Audience Engagement and the Dynamics of Online Activism: Far-Right Mobilization on Facebook

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Forthcoming in *Mobilization*, please cite the published version

Far-right activists have recently used social media to attract audiences of unprecedented scale. This paper argues that this online popularity can be explained by processes endogenous to social media, specifically the role of audience engagement. A case study of the far-right, anti-Muslim group Britain First and its online activism on Facebook is used to test this theory. The relationship between audience engagement and Britain First's activity, recruitment, and support on Facebook is modeled using time series regression, controlling for other relevant factors, including protests, framing, and exogenous events. The results show that changes in audience engagement are associated with long-term shifts in online activism, resulting in feedback loops where engagement begets further engagement. The findings demonstrate how the incentive structures of social media platforms can enable and constrain contemporary activism and how activists can develop tactics to exploit these systems to their advantage.

Acknowledgements: An earlier version of this work was presented at the 2019 American Sociological Association Annual Meeting. I thank Mabel Berezin, Peter Enns, Filiz Garip, Sang Lee, Michael Macy, Paul McLean, Barum Park, Emily Parker, and Hana Shepherd for their comments and suggestions.

Supplemental materials: The Online Appendix is available at https://osf.io/cq5ye/. Replication data and code are available at https://github.com/t-davidson/audience-engagement-replication.

Social movements across the political spectrum routinely use social media platforms to develop collective identities and shared grievances, organize collective action, and attract recruits (Budak and Watts 2015; Earl 2010; González-Bailón, Borge-Holthoefer, Rivero, and Moreno 2011). A decade ago, platforms like Twitter and Facebook appeared to be the bedfellows of progressive social change (Castells 2012; Gerbaudo 2012), but far-right social movements and political parties have recently amassed some of the largest audiences on social media across a variety of contexts (Blassnig, Ernst, Engesser, and Esser 2019; Davidson and Berezin 2018; Stier, Posch, Bleier, and Strohmaier 2017). What explains the remarkable success of the far-right on social media? Unlike progressive, left-wing online activism, which typically coincides with large-scale protests (Bastos, Mercea, and Charpentier 2015; Freelon, Marwick, and Kreiss 2020), right-wing activism on social media is largely decoupled from offline collective action. Instead, recent scholarship draws attention to the manipulation of online information ecosystems, highlighting how far-right actors focus less on organizing and more on sharing information and evangelizing for their cause, efforts that Jen Schradie (2019) terms "informationalizing." To this end, right-wing actors have developed an alternative media ecosystem and used social media platforms to promote extreme, sensationalistic content and conspiracy theories (Benkler, Faris, and Roberts 2018; Freelon et al. 2020).

I build upon these observations by drawing attention to mechanisms *endogenous* to social media that may help explain the online successes of the far right. Activists receive feedback on social media platforms such as "likes," "comments," and "shares," known as engagements, which provide insights into what resonates with online audiences (Karpf 2016). Moreover, engagements can beget further engagements through classical and algorithmically-mediated diffusion processes, helping to sustain and expand online activism. Digitally savvy activists can optimize their campaigns by attempting to reverse-engineer the ranking and recommendation algorithms used by social media platforms to identify the most effective kinds of appeals (Tufekci 2018). All kinds of activists must work within these systems to compete for attention on social media, but right-wing actors appear to be particularly adept at exploiting these mechanisms (Freelon et al. 2020) and may have systematic advantages due to the incentive structures of major platforms (Huszár, Ktena, O'Brien, Belli, Schlaikjer, and Hardt 2022).

To assess the degree to which audience engagement impacts online activism, I conduct a quantitative case study of Britain First (BF), a far-right social movement founded in 2011 to campaign against the purported threat posed by Islam to Britain and its Christian heritage (Allen 2014). I focus on the period from 2014-2017 when BF's activism and support peaked. BF organized dozens of street protests and conducted a series of provocative direct actions against Muslim communities, including so-called "mosque invasions" and "Christian patrols." The group used social media, particularly Facebook, to publicize these activities and disseminate anti-Muslim content. BF frequently shared content known as "engagement bait," material explicitly calling for users to engage, such as a picture of Queen Elizabeth II accompanied by the statement "SHARE and LIKE if you love your Queen and Country." While the group rarely attracted more than a few hundred supporters to its protests, it built a large following on Facebook, attracting over two million followers, the largest online audience of any political organization in the country (Davidson and Berezin 2018).

I use digital trace data from Facebook to analyze the relationship between audience engagement and online activism. Specifically, I examine BF's activity, its recruitment of new social media users, and its ability to sustain the attention of its existing supporters. These relationships are analyzed over three years using time series regression, controlling for several factors that may explain variation in online activism, including framing, events, and media coverage. Error-correction models are used to account for the temporal structure of the data (De Boef and Keele 2008; Philips 2018) and to identify dynamic equilibria between time series, known as cointegration (Engle and Granger 1987). Often neglected or treated as a statistical nuisance, the temporal properties of these processes provide critical theoretical insights into the dynamics of online activism.

The results show strong evidence of feedback loops between social movement activity and audience engagement: BF was more active when Facebook users liked its posts; more new users liked BF's posts when its content was commented on and shared more frequently; and its existing supporters also increased their participation in response to shares. The framing used in BF's posts, measured using structural topic modeling, did not directly impact these processes, but additional analyses show that engagement bait was effective and that issues including Islam, immigration, and the military tended to attract higher engagement rates. I also find evidence of associations between BF's street protests, elections, and right-wing terrorism on these dynamics, while media coverage had little discernable impact. Overall, I conclude that changes in BF's activity, support, and recruitment were largely endogenous to social media.

These results highlight the centrality of audience engagement to contemporary online activism. By attracting online engagement, activists can disseminate their messages to a vast audience, even without substantial or sustained offline mobilization. Resourceful activists can game the incentive structures of social media platforms to attract further engagement and sustain attention. However, social movements dependent on the opportunities afforded by social media platforms are vulnerable to de-platforming or changes to how platforms operate. In this case, BF's support collapsed once it was banned from Facebook and other major social media platforms. The study concludes by reflecting on the implications of these findings for other social movements and directions for further research on the relationship between activists, audiences, and algorithms.

ONLINE ACTIVISM AND OFFLINE PROTEST

Charles Tilly (2004) famously argued that one of the primary goals of a social movement is to show the *number* of people that support it—along with the worthiness of their claims, their unity around a common goal, and their shared commitment to achieving that goal. Social media constitute a valuable resource in this respect, enabling activists to rapidly reach large numbers of people at low-cost (Earl and Kimport 2011; Eltantawy and Wiest 2011). Moreover, social media platforms render the numeric dimension of activism highly visible, showing the precise number of people who have decided to "like" a Facebook page, "follow" a Twitter account, or "share" or "retweet" a particular item of content. Far-right movements and parties have been particularly successful in this respect, attracting considerably larger online audiences than other political actors across various contexts (Blassnig et al. 2019; Davidson and Berezin 2018; Stier et al. 2017).

Prior work emphasizes the linkage between offline protest and online activism, identifying a symbiotic relationship where offline protest increases engagement from online audiences, which can, in turn, stimulate further offline participation (Bastos et al. 2015; Budak and Watts 2015; Tufekci and Wilson 2012; Vasi and Suh 2016). Far-right protests have recently attracted extensive media attention, and some events have attracted tens of thousands of attendees, like anti-immigrant marches organized by PEGIDA in Germany (Rucht 2018), the Unite the Right march in Charlottesville in 2017 (Andrews, Caren, and Browne 2018), and the riot at the US Capitol on January 6, 2020. However, these events are outliers, as the number of attendees at most right-wing protests is typically small, paling in comparison to the mass mobilizations organized by progressive movements (Andrews et al. 2018; Heaney 2018), and field experiments show lower commitment to protest attendance on the right (Hager, Hensel, Hermle, and Roth 2022). Given the relative dearth of large-scale protests, how have far-right social movements generated such large audiences on social media?

AUDIENCE ENGAGEMENT AND THE DYNAMICS OF ONLINE ACTIVISM

I argue that mechanisms endogenous to social media enable activists to build online support without concomitant offline mobilization and thus explain the online success of the far-right. Specifically, I highlight the importance of audience engagement, which is fundamental to the infrastructure of contemporary social media platforms. Engagement can help generate, sustain, and expand online activism via two related mechanisms. First, engagement begets further engagement via social influence. For example, if a Facebook user "likes," "shares," or "comments" on a post, this information will likely be conveyed to some of their Facebook "friends." These friends see the original post and their friend's endorsement. Social endorsements can enhance the credibility of a message, making it more likely that people will engage with content, and have been shown to impact political participation (Bond, Fariss, Jones, Kramer, Marlow, Settle, and Fowler 2012). This social influence mechanism allows information to flow through online social networks in a classical diffusion process (Strang and Soule 1998). While the capacity for information to diffuse rapidly and widely on social media has been extensively studied by scholars of social movements (Bennett and Segerberg 2012; Earl 2010; González-Bailón, Borge-Holthoefer, and Moreno 2013; Vasi and Suh 2016), a second type of diffusion mechanism has become central to the way most prominent social media platforms function but has received far less attention.

Social media platforms increasingly use algorithms to automatically curate content shown to social media users, sifting through vast quantities of data to identify the content considered most relevant, thus sustaining users' attention and maximizing advertising revenue (DiResta 2018; Tufekci 2018). One of the easiest ways to do this is to promote content other people engage with. Engagement-based ranking and recommendation algorithms *amplify* diffusion processes by positively selecting and promoting popular content or content predicted to attract engagements (Eckles 2021). Such systems can produce vast inequalities in popularity and rich-get-richer dynamics as initial successes congeal into cumulative advantages (Salganik, Dodds, and Watts 2006). The main difference between classical and algorithmically-mediated diffusion processes is scale, as algorithms can prioritize content and spread it more widely. In both cases, activists can benefit from the resulting feedback loops as engagement begets further engagement. In practice, it is difficult to observe the intervention of the algorithms used by social media platforms (Pasquale 2015), and the two types of diffusion processes are intrinsically related. For example, a diffusion process can begin as person-to-person transmission before attracting algorithmic amplification, and material promoted by the algorithm can continue to diffuse via social interactions. Therefore, I assume that both kinds of diffusion occur and focus on the outcome, the level of audience engagement, which can be readily observed from digital trace data (Golder and Macy 2014).

Social media platforms can help or hinder collective action by controlling whether certain information becomes visible to online audiences, shaping "the opportunity structure for social movement organizations" (Karpf 2016: 25). For example, Twitter was accused of censorship when the #occupywallstreet hashtag did not appear in the platform's "Trending" topics section, despite widespread awareness of the protests, leading the company to explain that the usage of the hashtag had not met the criteria used by the trending algorithm (Gillespie 2012). Similarly, Facebook posts about police brutality and racism in Ferguson, Missouri, were initially overshadowed by the concurrent Ice Bucket Challenge, which was widely promoted by Facebook's recommendation algorithms due to high positive engagement (Tufekci 2018).

While platforms can impose constraints, it is crucial to avoid technological determinism (Winner 1980). Zeynep Tufekci (2018) argues that success on social media requires activists to "reverse-engineer" the ranking and recommendation systems to identify the most effective kinds of framing and appeals. The low cost of digital communication and real-time audience feedback enables activists to quickly test many different messages to determine what works through a trial-and-error process (Schradie 2019), and more sophisticated actors engage in what David Karpf (2016) calls "analytic activism," systematically testing a range of different messages to optimize their efforts. For example, activists in India used WhatsApp to coordinate a strategic manipulation campaign on Twitter to get hashtags related to Narendra Modi and the Bharatiya Janata Party to trend on the platform during the 2019 election (Jakesch, Garimella, Eckles, and Naaman 2021). This constitutes a form of "gaming strategy" (Espeland and Sauder 2007), as activists attempt to optimize their outreach efforts and improve their ranking vis-à-vis all other actors competing for attention. Activists that identify how to capitalize upon online diffusion mechanisms have the potential to rapidly expand their online audiences and benefit from feedback loops.

