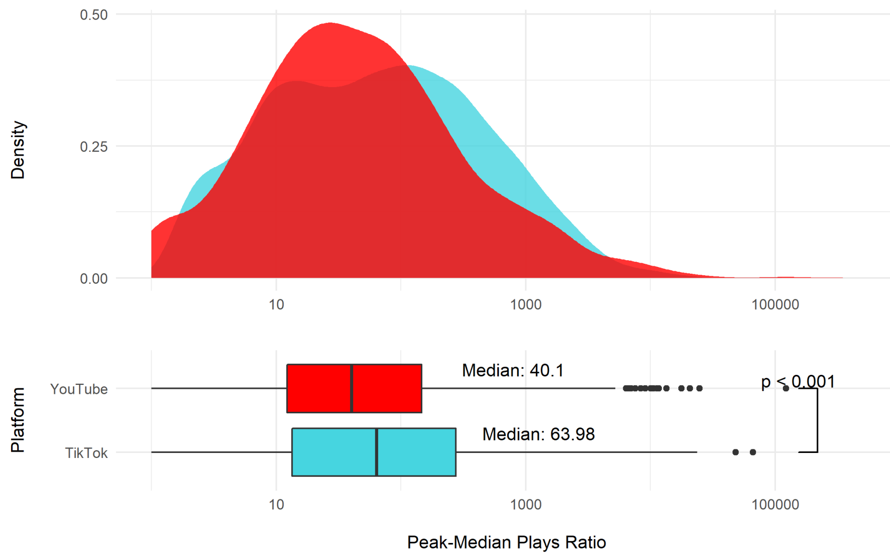
Figure 6: Bootstrapped Correlation between Subscribers and Video Views



are statistically significant, $W = 9048077, p < 0.001, r = 0.05, CI_{95\%}[0.04, 0.07]$. The results indicate that the Peak-Median Play Ratio is, as expected by H3, higher on TikTok.

As a robustness check to this relatively fragile estimator, the bottom panel of Figure 7 plots the Gini Coefficient for views for a given account. Checking the values for both platforms, the Gini Coefficient indicates severe inequality with a median of 0.62 for YouTube and a median of 0.70 for TikTok. A Wilcoxon rank sum test indicates the differences between the two platforms are statistically significant, $W = 6897485, p < 0.001, r = 0.09, CI_{95\%}[0.07, 0.11]$. The results indicate that the Gini Coefficient of views is higher on TikTok, meaning *greater inequality in the distribution of video views* as we would expect in H3. To illustrate the relation, we can also take a look at how many views per account are coming from which percentage of videos: on TikTok the top 20% of the videos rake in 75.76% of views whereas on YouTube the top 20% only get 72.52% of all views per account, on average (mean).

Figure 7: Peak-Median Views Ratio is Higher on TikTok



Gini Coefficient in Views are More Unequal on TikTok

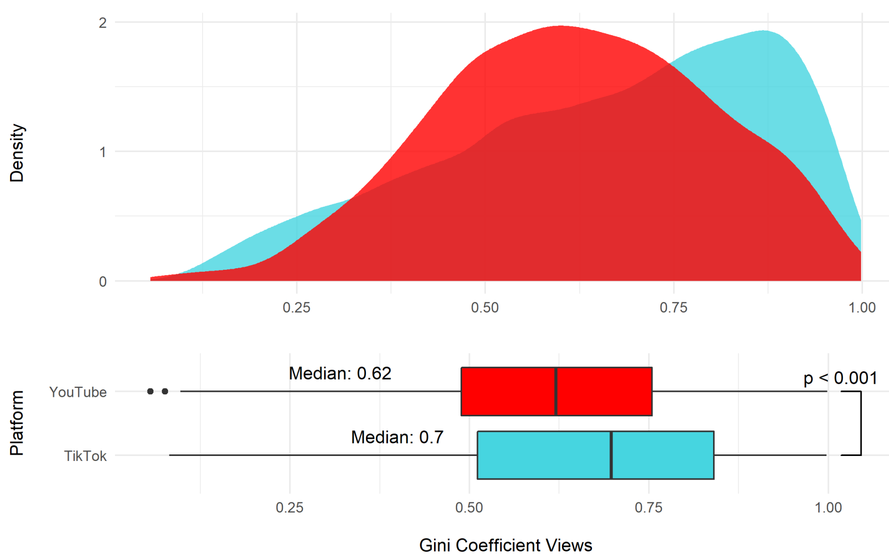
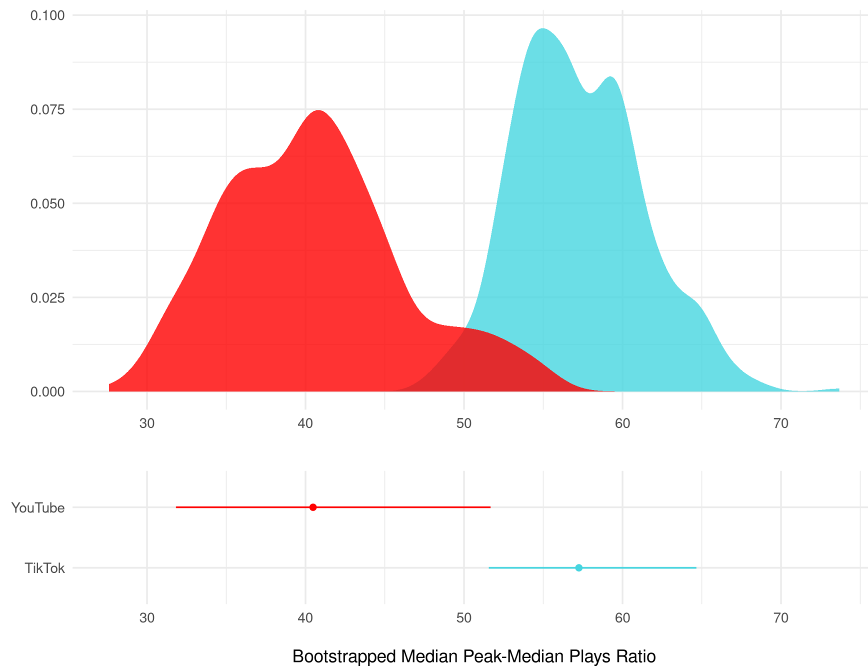
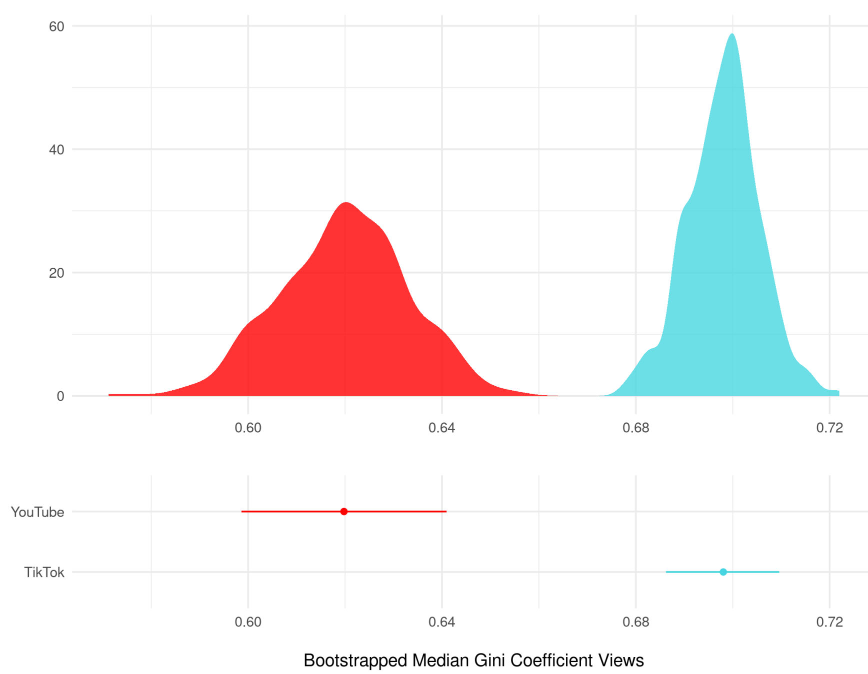


Figure 8 shows the bootstrapped mean values of peak-median views ratios and gini coefficients per platforms. The non-overlapping 5th and 95th boundaries between the two platforms suggests the evidence for H3 is robust to our sample construction.