While all actors seeking to gain support online must grapple with the incentive structures of social media platforms, far-right activism presents an ideal case for exploring these mechanisms due to the demonstrated ability of these groups to rapidly attract large audiences without concomitant offline mobilization. Previous studies have found that right-wing activists tend to focus their efforts on communication and the manipulation of recommendation algorithms (Freelon et al. 2020; Schradie 2019), and recent evidence shows that these efforts may be paying off, as content produced by right-wing political groups is algorithmically-amplified on Facebook and Twitter (Huszár et al. 2022; Reuning, Whitesell, and Hannah 2022). Far-right activism is, therefore, a "most-likely" case (Beach and Pedersen 2018) to examine the relationship between audience engagement and online activism. In what follows, I assess the extent to which the online activism of far-right groups, including their ability to attract and sustain the attention of online audiences, can be attributed to processes endogenous to social media.

FRAMING, EVENTS, AND MEDIA COVERAGE

In addition to the literature on protests and online activism, existing research points to three factors that may explain variation in online support for the far-right: framing, events, and media coverage. These factors must be accounted for to isolate the effects of audience engagement. Frames are the interpretative schemas that activists use to highlight salient situations, events, and experiences to promote their cause and encourage participation (Snow and Benford 1988; Snow, Rochford, Worden, and Benford 1986). Prior work finds that some frames are more effective than others for attracting online participation, with evidence that confrontational language and calls for solidarity are most effective at attracting recruits to progressive causes (Gaby and Caren 2012). Framing may be particularly important for right-wing groups due to their tendency to focus on informationalizing (Schradie 2019). Indeed, Carsten Schwemmer (2021) finds that audience engagement on Facebook with the German PEGIDA movement was primarily a function of framing, with posts about Islam and alleged sexual assaults attracting particularly large numbers of comments. In contrast, posts about protests received far less engagement. More generally, mentions of out-groups are the most important predictor of engagement with U.S. politicians on both Facebook and Twitter (Rathje, Van Bavel, and van der Linden 2021), suggesting the negative, xenophobic appeals used by the far-right may be particularly effective at attracting audience engagement. The engagement metrics provided by social media platforms can also help facilitate frame alignment (Snow et al. 1986), as activists can use social media to test different kinds of framing and gauge the reactions from online audiences (Karpf 2016; Schradie 2019). Thus, to a certain extent, engagement can be considered a second-order effect of framing, making it essential to disentangle these processes empirically.

Social media platforms are not closed systems but must be situated within broader political opportunity structures. Exogenous factors enhance or inhibit mobilization efforts, influence strategic choices, and condition the potential impact of activism (McAdam [1982]2010; Kitschelt 1986; Meyer and Minkoff 2004). Events can modify these political opportunity structures, altering the potential for activism. There is evidence that far-right actors strategically respond to salient events by modifying their online behavior (Schwemmer 2021). I consider the role of two different classes of events relevant to contemporary far-right activism. Terrorist attacks are an ideal-typical example of an "unanticipated event" (Ostrom and Simon 1985) that have been shown to increase anti-immigrant sentiment (Frey 2022; Legewie 2013), providing discursive opportunities for far-right mobilization. Islamist terrorism has been associated with increased volumes of online hate speech (Czymara, Dochow-Sondershaus, Drouhot, Simsek, and Spörlein 2022; Williams and Burnap 2016) and far-right activity (Davidson 2013) and could explain some of the growth of far-right activism on social media. On the other hand, right-wing terrorism can dampen support for far-right groups. Survey evidence shows people shift their attitudes toward more moderate positions following right-wing terror attacks (Pickard, Efthyvoulou, and Bove 2023). In contrast, elections are routine, anticipated events and constitute significant opportunities to influence institutionalized politics (McAdam and Tarrow 2010). Far-right social movements—including the group considered in this paper—have mobilized online during elections to support right-wing populist political parties (Davidson and Berezin 2018; Stier et al. 2017). In the following analysis, I consider the impact of Islamist and far-right terrorism and national elections on the dynamics of online activism.

Media coverage renders some ideas "visible" and "legitimate," while others are marginalized or delegitimated (Ferree 2003; Koopmans and Olzak 2004). Mass media have traditionally played an important gatekeeping role, and favorable coverage has become a key strategic objective for many social movements (Gamson and Wolfsfeld 1993). Media attention can produce positive feedback loops by generating publicity that helps to sustain mobilization (Seguin 2016). Concerning the far-right, the empirical evidence is mixed, with findings that media attention can help or hinder (Koopmans and Muis 2009; Koopmans and Olzak 2004; Skocpol and Williamson 2012). Social media have arguably reduced social movements' dependence on mass media, enabling them to directly reach large audiences without any mediation (Caren, Andrews, and Lu 2020). Activists can quickly and easily produce and communicate textual and audiovisual content to their supporters. Right-wing actors appear particularly adept at this and are increasingly proliferating alternative media sources (Benkler et al. 2018; Freelon et al. 2020). In what follows, I control for each of these factors to isolate the effect of audience engagement on online activism.

CASE STUDY: BRITAIN FIRST AND FACEBOOK

This study examines Britain First (BF), a far-right, anti-Muslim social movement founded in 2011 that claimed to defend British people, culture, and values against the purported threats of Islamic extremism and sharia law (Allen 2014). BF organized dozens of marches against mosque construction and alleged child sexual exploitation by "grooming gangs." It also conducted so-called "mosque invasions," where activists entered mosques and harassed worshippers, and "Christian patrols," militaristic parades through neighborhoods in London with large Muslim populations. BF used several online platforms to promote its views, attract supporters, and raise funds, but Facebook was its most potent organizing tool (Davidson and Berezin 2018). While BF rarely drew more than a couple of hundred supporters to its protests and had at most several thousand dues-paying members,[1] it developed an enormous Facebook following, eventually amassing over two million followers. The group's ability to rapidly attract such a large online audience makes it an ideal case to examine.

BF used its Facebook page to share extreme anti-Muslim content, footage from protests, and an eclectic assortment of more innocuous, nationalistic imagery. **Figure 1** shows a sequence of images posted by BF in 2017. Note how more extreme material—two posts promoting protests against mosques and one supporting capital punishment—is interspersed with benign content evoking British identity and culture. Many of BF's posts included requests for social media users to engage with them by liking and sharing, such as "If this makes YOU proud to be British, please Like and Share!". Such content has since been characterized as "engagement bait" by Facebook, which considers these appeals as attempts to game the platform's News Feed algorithm to attract attention (Facebook 2017). A report published by a countermovement, Hope Not Hate, showed that BF's posts resonated with social media users, as millions of people engaged with its content, and some of its posts went "viral," spreading widely through the social network (Hope Not Hate 2014). The group boasted about its reach, declaring in September 2014 that its "Facebook page [was] seen by over 50 million people in the last 7 days—more than Labour, Conservative, and Lib-Dem combined!". By mid-2017, BF had accumulated more followers than any other political organization in the country. The subsequent analysis quantifies the group's online activity on

Facebook over three years of sustained mobilization to understand the extent to which its online activism, support, and recruitment can be explained by processes endogenous to social media.

DATA AND METHODOLOGY

Britain First's Facebook posts were collected using Facebook's Pages Application Programming Interface (API). Each post included the date and time, any associated text, and information on engagements. Three types of engagements were available to Facebook users at the time of data collection: "likes," which indicate agreement with a post; "comments," written directly in response to the post or other users' comments; and "shares," which allows users to relay the post to their networks. User identification numbers (UIDs) associated with these engagements are used to trace specific users over time (the API provided UIDs for likes and comments but not shares). BF was active on Facebook from October 2013 until March 2018, when it was banned from the platform. The group's activity was highly variable during the first several months and towards the end of its tenure on the platform (several periods had no activity due to enforcement actions by Facebook, such as temporary suspensions). Moreover, Facebook stopped providing UIDs in May 2017, making it impossible to define key variables. I therefore restrict the analyses to the three years from April 1st, 2014, until May 21st, 2017. The goal of this study is not to explain the entire *trajectory* of BF's career on Facebook but rather to understand the dynamics of its online activism during an extended period of online activity.

Dependent variables

Three dependent variables measure different aspects of BF's activism on Facebook: the group's activity, its supporters' engagement, and the recruitment of new supporters. Each is represented as a time series at the weekly level, as shown in the left column of **Figure 2**. The top-left panel shows BF's activity, defined as the number of posts published on the group's Facebook page each week. On average, BF posted 255 (SD = 98) times per week, equating to around thirty-six posts per day. The series exhibits an upwards trend, indicated by the dashed line, as BF increased the volume of content shared over time, similar to other far-right movements (Schwemmer 2021). I use this variable to assess how BF responded to audience engagement by varying its online activity. It is important to note that each post was not necessarily unique since the group often shared the same content multiple times. As such, this measure captures the general volume of activity rather than the rate at which the group produced and shared new content.

The remaining two dependent variables are derived from information on users who liked BF's posts. Likes are a relatively unambiguous measure of agreement, unlike comments, and provide a proxy for positive endorsement of BF's posts (Stier et al. 2017).[2] Any Facebook user who sees BF's posts can leave a like, so these engagements are not restricted to those who have decided to follow the group's page, and capture users who directly liked BF's posts by visiting the group's Facebook page as well as those who liked posts that appeared in their News Feeds due to their friends' interactions with the group. Following prior work, I measure recruitment by counting the number of new users who liked BF's content (Bail 2016; Gaby and Caren 2012; González-Bailón et al. 2011; Lewis, Gray, and Meierhenrich 2014).[3] The middle-left panel of **Figure 2** shows the weekly levels of recruitment over the period. On average, 47,756 (SD = 76,656) Facebook users liked BF's posts each week. There are considerable fluctuations, particularly in 2014, when BF extensively used engagement bait to attract attention. At one point, more than half a million new Facebook users liked the group's posts in a week—over a quarter of a million in one day. This series exhibits a downward trend, presumably indicating that the group gradually exhausted the pool of potential recruits. Approximately 7.8 million unique Facebook users liked one or more of the group's posts over the duration considered.

Finally, I measure support for BF by identifying users who repeatedly engaged with the group's content. I define an active supporter as someone observed to like one or most posts on a particular day and has liked at least one other post thirty days or more in the past.[4] On average, 91,797 (SD = 46,013) supporters were active in a given week. Several spikes in activity are visible in the bottom-left panel of **Figure 2**. There is also evidence of a downward trend, showing that supporter engagement diminished over time. Each dependent variable and all independent variables related to social media engagement are log-transformed to account for skewed distributions.[5] I discuss further transformations related to temporal properties below.

Independent variables

Audience engagement is measured by counting the likes, comments, and shares BF's posts received each week. The number of likes is omitted from the recruitment and support models since the dependent variables are a function of likes. The support and recruitment models also include measures of BF's activity to assess the degree to which changes in activity affect these dynamics. *Ceteris paribus*, there can be no engagement without activity, but prior work finds relatively weak associations between post frequency and engagement (Schwemmer 2021). In this case, there are weak bivariate correlations between weekly posts and each kind of engagement, with negative relationships for likes (r=-0.24) and shares (r=-0.25) and a positive relationship for comments (r=0.14). The negative correlations are consistent with the trends in the dependent variables, as we see that the group tended to increase its activity over time despite general declines in recruitment and support.

Controls

I take an agonistic approach to the measurement of framing, using topic modeling to inductively discover latent themes in BF's posts rather than attempting to specify frames *a priori* using keywords or related approaches. The approach is suitable for measuring framing since it can identify different types of themes, including substantive issues and other types of appeals (DiMaggio, Nag, and Blei 2013), and because each document can contain multiple topics and thus multiple frames (Snow et al. 1986). The method has been used to measure framing across a range of empirical contexts (Bail 2016; Espinoza-Kulick 2020; Light and Cunningham 2016). Specifically, I use a structural topic model, and allow the topic distributions to vary over time (Roberts, Stewart, Tingley, Lucas, Leder-Luis, Gadarian, Albertson, and Rand 2014). I tested several specifications and used quantitative metrics and qualitative evaluation of candidate models to select a model with thirty topics. I then analyzed the results of this model to develop interpretations of each topic by reading the documents with the highest weights in each topic and examining the words with the strongest associations (the training and validation procedures are discussed in more detail in Appendix B).