Figure 8: Bootstrapped Peak-Median Views Ratios



Bootsrapped Mean Gini Coefficient



6 Conclusion

Both the history of broadcast media and present trends in usage rates suggest that video is the future of social media. YouTube is the current king of online video, and is the most popular social media platform among young people in the United States. TikTok offers certain affordances that have never before been combined into a single social media platform.

Snapchat pioneered mobile-first video editing technology and low-friction video production, but it is a fundamentally closed system that relies on users to curate their networks for video distribution. YouTube's recommendation algorithm allows it to show videos to people who have never opted into the creators of those videos, but the long-form nature of those videos and importance of community means that traditional networks are still very important. The synthesis of these two affordances makes TikTok a viral machine that everyone wants to participate in, without even needing to develop networks.

We demonstrate that these affordances have significantly shifted the incentives for and experience of video content creation, the importance of cultivating followers, and the distribution of video popularity for a given account. Through comparison of a dataset of political TikTok metadata with an analogous dataset from YouTube, we find support for each of our theoretically-driven hypotheses. Tiktoks have more views, on average, than do YouTube videos, and the distribution of these views are less easily modeled by looking at an accounts' follower/subscriber count; the latter finding, however, is dependent on the composition of our samples. The viral potential of TikTok is higher than YouTube, reflected in the former's higher peak-mean ratio of views and Gini Coefficient of views across a single account. Finally, TikTok is dramatically more successful in encouraging the majority of its users who leave comments to also produce videos, deepening and broadening this engaging behavior.

In the aggregate, these results inform our understanding of how the "supply side" of content on TikTok differs from other platforms. Social media platforms are created by their users; TikTok enables encourages more of their userbase to create televisual content aimed at a large, public audience than any previous platform.

More broadly, our experience in conducting this research suggests that TikTok is an unusually mercurial object of study. First, the platform has seen explosive growth during the 18 months of data we analyze, reflected in the aggregate number of videos produced and the rate at which they have been viewed.

This expansion of the userbase beyond the (still prominent) teenagers making dance videos has similarly led to an explosion in variance in *how* TikTok is used. For example, the prominent Black Lives Matter Protests in the summer of 2020 were reflected in both heated political discussions in the traditional form of bedroom vlogs as well as the kind of evidentiary protest videos more commonly associated with Twitter. TikTok leaves its fingerprint on the latter, as the sound library and advanced, accessible video editing software move beyond democratizing the capacity to produce journalistic video (which comes standard with the smartphone) to democratizing the capacity to produce slick, emotionally-resonant video previously reserved to advertisers, large film studios and established propagandists.

Another example is the migration of established political media brands to the platform. Major political YouTubers have shifted to TikTok, suggesting that political discourse will soon become increasingly professionalized. In tandem, fringe or conspiratorial viewpoints have flourished, and while TikTok has been comparatively aggressive in its stance towards this content, its rapid growth means that it lacks the organizational capacity of more established platforms. Furthermore, the same frictionlessness that has enabled its rapid growth and which entices so many different individuals to upload videos has proven to be a vector for attacks: in September 2020, a coordinated group uploaded thousands of minorly edited versions of a suicide. TikTok's ease of account creation and the auto-play video feed made its users more vulnerable to accidental exposure than other platforms.

And these developments pale in comparison to the geopolitical background of the company, which in fall 2020 was involved in one of the highest-profile US government interventions in the brief but momentous history of social media. At the time of writing, TikTok sued to government to delay the effect of an executive order that would have prevented further downloads of the app. Although a deal appears to have been secured, the company's Chinese origins seem likely to persist in political discourse.

This ephemerality is why we have chosen to study the platform through the theoretical lens of affordances and to focus on the structure of content production. TikTok may be the first platform to upend the social media establishment by remixing and combining previously disparate affordances, but it will not be the last.

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7 Appendix

Figure 9: Bootstrapped Mean View to Follower Ratios