The resulting topics can be grouped into two broad categories. Topics related to issues frequently emphasized in BF's posts are termed *issue frames*. Two of these—Crime and Military—are single topics, while the remaining four—Islam, Terrorism, Immigration, and Politics—are "metatopics," composites of two or more closely related topics (Wilkerson and Casas 2017). For example, the Terrorism metatopic consists of three topics: the Islamic State and conflict in the Middle East; terrorism in Europe; and a more general topic about Islamic extremism and jihad. Second, I refer to four (meta)topics pertaining to the movement and its mobilization efforts as *instrumental frames*. Respectively, these topics cover appeals for people to act in support of BF that are consistent with the concept of "motivational" framing (Snow and Benford 1988); claims that Facebook and the British government were repressing the group; the promotion of BF's website, merchandise, and calls for Facebook users to engage with its content; and, logistical discussion related to protests. Examples of posts using each (meta)topic are provided in **Table 1** (see Appendix B for an extended version, disaggregated by topic). To assess the extent to which the use of these frames affects the dynamics of recruitment and support, I construct variables measuring the weekly mean percentage of each (meta)topic in BF's posts.[6] The topic distribution over the period considered is shown in **Figure 3**. The Other category at the bottom captures text from a handful of topics that were uninterpretable or did not fit into the main schema.[7] These topics are not included in the regression models, avoiding the issue of perfect multicollinearity that would arise if all (meta)topics were included in a regression model.

I compiled a timeline of BF's protests and direct actions using information from Facebook posts, YouTube videos, and related newspaper articles. I distinguish between planned street protests, which were widely promoted to attract a large number of attendees, and direct actions, which involved small cadres of activists and were not announced in advance. Fifteen street protests occurred during the period considered, mainly against the construction of mosques and child sexual exploitation by "grooming gangs." The direct actions included two "Christian patrols" and sixteen mosque invasions (twelve occurred over a weekend in 2014). Consequently, BF and its leaders were served with court injunctions banning them from such activities for much of the period considered. For terrorist attacks, I consider attacks perpetrated by Islamic extremists in Europe that resulted in fatalities or attacks elsewhere that killed British citizens. Six such attacks occurred during the period considered.[8] To assess the impact of right-wing terrorism, I account for the murder of MP Jo Cox, which occurred the week before the Brexit referendum. This event was particularly salient as her attacker allegedly shouted the words "put Britain first" as he shot and stabbed her, although no evidence of any connection to BF was identified. There was approximately one national election each year: the 2014 local and European parliament elections, the 2015 general election, and the 2016 Brexit referendum. All events are measured using dummy variables. I added one-week leads and lags to capture the anticipation of and response to protests and events, except terrorist attacks and direct actions, where leads were omitted due to their unanticipated nature. BF was particularly active in support of the campaign to leave the European Union (Davidson and Berezin 2018), so I included an additional dummy for all weeks following the Brexit referendum to ascertain whether BF or its supporters changed their online behavior in response to the outcome. **Figure 4** shows the frequency of each type of event over the period considered.

To measure coverage of BF in the mainstream media, I used LexisNexis to collect newspaper articles mentioning the term "Britain First" from seven major national newspapers.[9] In total, 471 articles were identified, and coverage was almost universally negative, mostly in two left-leaning outlets, *The Guardian* and *The Independent*. The highest volume of coverage occurred in the week of Cox's murder when the group was mentioned in 56 articles. Media coverage is included as a count variable corresponding to the number of newspaper articles mentioning BF each week.

Nonstationarity, cointegration, and the error correction model

Each outcome is measured repeatedly at regular intervals, making these data suitable for time series analysis, an ideal method for studying social processes through a case study (Abbott 1992).

Much existing work using time series methods to study online activism relies upon pairwise Granger "causality" tests, which indicate whether one series forecasts another after accounting for autocorrelation (e.g. Bastos, Mercea, and Charpentier 2015; Freelon, McIlwain, and Clark 2018; Schwemmer 2021). These tests can identify associations between series but do not necessarily detect causality (as the name implies) and do not account for other confounding factors. More seriously, most existing studies do not check whether series are stationary despite well-known methodological problems that arise if dynamics are unaccounted for. A stationary times series has a constant mean and variance. If these assumptions are violated, a time series is considered nonstationary, implying that it has a long, even infinite memory, such that shocks to the series tend to persist, also known as a "unit root" (Box-Steffensmeier, Freeman, Hitt, and Pevehouse 2014). Regression models that naively use nonstationary data can yield spurious results and inflated R^2 statistics (Engle and Granger 1987). I test for stationarity and find evidence of unit roots in all dependent variables and most independent variables (see Appendix C).

Nonstationarity is not merely a statistical nuisance but provides theoretical insights into the relationship between the time series. Nonstationary series can be *cointegrated*, meaning they are related to one another through dynamic equilibria. Formally, two nonstationary series are cointegrated if there exists a stationary linear combination of the series (Engle and Granger 1987). In this case, I expect BF's online activism to be cointegrated with audience engagement, such that shifts in engagement lead to changes in activity, support, and recruitment. Theoretically, cointegration signals the presence of feedback loops between time series as they adjust towards equilibrium in response to shocks to each other. I use the error correction model (ECM) to analyze these relationships, which captures both the short-run dynamics and the long-run relationships between nonstationary time series (De Boef and Keele 2008). The ECM takes the following basic form and is estimated using ordinary least squares regression:

$$\Delta y_t = \alpha_0 + \alpha_1 y_{t-1} + \beta_0 \Delta x_t + \beta_1 x_{t-1} + \varepsilon_t \qquad (1)$$

The nonstationary outcome y_t is transformed into a stationary variable by taking the first-difference, $\Delta y_t = y_t - y_{t-1}$. The change in the dependent variable is a function of its previous value in levels, y_{t-1}, and an independent variable, x, entered into the equation in both contemporaneous first-differences, Δx_t, and lagged levels, x_{t-1}. To use the ECM, we must verify that the differenced variables are indeed stationary (De Boef and Keele 2008). I apply the first-difference transformation to each series and repeat the stationarity tests to confirm this (see Appendix C). The column on the right of **Figure 2** shows each dependent variable after log transformation and first-differencing. Each series varies around a constant mean with random perturbations but no apparent trends, as indicated by the flat trend lines.

The coefficient α_1, known as the *error correction term*, captures the rate at which y_t returns to long-run equilibrium with x_t, following a shock to x_t. The coefficient should range from between -1 and 0, where higher values indicate a more gradual return to equilibrium. It is expected to be negative because any adjustment moves in the opposite direction to the disequilibrium (Keele, Linn, and Webb 2016). The coefficient for the first-differenced independent variable, β_0, captures the short-term effect of a change in x on change in y, and the β_1 represents the long-run effect of the level of x on the change in y. The basic ECM can be extended to include multiple independent variables, represented by X, and event dummy variables, Z. Dummy variables are stationary and, therefore, exogenous to cointegrating relationships.

$$\Delta y_t = \alpha_0 + \alpha_1 y_{t-1} + \boldsymbol{\beta_0} \Delta X_t + \boldsymbol{\beta_1} X_{t-1} + \boldsymbol{\gamma} Z_t + \varepsilon_t \quad (2)$$

Here the effect of the dummy variables on the change in the dependent variable is captured by the vector of coefficients $\boldsymbol{\gamma}$.

The following three conditions must be satisfied for any predictor x to be considered cointegrated with the outcome: (1) y and x contain unit roots; (2) the error correction parameter α_1 is statistically significant using MacKinnon critical values (Ericsson and MacKinnon 2002);[10] and (3) $\beta_1 x_{t-1}$ is statistically significant (Enns, Kelly, Masaki, and Wohlfarth 2017). The first condition is satisfied by the unit root tests (except for media coverage, which is stationary, so cannot enter into cointegrating relationships).[11] For robustness, I also use the bounds test for cointegration, also known as the PSS test (Pesaran, Shin, and Smith 2001; Philips 2018). The procedure consists of two tests: an F-test to test the hypothesis that coefficients for lagged explanatory variables are jointly equal to zero and a one-sided t-test to assess whether the coefficient on the lagged dependent variable is equal to zero. For the assumptions of these tests to hold, the residuals must be "white noise," meaning that they are purged of serial correlation and normally distributed. These properties are assessed using the Breusch-Godfrey and Shapiro-Wilk tests, respectively.

To visualize the relationships between variables over time and provide a more substantive interpretation, I use a model-based simulation procedure developed for ECMs (Jordan and Philips 2019). A specified independent variable is shocked by a standard deviation, other variables are held at their means, and differenced variables are set to zero. Simulated coefficients are drawn from a multivariate normal distribution parameterized using the estimates from the model, along with a small amount of stochastic noise. The process is repeated 10,000 times to produce a range of simulated estimates. Whereas the outcome in the model is a first-difference, the simulations show the effect of a shock to the *level* of a given independent variable on the *level* of the dependent variable over time, providing a more intuitive summary of the results in the original units of measurement.

RESULTS

Cointegration tests

In all models, the error correction terms, α_1, denoted by the coefficients for the lagged dependent variables (LDV), are within the expected range and are statistically significant at the relevant MacKinnon critical values. This implies that the models are correctly specified and that all three outcomes are cointegrated with one or more predictors (Enns et al. 2017). For each outcome, I estimate a set of models beginning with the activity and engagement covariates and incrementally adding the event, media, and topic covariates as relevant. I then use the bounds test to further assess cointegration in the fully parameterized models. Due to space constraints, the coefficients for media, event, and topic controls are omitted from all tables, but the full regression tables are available in Appendix D.

Table 2 shows the results from the models predicting BF's activity. The coefficient on the error correction term in the initial model is -.44, which indicates a relatively slow return to equilibrium, implying that only 44% of a shock dissipated over a week. However, the Shapiro-Wilk test indicates heteroskedasticity in the residuals, so the bounds tests cannot be calculated. In the second model, which controls for media coverage and events, the term drops to -0.52, indicating that these exogenous factors explain some of the dynamics. The residuals in this model are white noise, and both bounds tests, shown at the bottom of the table, agree that cointegration is present. **Table 3** shows the results of the ECMs estimating the weekly change in recruitment. The first model includes the same covariates as the first activity model with two exceptions: likes are omitted due to the measurement strategy, and the previous dependent variable is included on the right side of the equation to account for the effect of activity on recruitment. The results show evidence of an error correction process with a faster return to equilibrium. The residuals only become white noise in the final specification, including all topic, media, and event covariates. Both bounds tests agree that cointegration is present in this specification. The LDV coefficient is close to -1, implying that recruitment rates rapidly return to equilibrium following shocks to any cointegrated variables. Finally, the models explaining changes in BF's support are shown in **Table 4**. Like the previous model, the residuals are only white noise after topic covariates are included, although this is achieved in the model without events or media coverage. The coefficient on the LDV exhibits a slower rate of adjustment to equilibrium compared to recruitment. Overall, these results show that each of the three outcomes is cointegrated with one or more predictor variables. I now examine the coefficients for the social media activity and engagement variables to identify which are involved cointegrating and short-term relationships with each outcome.

Social media activity and engagement

Beginning with the model predicting BF's activity, the coefficient for the lagged number of likes is positive, implying that BF posted more in response to earlier engagement levels. A 1% increase in the lagged number of likes is associated with a 0.21% shift in BF's activity in the fully parameterized specification. The relationship between activity and each type of engagement is visualized in **Figure 5**. The simulations run over a hypothetical thirteen-week period, with a shock occurring at week five and its impact tracked for two months (weeks six through thirteen). Each set of predictions trends upwards over time, consistent with the descriptive finding that BF gradually increased its output over the period considered. A standard-deviation shock to the number of likes generates an increase in the rate of activity that persists for several weeks. This is precisely what we should expect when two series are cointegrated, as a shift in one series has a long-term effect on the level of another series. It is helpful to compare this to the effect of a shock to shares and comments, which are not cointegrated with BF's activity, as neither lagged coefficient is statistically significant. In both cases, there is little discernable change in the activity level. Turning to the variables in differences, there is also evidence of a contemporaneous relationship between activity and likes: a one-percent change in the number of likes is associated with a 0.25% change in posts that week. This implies that the group immediately responds to increased short-term engagement by posting more content.

Recruitment is cointegrated with both comments and shares. In the full model, a 1% increase in the *level* of each variable in the previous week is associated with respective 0.57% and 0.47% increases in recruitment in the full model. The coefficients for BF's activity, on the other hand, are not statistically significant in any specification. The middle row of **Figure 5** shows the simulated effects of shocks to each variable on recruitment. Note how a shock to shares is associated with a particularly large, sustained increase in recruitment, whereas comments lead to a more modest increase. There is also strong evidence of short-term impacts of engagement, as 1% *changes* in comments and shares are associated with 0.99% and 0.54% changes in the number of recruits, respectively. These results show that user engagement with BF's posts, rather than the volume of BF's activity, is associated with immediate and longer-term recruitment.

The final set of models shows that BF's supporters responded to the group's activity and other users' engagement. Only shares are cointegrated with the dependent variable, with a 1%

increase associated with a 0.12% increase in the number of supporters who like BF's posts. The simulation results in the bottom row of **Figure 5** depict the effect of shocks to activity, comments, and shares on the outcome. These results show how shocks to shares result in a sustained change in the level of support. A shock to the level of BF's posting activity does exhibit a similar trend, but the lagged variable is not statistically significant, so we cannot conclude cointegration. The results for comments are more consistent with a short-term bump in engagement. The short-term impact of activity and comments is further highlighted when considering the first-differences. A 1% change in activity is associated with a 0.42% change in supporter engagement. An analogous change in comments has a similar effect, while a 1% change in shares is associated with a 0.13% change in support. Thus, while only shares have a sustained impact on supporter engagements, shifts in activity and comments also have immediate effects.

Framing and engagement bait

To what extent did the frames used in BF's Facebook posts impact the dynamics of recruitment and support? Full regression results reported in Appendix D show that only one topic repression is statistically significant across the two different outcomes, and this significance wanes after controlling for events and media coverage. Despite these null results, the addition of these covariates increases the variance explained, moderates the engagement coefficients, and ensures the residuals are white noise. Moreover, several of the topics are highly correlated (see Appendix B), and the sample size is relatively small, so multicollinearity may impede the detection of statistically significant relationships.

To better understand the relationship between framing and engagement, I estimated an additional set of regression models, using negative binomial regression to predict the number of engagements each post received as a function of the frame composition, measured using the percentage of each (meta)topic. These models also control for the type of post (text, image, or video), number of words used, and time of day. The results, reported in **Figure 6A**, highlight the relationships between framing and the rates of likes, shares, and comments, respectively (see Appendix F for full regression tables). The larger sample size (N=36,196) makes it possible to detect statistical significance despite strong correlations between some topics. I observe negative or null effects for the (meta)topics representing instrumental framing, implying posts containing more instrumental framing tend to receive fewer likes, comments, and shares. The opposite pattern is present for most issue topics, with content about the military and politics attracting exceptionally high engagement rates. Posts focused on crime, immigration, and Islam also received more engagement, on average, while those with more discussion devoted to terrorism tend to attract less. The patterns are generally consistent across the three types of engagement considered. This highlights how certain kinds of framing attracted audience engagement, subsequently impacting the dynamics of BF's activity, support, and recruitment.

How effective was engagement bait? The Promotional metatopic, which captures some terms associated with engagement bait, was not statistically significant in either set of models. Since this topic also included other unrelated information, such as material promoting BF's website and merchandise, I also estimated supplementary models to more precisely capture engagement bait, using a covariate denoting the weekly number of posts containing any of the terms "like," "share," or "comment," however the results were unchanged (see Appendix E). To further examine the effects of engagement bait, I estimated an additional set of negative binomial models predicting the number of engagements a post received as a function of these engagement bait keywords, controlling for topic distributions and other post characteristics described in the previous analyses. The results, shown in **Figure 6B**, highlight strong, positive relationships between the use of each term and the corresponding type of engagement. Posts containing the word "like" received 1.6 times as many likes, those mentioning "share" received 1.8 times as many shares, and those using the term "comment" received more than twice as many comments as posts without each of these terms. This provides robust evidence that engagement bait worked as intended.

Protests, events, and media coverage

The relationship between protests, other exogeneous variables, and BF's online activism are reported in the full regression tables in Appendix D. I find that BF was less active following street protests but did tend to see an increase in recruitment and support during these weeks, suggesting that these protests may have positively impacted online activism. However, the evidence is relatively weak in both cases, as the coefficients are not statistically significant after controlling for framing. BF's direct actions, on the other hand, did not have any immediate or lagged impact on any of the outcomes. Turning to elections, BF posted less following national elections and in the post-Brexit period. Nonetheless, the results show evidence that BF saw increases in recruitment in the week preceding elections. Islamist terrorist attacks are not associated with any changes in the dynamics under consideration, but the murder of Jo Cox is associated with a substantial drop in recruitment. Finally, there is scant evidence that BF or its supporters responded to media coverage. The media coefficient in the recruitment model is statistically significant without topic covariates, and none of the other models show evidence of a relationship. Overall, these results indicate that BF and its supporters responded to offline events, but these factors do not explain away the importance of dynamics endogenous to social media.

DISCUSSION

This case study demonstrates how audience engagement is central to understanding online activism on contemporary social media platforms. Time series regression and cointegration tests reveal the presence of feedback loops, revealing how BF and its online audience dynamically adjusted their behavior in response to one another. BF increased its social media output when its posts received more likes, demonstrating that social movement organizations are responsive to audience engagements. More Facebook users engaged with BF for the first time when its content was commented on and shared more frequently by other Facebook users. BF's existing supporters also increased their participation when the group's posts were shared more frequently. Neither recruitment nor support was cointegrated with BF's activity, providing further evidence that frequent posting is an ineffective tactic for increasing support or recruitment (Schwemmer 2021). Beyond the cointegrated relationships, there is evidence of contemporaneous relationships between activity, engagement, and each of the three outcomes, demonstrating that BF and its online audience also responded to short-term fluctuations in these processes. Overall, these findings demonstrate how engagement from BF's online audience led to further activity and engagement, which, in turn, helped to attract recruits and sustain the attention of supporters.

The variables capturing BF's framing helped to stabilize the time series regressions and explained some of the variance in recruitment and support, but there was no evidence of relationships between content and the dynamics of BF's support and recruitment. This, however, does not imply that framing was inconsequential since engagements can be considered a second-order effect of the content shared by BF. Additional models using Facebook posts as the unit of analysis show how framing can help or hinder audience engagement. Issue framing related to the military, crime, immigration, politics, and Islam was associated with higher engagement rates, particularly shares and comments. The only issue frame that attracted lower engagement was terrorism. Instrumental framing, including fundraising drives and efforts to attract people to participate in street protests, was less popular, consistent with studies of other far-right groups (Schwemmer 2021). Moreover, these analyses highlight the power of engagement bait, demonstrating how explicit appeals to like, share, and comment yielded substantial increases in each kind of engagement. These results provide robust evidence that issue framing and engagement bait generated engagements that consequently impacted the dynamics of online activism.

Moving to the offline factors, BF's street protests did appear to boost online support and recruitment but the coefficients are not statistically significant after accounting for framing. The absence of a strong relationship is consistent with previous findings that far-right online activism is largely decoupled from street protests (Freelon et al. 2020; Schradie 2019). BF's direct actions had no immediate or lagged impact on these dynamics, although footage from these events was repeatedly used in the following weeks and months, and these events attracted media coverage, so it is plausible they were still useful at sustaining or attracting attention in the longer term. Turning to the exogenous factors, BF altered its activity in response to elections, tending to post less the week after elections and following the Brexit referendum, consistent with Heaney and Rojas' (2011) demobilization theory since the election results were favorable to the group. BF also saw increased recruitment preceding elections, suggesting that the group's interventions in electoral politics helped to attract new adherents (Davidson and Berezin 2018). Despite BF's extensive focus on terrorism and prior work finding that terrorism can benefit the far-right (Frey 2022; Legewie 2013), there was no evidence that Islamist attacks systematically led to changes in support or recruitment. But right-wing terrorism did have an impact, as the murder of MP Jo Cox dampened recruitment, consistent with evidence from opinion surveys showing that it weakened identification with right-wing ideology (Pickard et al. 2023). Finally, media coverage had little impact on the processes under study, consistent with the observation that social media has reduced movements' dependence upon conventional media (Caren et al. 2020).

These results provide strong evidence that BF's online activism was largely a function of processes endogenous to social media. Nonetheless, it is important to note that the temporal resolution of exogenous events prevents us from observing the same kinds of cointegrating dynamics as identified on social media. It is plausible that events known to predict far-right support, such as changes in the economy or immigration levels, may be associated with variation in online support in the longer term (Muis and Immerzeel 2017). Similarly, subtle shifts in public discourse, such as increasing hostility towards immigrants, could have created discursive opportunities for BF to mobilize (Koopmans and Olzak 2004). With only a relatively limited observation window, it is difficult to trace the connections between these more sluggish processes and the fast-paced world of social media. As more evidence from social media accumulates, we should be able to better understand the relationship between the dynamics of online activism and broader political opportunity structures.

CONCLUSION

British politics shifted rightwards over the past two decades as immigration has become a central issue for voters (Ford, Jennings, and Somerville 2015), culminating in the Brexit referendum, which was considered by many as a referendum on immigration and multiculturalism (Norris and Inglehart 2019). Despite favorable discursive opportunities, the far-right faced difficulty breaking into institutionalized politics. The British National Party (BNP) was marginalized in the electoral arena, losing votes to mainstream conservatives and effectively collapsing due to internal strife (Art 2011; Goodwin 2014). Nonetheless, many voters sympathized with the BNP on key policies, with surveys showing that "a large sub-section of the British electorate might consider voting for an extreme right party" (John and Margetts 2009:497). Social media arguably unlocked this potential, equipping the far-right with a means to reach and activate latent supporters and to persuade others of their cause. In this case, the ascendancy of mainstream conservatives blocked the far-right in the electoral arena, contributing to the explosive online growth of extra-parliamentary groups like BF and the English Defence League (Busher 2015), consistent with the observation that extremist movements tend to thrive online when institutionalized opportunities are closed (Klein and Muis 2019). Through the savvy use of social media, BF attracted and maintained the attention of large numbers of people without a substantial offline base or organizational infrastructure. Every week, BF's activists shared hundreds of Facebook posts about Islam, immigration, British politics, and a variety of other topics. These posts attracted hundreds of thousands of likes, shares, and comments from individual Facebook users. These engagements, in turn, stimulated more people to join the group, its existing supporters to be more active, and the group to share more posts. Through feedback loops between audience engagement and online activism, BF reached millions of people within a relatively short period.

The rapid growth of BF's online audience points towards its activists' ability to exploit Facebook to its advantage. The results demonstrate that engagement bait worked, as posts containing appeals to like, share, and comment tended to attract substantially higher rates of likes, shares, and comments, respectively. The fact that Facebook took action to restrict the practice (Facebook 2017) demonstrates that the company was aware that actors like BF were using this tactic to game its systems. While it is impossible to distinguish between classical and algorithmically-mediated diffusion processes using observational data, leaked internal research shows how the platform's algorithms pushed users towards extremist groups and amplified misinformation, toxicity, and violent content, leading some employees to conclude that the platform's "algorithms exploit the human brain's attraction to divisiveness" (Hagey and Horwitz 2021; Horwitz and Seetharaman 2020). This study points to how activists can manipulate social media platforms' algorithms to their advantage, but further research is needed to disentangle these mechanisms and understand the extent to which these algorithmic opportunity structures may have contributed to the rapid online growth of far-right social movement organizations.

What are the implications of these findings for other social movements? Existing work shows that right-wing and left-wing activists approach social media differently (Freelon et al. 2020; Schradie 2019). Left-wing movements pioneered the use of short social media posts to rapidly accumulate online audiences (Gaby and Caren 2012), a tactic later adopted by the right (Froio, Castelli Gattinara, Bulli, and Albanese 2020; Schwemmer 2021; Stier et al. 2017). Similar to findings from studies of traditional media sources (Sobieraj and Berry 2011), conservatives on social media tend to use language that incites outrage and aggressively targets outgroups, and this material appears to be highly effective at eliciting audience engagement (Brady, Wills, Burkart, Jost, and Van Bavel 2019; Rathje et al. 2021). Left-wing movements have also undoubtedly benefitted from online outrage, as hashtag activism associated with the Black Lives Matter and Me Too movements gained global attention by using social media to bring attention to injustices, including racial discrimination and sexual harassment (Jackson, Bailey, and Welles 2020). But conservatives appear to disproportionately benefit from evoking online outrage (Brady et al. 2019), and their advantages may have solidified. As such, it appears that right-wing actors, including far-right activists and mainstream conservative parties, have benefitted most from the incentive structures of contemporary social media platforms. Further comparative work is needed to shed light on how activists across the political spectrum interact with these structures and the extent to which these mechanisms vary across platforms and contexts.

When considering the relationship between social media and contemporary activism, it is important to emphasize that social media platforms are constantly in flux. Thousands of engineers continually tweak Facebook and other platforms, and most changes are not apparent to the public. While the basic incentive structures remain, as most social media platforms use engagements to rank and recommend content as they compete with one another for people's limited attention, it is unlikely that other groups could directly replicate the tactics used by BF. For example, activists using engagement bait today will likely find their content is *demoted* rather than *promoted* by Facebook's algorithms (Gillespie 2022). Activists seeking to gain traction on social media must therefore work to identify how different aspects of platforms can be used to their advantage through continual experimentation (Karpf 2016; Schradie 2019) and adapt to changes implemented by platforms that can render specific tactics ineffective overnight. These developments highlight the entanglement of politics with platform capitalism, as the corporate architects of these systems in Silicon Valley can unilaterally change the rules of the game in ways that can alter the flow of information in the public sphere and transform the potential for activism.

In late 2017, Twitter banned BF and its leaders after Donald Trump, then President of the United States, retweeted a series of anti-Muslim videos shared by BF's deputy leader Jayda Fransen. BF was subsequently banned by Facebook, which cited how it "repeatedly posted content designed to incite animosity and hatred against minority groups" (Facebook 2018), and was also banned from YouTube and dropped by its website provider. Lacking a substantial offline base, BF's dependency on social media was ultimately its Achilles' heel. Almost overnight, BF lost its ability to communicate with the vast majority of its supporters. While leaders and more dedicated activists have remained active on less regulated platforms like Gab, these sites have much smaller user bases, limiting their ability to reach large, mainstream audiences.[12] As major social media platforms develop more robust policies against hate speech and other extreme content, extremist groups will either retreat to the fringes of the internet or be forced to change their tactics, much like the radical right in the electoral arena (Art 2011). BF has since faded to the margins of British politics, highlighting the ephemerality of online audiences and the brittleness of informationalizing without concomitant organization building.

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[1] BF did not publicize its membership, but one can estimate its size by comparing membership fees and financial reports filed with the Electoral Commission. Assuming everyone paid the standard dues, the membership grew from 121 in 2013 to 1514 by the end of 2016. If we consider the range of different dues options, the estimates range from 73-455 members in 2013 to 379-5678 in 2016. See Appendix A for further details on these estimates.

[2] I only consider standard likes and not the other kinds of reactions Facebook introduced in spring 2016 ("haha", "love", "wow", "sad", and "angry"). These reactions are more ambiguous and have potential to indicate opposition rather than support. The shorter time period (64 weeks from introduction to the end of data collection) also means that models examining the dynamics of these alternative reactions would lack sufficient statistical power. Likes therefore provide a cleaner and more constant measure of engagement with the group. Nonetheless, robustness checks reported in Appendix E show consistent results when these reactions are also considered when defining recruitment and support.

[3] Since likes do not have unique timestamps, I assume that the timestamp of the associated post is a reasonable proxy for when a user first liked BF's content. It is plausible that some users could go through BF's timeline and like older posts and thus appear to be recruited at an earlier date than when they first engaged with the group. However, given the large volume of content shared by BF, the repetitiveness of much of this content, and the tediousness of scrolling back through the timeline, I do not expect this to have a substantial impact on the results, particularly given the use of weekly aggregation. The change in the number of followers on BF's page would provide an alternative measure of recruitment but Facebook did not make this data available via its API.

[4] These variables were defined using the untruncated data so recruitment and support are observed from week 1 of the present analysis.

[5] While the variables are counts, as I discuss below, they are modeled as first-differences and presence of negative values in the transformation makes count models unsuitable. In this case, the natural logarithm is used to help account for temporal heteroskedasticity. This also makes the interpretation of the models more intuitive, as relationships between logged variables can be interpreted as elasticities.

[6] A limitation of these measures is that they do not account for the number of posts related to each topic. I therefore also consider an alternative measure where the topic model results are discretized to measure the number of posts using each topic. The results are reported in Appendix E and are substantively similar to those obtained from the main specification.

[7] Following previous work, we exclude these topics from the analysis (Bail, Brown, and Mann 2017; Karell and Freedman 2019).

[8] The six attacks are the shootings at Charlie Hebdo (Paris), Sousse (Tunisia), and Paris in 2015; the Brussels airport bombing and Nice truck attack in 2016; and the 2017 stabbing of a police officer at Westminster Palace.

[9] *The Guardian*, *The Independent*, *The Daily Mirror*, *The Times*, *The Telegraph*, *The Sun*, *and The Daily Mail* and respective Sunday editions.

[10] The critical values are obtained from Table F of the Supplementary Manual of Enders (2015). The 1% critical value is -4.831, and the 5% critical value is -4.182.

[11] Monte Carlo simulations using two regressors show that only one of the regressors need to cointegrate with the dependent variable to determine whether cointegration is present (Enns, Kelly, Masaki, and Wohlfarth 2017). The addition of the stationary media coverage variable should therefore not affect inferences regarding other variables.

[12] As of May 9th, 2023, BF has fewer than eighteen thousand followers Gab, despite using the platform for several years (https://gab.com/BritainFirst).

REFERENCES

Abbott, Andrew. 1992. "From Causes to Events: Notes on Narrative Positivism." *Sociological Methods & Research* 20(4):428–55.

Allen, Chris. 2014. "Britain First: The 'Frontline Resistance' to the Islamification of Britain." *The Political Quarterly* 85(3):354–61.

Andrews, Kenneth T., Neal Caren, and Alyssa Browne. 2018. "Protesting Trump." *Mobilization: An International Quarterly* 23(4):393–400.

Art, David. 2011. *Inside the Radical Right: The Development of Anti-Immigrant Parties in Western Europe*. Cambridge: Cambridge University Press.

Bail, Christopher A. 2016. "Cultural Carrying Capacity: Organ Donation Advocacy, Discursive Framing, and Social Media Engagement." *Social Science & Medicine* 165:280–88.

Bail, Christopher A., Taylor W. Brown, and Marcus Mann. 2017. "Channeling Hearts and Minds: Advocacy Organizations, Cognitive-Emotional Currents, and Public Conversation." *American Sociological Review* 82(6):1188–1213.

Bastos, Marco T., Dan Mercea, and Arthur Charpentier. 2015. "Tents, Tweets, and Events: The Interplay Between Ongoing Protests and Social Media: Tents, Tweets, and Events." *Journal of Communication* 65(2):320–50.

Beach, Derek, and Rasmus Brun Pedersen. 2018. "Selecting Appropriate Cases When Tracing Causal Mechanisms." *Sociological Methods & Research* 47(4):837–71.

Benkler, Yochai, Robert Faris, and Hal Roberts. 2018. *Network Propaganda: Manipulation, Disinformation, and Radicalization in American Politics*. New York, NY: Oxford University Press.

Bennett, W. Lance, and Alexandra Segerberg. 2012. "The Logic of Connective Action: Digital Media and the Personalization of Contentious Politics." *Information, Communication & Society* 15(5):739–68.

Blassnig, Sina, Nicole Ernst, Sven Engesser, and Frank Esser. 2019. "Populism and Social Media Popularity." Pp. 97–111 in *Power Shift? Political Leadership and Social Media*, edited by R. Davis and D. Taras. London: Routledge.

Bond, Robert M., Christopher J. Fariss, Jason J. Jones, Adam D. I. Kramer, Cameron Marlow, Jaime E. Settle, and James H. Fowler. 2012. "A 61-Million-Person Experiment in Social Influence and Political Mobilization." *Nature* 489(7415):295–98.

Box-Steffensmeier, Janet, John R. Freeman, Matthew P. Hitt, and Jon C. W. Pevehouse. 2014. *Time Series Analysis for the Social Sciences*. New York, NY: Cambridge University Press.

Brady, William J., Julian A. Wills, Dominic Burkart, John T. Jost, and Jay J. Van Bavel. 2019. "An Ideological Asymmetry in the Diffusion of Moralized Content on Social Media among Political Leaders." *Journal of Experimental Psychology: General* 148(10):1802–13.

Budak, Ceren, and Duncan Watts. 2015. "Dissecting the Spirit of Gezi: Influence vs. Selection in the Occupy Gezi Movement." *Sociological Science* 2:370–97.

Busher, Joel. 2015. *The Making of Anti-Muslim Protest: Grassroots Activism in the English Defence League*. London: Routledge.

Caren, Neal, Kenneth T. Andrews, and Todd Lu. 2020. "Contemporary Social Movements in a Hybrid Media Environment." *Annual Review of Sociology* 46(1):443–65.

Castells, Manuel. 2012. *Networks of Outrage and Hope: Social Movements in the Internet Age*. Cambridge: Polity Press.

Czymara, Christian S., Stephan Dochow-Sondershaus, Lucas G. Drouhot, Müge Simsek, and Christoph Spörlein. 2022. "Catalyst of Hate? Ethnic Insulting on YouTube in the Aftermath of Terror Attacks in France, Germany and the United Kingdom 2014–2017." *Journal of Ethnic and Migration Studies* 49(2):535–53.

Davidson, Thomas. 2013. "Social Media and Participant Interaction: A Challenge for Social Movement Framing? A Case Study of the English Defence League and Facebook Usage in a Period of Moral Shock." Master's thesis, London School of Economics and Political Science, London.

Davidson, Thomas, and Mabel Berezin. 2018. "Britain First and the UK Independence Party: Social Media and Movement-Party Dynamics." *Mobilization: An International Quarterly* 23(4):485–510.

De Boef, Suzanna, and Luke Keele. 2008. "Taking Time Seriously." *American Journal of Political Science* 52(1):184–200.

DiMaggio, Paul, Manish Nag, and David Blei. 2013. "Exploiting Affinities between Topic Modeling and the Sociological Perspective on Culture: Application to Newspaper Coverage of U.S. Government Arts Funding." *Poetics* 41(6):570–606.

DiResta, Renee. 2018. "Computational Propaganda: If You Make It A Trend, You Make It True." *The Yale Review* 106(4):12–29.

Earl, Jennifer. 2010. "The Dynamics of Protest-Related Diffusion on the Web." *Information, Communication & Society* 13(2):209–25.

Earl, Jennifer, and Katrina Kimport. 2011. *Digitally Enabled Social Change: Activism in the Internet Age*. Cambridge, MA: MIT Press.

Eckles, Dean. 2021. *Algorithmic Transparency and Assessing Effects of Algorithmic Ranking*. Testimony before the Senate Subcommittee on Communications, Media, and Broadband.

Eltantawy, Nahed, and Julie B. Wiest. 2011. "Social Media in the Egyptian Revolution: Reconsidering Resource Mobilization Theory." *International Journal of Communication* 5:1207–24.

Enders, Walter. 2015. *Applied Econometric Time Series*. Fourth edition. Hoboken, NJ: Wiley.

Engle, Robert F., and C. W. J. Granger. 1987. "Co-Integration and Error Correction: Representation, Estimation, and Testing." *Econometrica* 55(2):251.

Enns, Peter K., Nathan J. Kelly, Takaaki Masaki, and Patrick C. Wohlfarth. 2017. "Moving Forward with Time Series Analysis." *Research & Politics* 4(4):1–7.

Ericsson, Neil R., and James G. MacKinnon. 2002. "Distributions of Error Correction Tests for Cointegration." *The Econometrics Journal* 5(2):285–318.

Espeland, Wendy Nelson, and Michael Sauder. 2007. "Rankings and Reactivity: How Public Measures Recreate Social Worlds." *American Journal of Sociology* 113(1):1–40.

Espinoza-Kulick, Alex. 2020. "A Multimethod Approach to Framing Disputes: Same-Sex Marriage on Trial in Obergefell v. Hodges." *Mobilization: An International Quarterly* 25(1):45–70. doi: 10.17813/1086-671X-25-1-45.

Facebook. 2017. "Fighting Engagement Bait on Facebook." *Facebook*. Retrieved October 13, 2018 (https://newsroom.fb.com/news/2017/12/news-feed-fyi-fighting-engagement-bait-on-facebook/, Accessed 5/1/23).

Facebook. 2018. "Taking Action Against Britain First." *Facebook*. Retrieved October 13, 2018 (https://newsroom.fb.com/news/h/taking-action-against-britain-first/, Accessed 5/1/23).

Ferree, Myra Marx. 2003. "Resonance and Radicalism: Feminist Framing in the Abortion Debates of the United States and Germany." *American Journal of Sociology* 109(2):304–44.

Ford, Robert, Will Jennings, and Will Somerville. 2015. "Public Opinion, Responsiveness and Constraint: Britain's Three Immigration Policy Regimes." *Journal of Ethnic and Migration Studies* 41(9):1391–1411.

Freelon, Deen, Alice Marwick, and Daniel Kreiss. 2020. "False Equivalencies: Online Activism from Left to Right." *Science* 369(6508):1197–1201.

Freelon, Deen, Charlton McIlwain, and Meredith Clark. 2018. "Quantifying the Power and Consequences of Social Media Protest." *New Media & Society* 20(3):990–1011.

Frey, Arun. 2022. "Getting under the Skin: The Impact of Terrorist Attacks on Native and Immigrant Sentiment." *Social Forces* 101(2):943–73.

Froio, Caterina, Pietro Castelli Gattinara, Giorgia Bulli, and Matteo Albanese. 2020. *CasaPound Italia: Hybridization in the Contemporary Extreme Right*. 1st ed. London: Routledge.

Gaby, Sarah, and Neal Caren. 2012. "Occupy Online: How Cute Old Men and Malcolm X Recruited 400,000 US Users to OWS on Facebook." *Social Movement Studies* 11(3–4):367–74.

Gamson, William A., and Gadi Wolfsfeld. 1993. "Movements and Media as Interacting Systems." *The Annals of the American Academy of Political and Social Science* 528(1):114–25.

Gerbaudo, Paolo. 2012. *Tweets and the Streets: Social Media and Contemporary Activism*. London: Pluto Press.

Gillespie, Tarleton. 2012. "Can an Algorithm Be Wrong?" *Limn* 1(2).

Gillespie, Tarleton. 2022. "Do Not Recommend? Reduction as a Form of Content Moderation." *Social Media + Society* 8(3):1–13.

Golder, Scott A., and Michael W. Macy. 2014. "Digital Footprints: Opportunities and Challenges for Online Social Research." *Annual Review of Sociology* 40(1):129–52.

González-Bailón, Sandra, Javier Borge-Holthoefer, and Yamir Moreno. 2013. "Broadcasters and Hidden Influentials in Online Protest Diffusion." *American Behavioral Scientist* 57(7):943–65.

González-Bailón, Sandra, Javier Borge-Holthoefer, Alejandro Rivero, and Yamir Moreno. 2011. "The Dynamics of Protest Recruitment through an Online Network." *Scientific Reports* 1(1):197.

Goodwin, Matthew J. 2014. "Forever a False Dawn? Explaining the Electoral Collapse of the British National Party (BNP)." *Parliamentary Affairs* 67(4):887–906.

Hager, Anselm, Lukas Hensel, Johannes Hermle, and Christopher Roth. 2022. "Group Size and Protest Mobilization across Movements and Countermovements." *American Political Science Review* 116(3):1051–66.

Hagey, Keach, and Jeff Horwitz. 2021. "Facebook Tried to Make Its Platform a Healthier Place. It Got Angrier Instead." *Wall Street Journal*, September 15.

Heaney, Michael T. 2018. "Making Protest Great Again." *Contexts* 17(1):42–47.

Heaney, Michael T., and Fabio Rojas. 2011. "The Partisan Dynamics of Contention: Demobilization of the Antiwar Movement in the United States, 2007-2009." *Mobilization: An International Quarterly* 16(1):45–64.

Hope Not Hate. 2014. *Britain First: Army of the Right*. London: Hope Not Hate.

Horwitz, Jeff, and Deepa Seetharaman. 2020. "Facebook Executives Shut Down Efforts to Make the Site Less Divisive." *Wall Street Journal*, May 26.

Huszár, Ferenc, Sofia Ira Ktena, Conor O'Brien, Luca Belli, Andrew Schlaikjer, and Moritz Hardt. 2022. "Algorithmic Amplification of Politics on Twitter." *Proceedings of the National Academy of Sciences* 119(1):e2025334119.

Jackson, Sarah J., Moya Bailey, and Brooke Foucault Welles. 2020. *#HashtagActivism: Networks of Race and Gender Justice*. Cambridge, MA: MIT Press.

Jakesch, Maurice, Kiran Garimella, Dean Eckles, and Mor Naaman. 2021. "Trend Alert: How a Cross-Platform Organization Manipulated Twitter Trends in the Indian General Election." *Proceedings of the ACM on Human-Computer Interaction* 5(CSCW2):1–19.

John, Peter, and Helen Margetts. 2009. "The Latent Support for the Extreme Right in British Politics." *West European Politics* 32(3):496–513.

Jordan, Soren, and Andrew Philips Q. 2019. "Dynamic Simulation and Testing for Single-Equation Cointegrating and Stationary Autoregressive Distributed Lag Models." *The R Journal* 10(2):469.

Karell, Daniel, and Michael Freedman. 2019. "Rhetorics of Radicalism." *American Sociological Review* 84(4):726–53.

Karpf, David. 2016. *Analytic Activism: Digital Listening and the New Political Strategy*. New York, NY: Oxford University Press.

Keele, Luke, Suzanna Linn, and Clayton McLaughlin Webb. 2016. "Treating Time with All Due Seriousness." *Political Analysis* 24(1):31–41.

Kitschelt, Herbert P. 1986. "Political Opportunity Structures and Political Protest: Anti-Nuclear Movements in Four Democracies." *British Journal of Political Science* 16(1):57–85.

Koopmans, Ruud, and Jasper Muis. 2009. "The Rise of Right-Wing Populist Pim Fortuyn in the Netherlands: A Discursive Opportunity Approach." *European Journal of Political Research* 48(5):642–64.

Koopmans, Ruud, and Susan Olzak. 2004. "Discursive Opportunities and the Evolution of Right-Wing Violence in Germany." *American Journal of Sociology* 110(1):198–230.

Legewie, Joscha. 2013. "Terrorist Events and Attitudes toward Immigrants: A Natural Experiment." *American Journal of Sociology* 118(5):1199–1245.

Lewis, Kevin, Kurt Gray, and Jens Meierhenrich. 2014. "The Structure of Online Activism." *Sociological Science* 1:1–9.

Light, Ryan, and Jeanine Cunningham. 2016. "Oracles of Peace: Topic Modeling, Cultural Opportunity, and the Nobel Peace Prize, 1902–2012." *Mobilization: An International Quarterly* 21(1):43–64.

McAdam, Doug. 2010. *Political Process and the Development of Black Insurgency, 1930-1970*. Chicago, IL: University of Chicago Press.

McAdam, Doug, and Sidney Tarrow. 2010. "Ballots and Barricades: On the Reciprocal Relationship between Elections and Social Movements." *Perspectives on Politics* 8(2):529–42.

Meyer, David S., and Debra C. Minkoff. 2004. "Conceptualizing Political Opportunity." *Social Forces* 82(4):1457–92.

Muis, Jasper, and Tim Immerzeel. 2017. "Causes and Consequences of the Rise of Populist Radical Right Parties and Movements in Europe." *Current Sociology* 65(6):909–30.

Norris, Pippa, and Ronald Inglehart. 2019. *Cultural Backlash: Trump, Brexit, and Authoritarian Populism*. New York, NY: Cambridge University Press.

Ostrom, Charles W., and Dennis M. Simon. 1985. "Promise and Performance: A Dynamic Model of Presidential Popularity." *American Political Science Review* 79(2):334–58.

Pasquale, Frank. 2015. *The Black Box Society*. Cambridge, MA: Harvard University Press.

Pesaran, M. Hashem, Yongcheol Shin, and Richard J. Smith. 2001. "Bounds Testing Approaches to the Analysis of Level Relationships." *Journal of Applied Econometrics* 16(3):289–326.

Philips, Andrew Q. 2018. "Have Your Cake and Eat It Too? Cointegration and Dynamic Inference from Autoregressive Distributed Lag Models." *American Journal of Political Science* 62(1):230–44.

Pickard, Harry, Georgios Efthyvoulou, and Vincenzo Bove. 2023. "What's Left after Right-wing Extremism? The Effects on Political Orientation." *European Journal of Political Research* 62(1):338–51.

Rathje, Steve, Jay J. Van Bavel, and Sander van der Linden. 2021. "Out-Group Animosity Drives Engagement on Social Media." *Proceedings of the National Academy of Sciences* 118(26):e2024292118.

Reuning, Kevin, Anne Whitesell, and A. Lee Hannah. 2022. "Facebook Algorithm Changes May Have Amplified Local Republican Parties." *Research & Politics* 9(2):205316802211038.

Roberts, Margaret E., Brandon M. Stewart, Dustin Tingley, Christopher Lucas, Jetson Leder-Luis, Shana Kushner Gadarian, Bethany Albertson, and David G. Rand. 2014. "Structural Topic Models for Open-Ended Survey Responses." *American Journal of Political Science* 58(4):1064–82.

Rucht, Dieter. 2018. "Mobilization Against Refugees and Asylum Seekers in Germany: A Social Movement Perspective." Pp. 225–45 in *Protest Movements in Asylum and Deportation*, edited by S. Rosenberger, V. Stern, and N. Merhaut. Cham: Springer International Publishing.

Salganik, Matthew J., Peter Sheridan Dodds, and Duncan J. Watts. 2006. "Experimental Study of Inequality and Unpredictability in an Artificial Cultural Market." *Science Reports* 311:854–56.

Schradie, Jen. 2019. *The Revolution That Wasn't: How Digital Activism Favors Conservatives*. Cambridge, MA: Harvard University Press.

Schwemmer, Carsten. 2021. "The Limited Influence of Right-Wing Movements on Social Media User Engagement." *Social Media + Society* 7(3):1–13.

Seguin, Charles. 2016. "Cascades of Coverage: Dynamics of Media Attention to Social Movement Organizations." *Social Forces* 94(3):997–1020.

Skocpol, Theda, and Vanessa Williamson. 2012. *The Tea Party and the Remaking of Republican Conservatism*. New York, NY: Oxford University Press.

Snow, David A., and Robert D. Benford. 1988. "Ideology, Frame Resonance, and Participant Mobilization." *International Social Movement Research* 1(1):197–217.

Snow, David A., E. Burke Rochford, Steven K. Worden, and Robert D. Benford. 1986. "Frame Alignment Processes, Micromobilization, and Movement Participation." *American Sociological Review* 51(4):464.

Sobieraj, Sarah, and Jeffrey M. Berry. 2011. "From Incivility to Outrage: Political Discourse in Blogs, Talk Radio, and Cable News." *Political Communication* 28(1):19–41.

Stier, Sebastian, Lisa Posch, Arnim Bleier, and Markus Strohmaier. 2017. "When Populists Become Popular: Comparing Facebook Use by the Right-Wing Movement Pegida and German Political Parties." *Information, Communication & Society* 20(9):1365–88.

Strang, David, and Sarah A. Soule. 1998. "Diffusion in Organizations and Social Movements: From Hybrid Corn to Poison Pills." *Annual Review of Sociology* 24:265–90.

Tilly, Charles. 2004. *Social Movements, 1768-2004*. Abingdon, Oxford: Routledge.

Tufekci, Zeynep. 2018. *Twitter and Tear Gas: The Power and the Fragility of Networked Protest*. New York, NY.

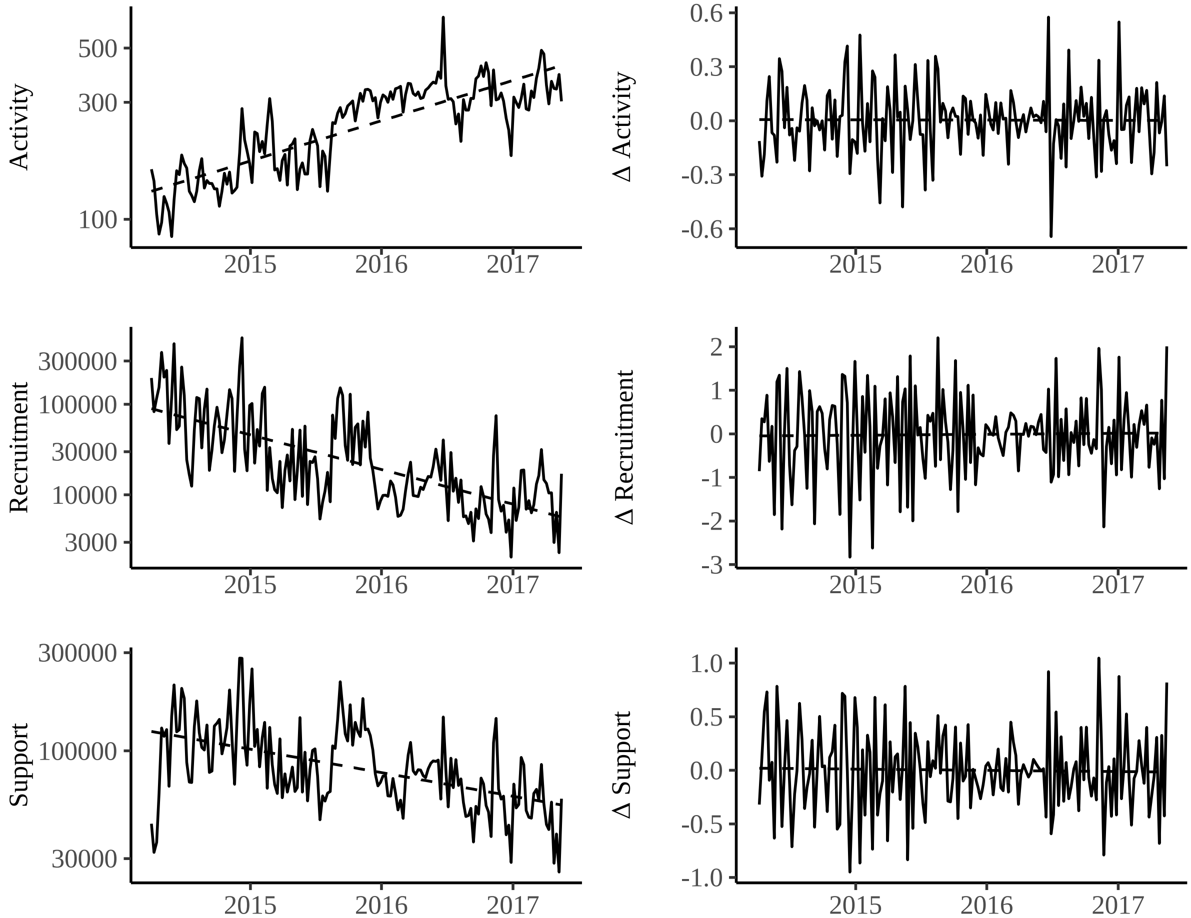
Tufekci, Zeynep, and Christopher Wilson. 2012. “Social Media and the Decision to Participate in Political Protest: Observations From Tahrir Square.” *Journal of Communication* 62(2):363–79.
Vasi, Ion Bogdan, and Chan S. Suh. 2016. “Online Activities, Spatial Proximity, and the Diffusion of the Occupy Wall Street Movement in the United States.” *Mobilization: An International Quarterly* 21(2):139–54.
Wilkerson, John, and Andreu Casas. 2017. “Large-Scale Computerized Text Analysis in Political Science: Opportunities and Challenges.” *Annual Review of Political Science* 20:529–44.
Williams, Matthew L., and Pete Burnap. 2016. “Cyberhate on Social Media in the Aftermath of Woolwich: A Case Study in Computational Criminology and Big Data.” *British Journal of Criminology* 56(2):211–38.
Winner, Langdon. 1980. “Do Artifacts Have Politics?” *Daedalus* 109(1):121–36.

FIGURES

Figure 1: Images posted on Facebook by Britain First

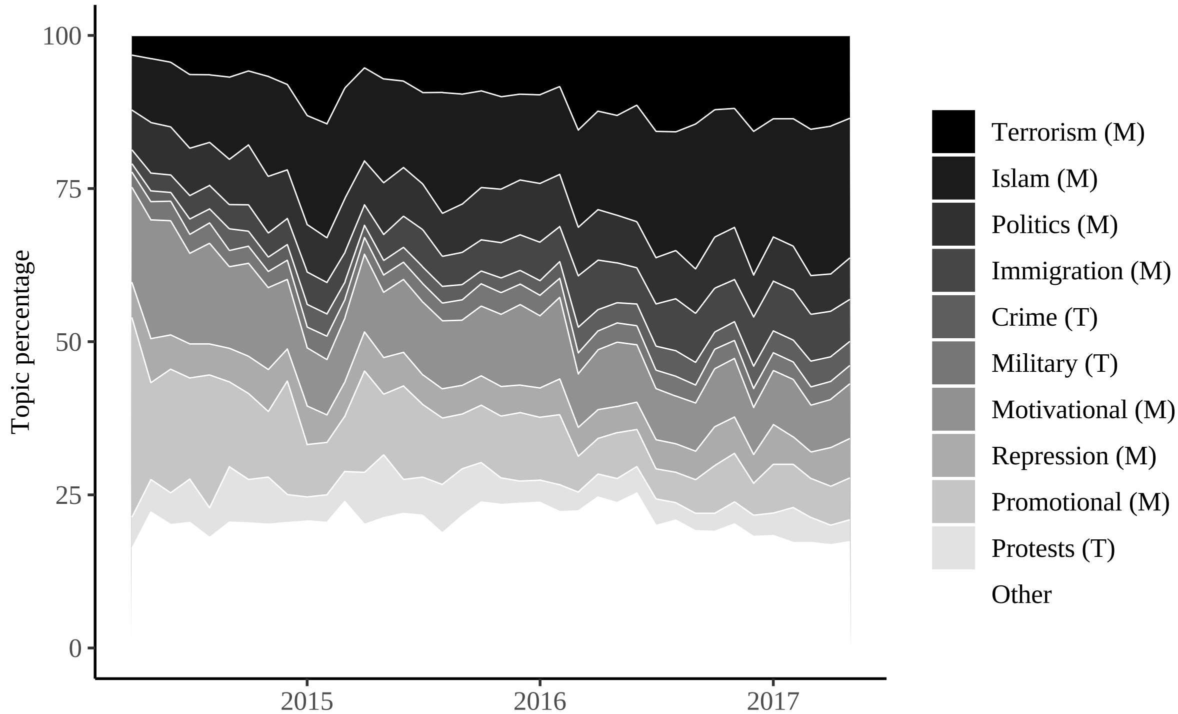
Note: Each thumbnail shows an image posted sequentially on the Britain First Facebook page. Many of the posts include text requesting users to "share" them. Screenshot by the author, 2017.

Figure 2: Dependent variables in levels and first-differences



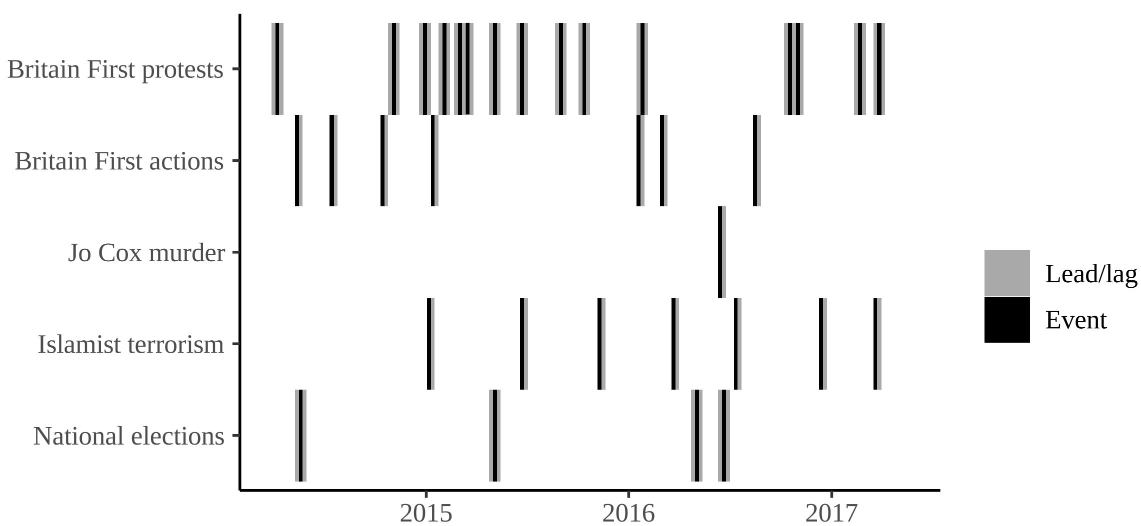
Note: In the left column, the black line in each panel shows the weekly counts of each variable using a logarithm scale on the y-axis. In the right column, each variable has been log transformed and first-differenced. Dashed lines in each plot show the linear trend.

Figure 3: Topic prevalence over time



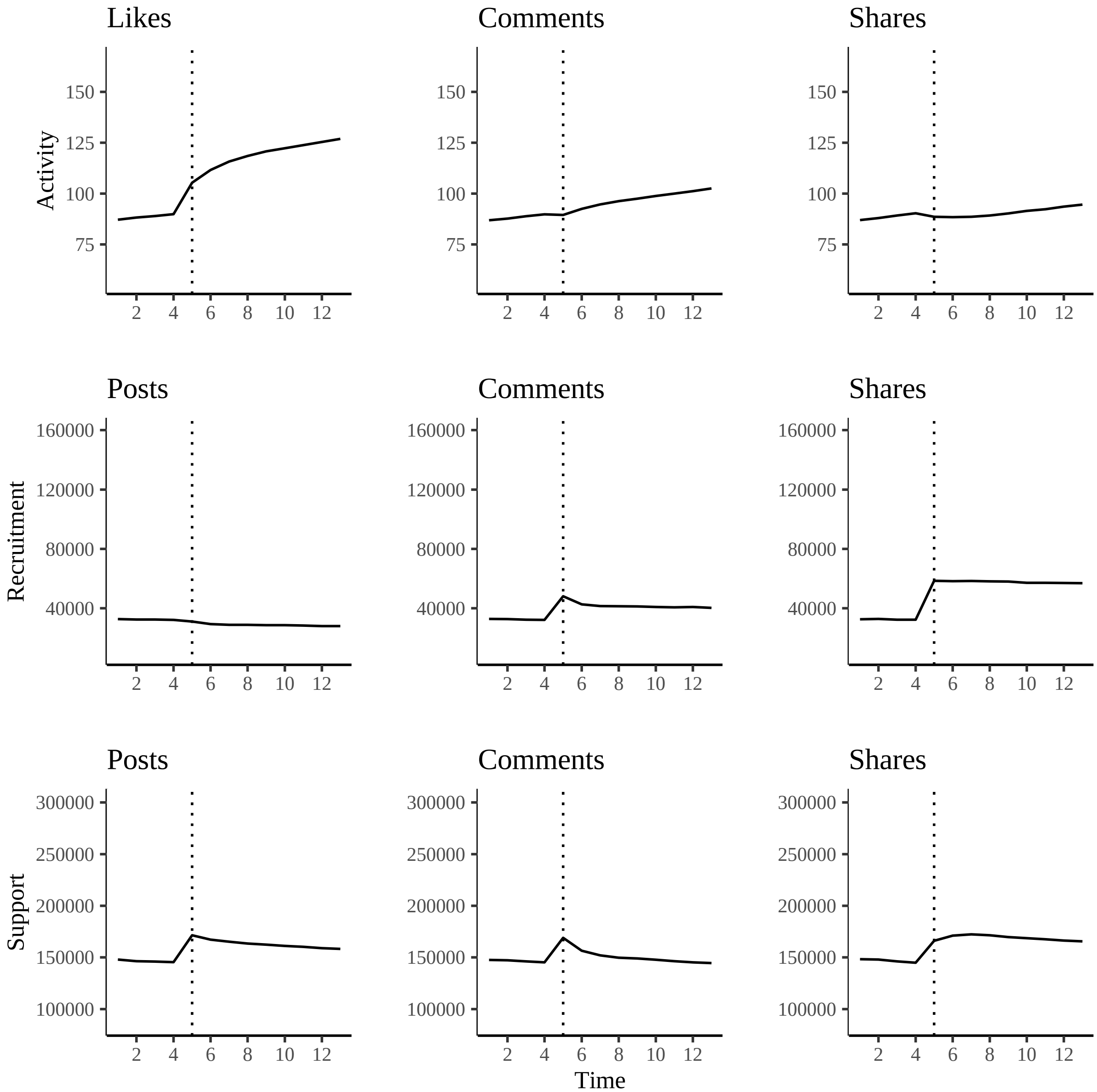
Note: (Meta)topic prevalence over time, four week averages. Topic names are prefixed to denote whether each is an individual topic ("T") or a metatopic ("M"). The Other category, shaded in white, represents residual topics not considered in the analysis.

Figure 4: Event occurrences, 2014-2017



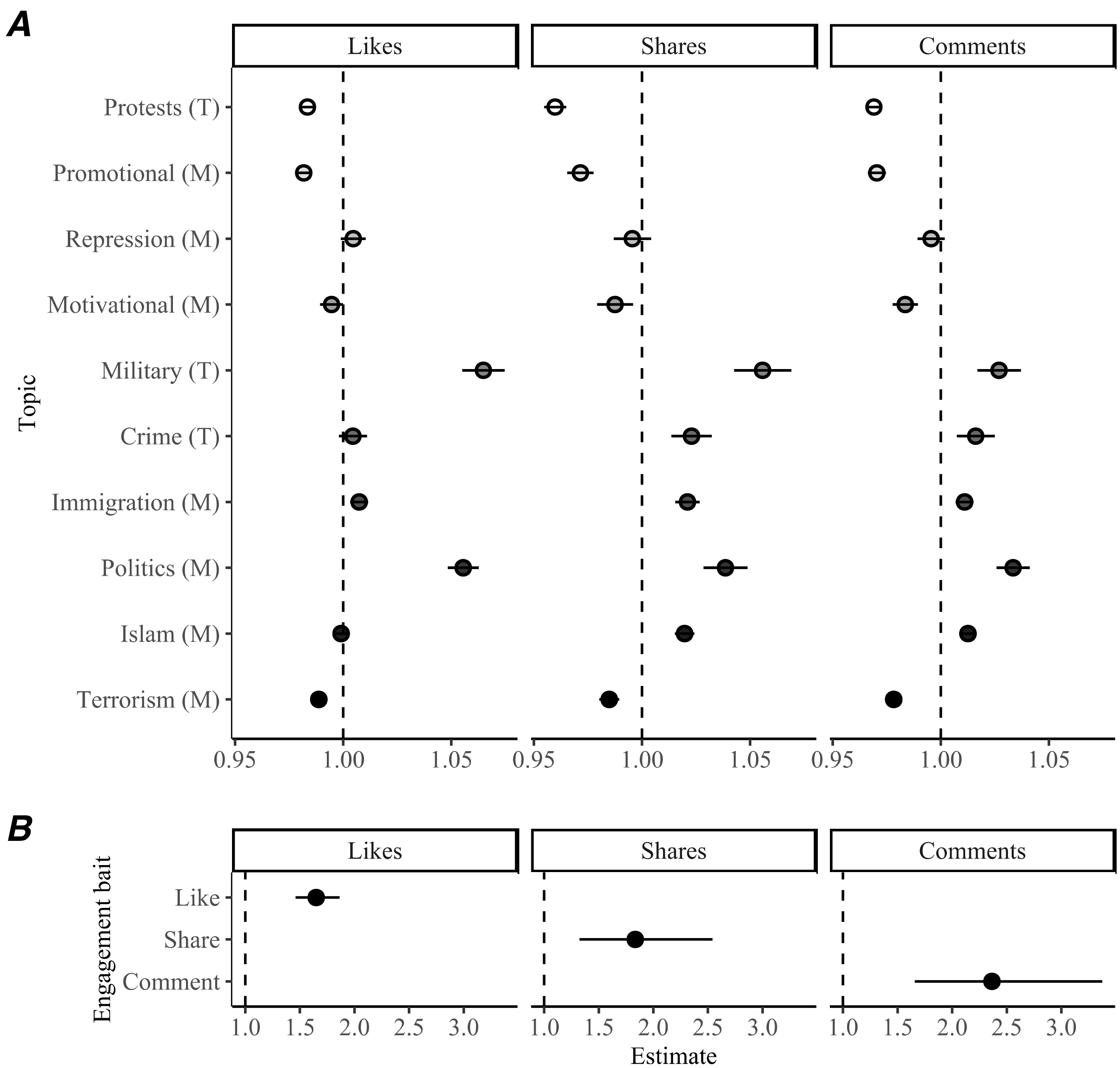
Note: Each row corresponds to a different event class, and each black vertical line represents a week where an event occurred. Grey lines indicate the weeks before and after events when included in the models as leads or lags.

Figure 5: Simulated effect of shocks to key independent variables



Note: Top row: Activity. Middle row: Recruitment. Bottom row: Support. The solid lines in each panel indicate the mean value of the dependent variable over all simulations. The shaded regions indicate the lower and upper percentiles for the 75%, 90%, and 95% density intervals, e.g., 75% of the estimates are within the dark gray region. The dotted vertical line denotes the period when the shock is applied.

Figure 6: Topics, engagement bait, and engagement metrics



Note: Negative binomial regression estimates the relationship between topics, engagement bait, and engagement. Each observation is a Facebook post by BF, N = 36,196. Coefficients are reported as incidence rate ratios, denoting the expected change in engagement rates in response to change in each independent variable. Models for topics (Panel A) control for post type (story/video/photo), word count, word count squared, hour of the day, and hour of the day squared. Models for engagement bait (Panel B) also control for topic. All models include day fixed effects and standard errors clustered by day. Full regression results are reported in Appendix F.

TABLES

Table 1: Example posts from each (meta)topic

Topic type	Meta(topic)	$\widehat{\theta_k}$	Example(s)
Issue	Crime	0.03	*"Armed police arrest man suspected of carrying knife outside gates of UK parliament!"*
	Military	0.03	*"The British armed forces are the best in the world!"*
	Islam	0.16	*"Pakistani mother handed death sentence for burning daughter alive in 'honor killing'!", "VIDEO: Muslims pray on the streets of Rome", "BAN HALAL SLAUGHTER! Animals are hung upside-down to bleed to death whilst conscious. Most Halal meat isn't labelled!", "VIDEO: KFC MUSLIM EMPLOYEE SCREAMS INSULTS AT CUSTOMER ASKING FOR BACON!"*
	Terrorism	0.09	*"Jordan vows to 'wipe Isis out completely' as it investigates claim US hostage killed in air strike", "UK AIRPORTS, NUCLEAR PLANTS PLACED ON TERROR ALERT AS EXPERTS WARN OF 'CREDIBLE' SECURITY THREAT!", "Islamic extremists infiltrating schools, universities and scout groups"*
	Immigration	0.06	*"Time to deport the lot of them and seal Europe's borders!", "INVASION! Fake refugees overrun Greek island"*
	Politics	0.07	*"Canada's Prime Minister is a treacherous leftwing snake!", "GO TRUMP: Donald Trump vows to stay in race amid calls to step down! ...", "… Britain First has nothing but contempt for the corrupt, media-rigged, phoney electoral system where the Old Gang parties of Lib-Lab-Con enjoy unchallenged supremacy …", "PRESSURE IS BUILDING ON THE LABOUR PAEDOPHILE APOLOGISTS …"*
Instrumental	Motivational	0.04	*"SO FAR WE HAVE OVERSEAS GUEST SPEAKERS CONFIRMED FROM POLAND, THE NETHERLANDS, THE 'PEGIDA' MOVEMENT, 'FORTRESS EUROPE' FROM GERMANY, FRANCE AND THE CZECH REPUBLIC, WITH MORE TO BE ANNOUNCED! …", "Time to take our country back!"*
	Repression	0.06	*"Sign the petition to DEMAND Twitter reinstates our profiles!", "TRIAL UPDATE Paul Golding is currently on trial at Chelmsford Magistrates Court. Prosecution are arguing their case."*
	Promotional	0.20	*"DO YOU AGREE? SHARE and LIKE!", "…Leftwing Greenwich Council have refused to give hero Lee Rigby a memorial, despite giving one for Stephen Lawrence. Click below and complain! Template letter provided! … Please add "newsletter@ britainfirst.org" to your email contacts.", "Britain First issue advice to activists. Britain First", "The Taliban Hunting Club T-Shirt Available in Small - 4XL FREE UK DELIVERY …"*
	Protests	0.05	*"JOIN US IN ROTHERHAM THIS SATURDAY 5TH SEPTEMBER! THERE ARE 1,400 REASONS WHY! …"*

Note: $\widehat{\theta_k}$ is the estimated proportion of each (meta)topic in the entire corpus. Examples are posts with high proportions of each topic. Metatopics include an example from each component topic. Some posts are truncated but original emphasis is retained.

Table 2: ECM predicting week change in Britain First's online activity

	(1)	(2)
LDV	-0.44***,α	-0.52***,α
	(0.06)	(0.07)
Likes (lag)	0.18**	0.21***
	(0.06)	(0.06)
Comments (lag)	0.04	0.03
	(0.05)	(0.05)
Shares (lag)	-0.02	-0.03
	(0.02)	(0.02)
Δ Likes	0.29***	0.25***
	(0.05)	(0.04)
Δ Comments	-0.04	-0.04
	(0.05)	(0.04)
Δ Shares	-0.03	-0.03
	(0.02)	(0.02)
Media controls		✓
Event controls		✓
N	163	163
R2	0.404	0.568
R2 Adj.	0.373	0.497
F	13.046	7.955
Breusch-Godfrey	✓	✓
Shapiro-Wilk	✗	✓
PSS F	-	✓
PSS t	-	✓

* p < 0.05, ** p < 0.01, *** p < 0.001. α indicates statistical significance with MacKinnon critical value for LDV (99%).

Table 3: ECM predicting weekly change in Britain First's online recruitment

	(1)	(2)	(3)	(4)
LDV	-0.63***,$^{\alpha}$	-0.81***,$^{\alpha}$	-0.69***,$^{\alpha}$	-0.86***,$^{\alpha}$
	(0.07)	(0.09)	(0.07)	(0.10)
Activity (lag)	-0.11	-0.25	0.10	-0.19
	(0.19)	(0.23)	(0.21)	(0.25)
Comments (lag)	0.18	0.58**	0.19	0.57**
	(0.14)	(0.19)	(0.14)	(0.20)
Shares (lag)	0.39***	0.44***	0.42***	0.47***
	(0.07)	(0.07)	(0.07)	(0.08)
Δ Activity	-0.22	-0.17	0.11	-0.08
	(0.21)	(0.24)	(0.24)	(0.28)
Δ Comments	0.91***	1.04***	0.86***	0.99***
	(0.12)	(0.13)	(0.12)	(0.14)
Δ Shares	0.56***	0.53***	0.56***	0.54***
	(0.05)	(0.05)	(0.05)	(0.05)
Media controls			✓	✓
Event controls			✓	✓
Topic controls		✓		✓
N	163	163	163	163
R2	0.800	0.850	0.837	0.867
R2 Adj.	0.789	0.818	0.810	0.820
F	76.817	27.065	31.003	18.118
Breusch-Godfrey	✗	✓	✗	✓
Shapiro-Wilk	✗	✗	✓	✓
PSS F	-	-	-	✓
PSS t	-	-	-	✓

* p < 0.05, ** p < 0.01, *** p < 0.001. $^{\alpha}$ indicates statistical significance with MacKinnon critical value for LDV (99%).

Table 4: ECM predicting weekly change in Britain First's online support

	(1)	(2)	(3)	(4)
LDV	-0.55***,$^{\alpha}$	-0.67***,$^{\alpha}$	-0.53***,$^{\alpha}$	-0.69***,$^{\alpha}$
	(0.07)	(0.08)	(0.07)	(0.09)
Activity (lag)	0.12	0.15	0.12	0.25
	(0.10)	(0.12)	(0.11)	(0.14)
Comments (lag)	0.11	0.10	0.09	0.10
	(0.07)	(0.09)	(0.07)	(0.09)
Shares (lag)	0.10**	0.14***	0.08*	0.12**
	(0.03)	(0.03)	(0.03)	(0.04)
Δ Activity	0.32**	0.30*	0.41**	0.42**
	(0.11)	(0.13)	(0.12)	(0.14)
Δ Comments	0.45***	0.40***	0.44***	0.39***
	(0.06)	(0.07)	(0.06)	(0.07)
Δ Shares	0.14***	0.15***	0.12***	0.13***
	(0.02)	(0.03)	(0.03)	(0.03)
Media controls			✓	✓
Event controls			✓	✓
Topic controls		✓		✓
N	163	163	163	163
R2	0.676	0.741	0.732	0.779
R2 Adj.	0.659	0.686	0.687	0.699
F	40.080	13.663	16.471	9.745
Breusch-Godfrey	✗	✓	✗	✓
Shapiro-Wilk	✓	✓	✓	✓
PSS F	-	-	-	✓
PSS t	-	-	-	✓

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. $^{\alpha}$ indicates statistical significance with MacKinnon critical value for LDV (99%).