

Does Facebook Lead Public Attention or Follow It? Facebook Engagement, Wikipedia Pageviews and Google Searches for British Parties and Leaders, 2015 to 2020

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Abstract

Engagement on politicians' Facebook pages is often read as a sign of public interest. I ask how closely it tracks two free measures of public attention, Wikipedia pageviews and Google searches, and whether it moves before or after them. I use 93,567 posts from 32 British pages (13 parties, 18 current or former leaders and Momentum) between July 2015 and October 2020, which drew 245 million interactions, matched to 126 million views of the corresponding English Wikipedia articles and to weekly Google Trends indices for 21 of the actors. Within each actor, Facebook engagement and the two attention measures rose and fell together, but loosely: the average correlation of detrended daily Facebook and Wikipedia series was 0.12, rising to 0.25 for weekly series, while Wikipedia and Google moved together far more closely (0.83). On timing, the strongest link was on the same day or in the same week. Wikipedia stayed raised for a few days after Facebook spikes, and Facebook usually peaked on the same day as a Wikipedia spike or within a day of it, with no clear tendency to come first. Panel Granger tests with actor and date fixed effects find small predictive links in both directions at the daily scale; at the weekly scale, rises in Facebook engagement went with somewhat higher Wikipedia and Google attention in the following weeks, but the summed effects are modest and sensitive to the sample. At the 2017 and 2019 general elections and the 2019 European Parliament election, shares of Facebook engagement and of Wikipedia views missed the parties' vote shares by similar margins (mean absolute errors of 8.0 and 7.4 points), Google search shares did worse (11.2), and all three were far less accurate than the final polls (1.1) or the previous result (4.1). Facebook engagement behaves like one more measure of attention: it moves with public interest rather than reliably ahead of it, and it is not a measure of support.

Keywords: public attention; Facebook; Wikipedia; Google Trends; digital trace data; lead-lag; Granger causality; British politics; election forecasting; CrowdTangle

1 Introduction

Numbers from social media are everywhere in political commentary. When a leader's video is shared widely, or a party's page draws more likes than its rivals, the figures are often read as a sign that the public is paying attention, and sometimes as a sign that the public is coming round. Academic work has

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been more cautious. Studies that tried to predict elections from Twitter mentions found that the results did not travel (Gayo-Avello 2013), and a careful review of the evidence concluded that digital traces mostly measure attention toward politics rather than support for any party (Jungheer et al. 2017). If that is right, the question becomes how good a measure of attention social media engagement is, and how it relates to other measures of the same thing.

Two such measures are free and easy to obtain. Wikipedia publishes how many times each of its articles is viewed every day, and Google Trends publishes an index of how often a term is searched. Both have been used to study elections and issue salience (Mellon 2013, 2014; Yasseri and Bright 2016; Smith and Gustafson 2017). Both capture people seeking information, which is a different act from liking or sharing a post on a page that a party controls. Facebook engagement mixes the audience's response with the page's own activity: a page that posts more will usually draw more interactions, whatever the public mood. Comparing engagement with search and pageviews therefore asks whether the attention that parties and leaders gather on their own pages moves with wider public interest, and whether it moves first.

The timing matters for how engagement is interpreted. If spikes in engagement come before spikes in public searching, engagement might be an early sign of what the wider public will soon look for, or the pages might be helping to create the attention. If they come after, engagement is better read as a response to events and to coverage elsewhere, an echo of attention that has already formed. If they come together, engagement is one more reading of the same moments. Work on Twitter and elections described tweets as predictive, reactive or buzz (Murthy 2015); work on agenda setting has used social media and search data to ask who leads and who follows (Neuman et al. 2014; Barberá et al. 2019). I ask the same questions of party and leader pages on Facebook.

I study British parties and leaders between July 2015 and October 2020, a period of four national votes: the 2016 referendum on membership of the European Union, the general elections of 2017 and 2019, and the 2019 European Parliament election. I use the posts of 32 pages, collected through CrowdTangle for my doctoral research, and match each page to the English Wikipedia article on the same party or person and, where available, to a Google search term. I ask three questions. **RQ1.** How closely does Facebook engagement with party and leader pages track Wikipedia pageviews and Google searches for the same actors? **RQ2.** Do spikes in Facebook engagement come before, with or after spikes in Wikipedia and Google attention? **RQ3.** At elections, do shares of Wikipedia views or Google searches come closer to the parties' vote shares than shares of Facebook engagement?

The short answers are these. Engagement tracks the two attention measures, but loosely: much more loosely than Wikipedia and Google track each other. The timing is mostly simultaneous. Where there is an asymmetry, it is that Wikipedia attention lingers after Facebook spikes, and the formal tests find small predictive links in both directions rather than a clear leader. At elections, Facebook and Wikipedia shares miss the result by similar margins, Google shares by more, and all three are far less accurate than polls. Given the observational design and the few elections, I describe these patterns and do not claim that one measure causes another.

The paper extends my earlier work with the same Facebook data. In a study of British leaders and party pages over a decade, I found that within a party, monthly engagement and polling moved together, with no evidence that engagement moved first (Hotham 2026c). In a working paper on 31 European elections, I found that parties' shares of Facebook engagement missed their vote shares by far more than the final polls, in every election (Hotham 2026b). Engagement also overstates populist parties relative to their vote (Hotham 2026a). This paper is about something different: not support but attention, and not

monthly polls but the daily and weekly timing of attention measured outside Facebook. The election comparison returns to the forecasting question only to ask whether two other attention measures do better than Facebook, which those papers could not test.

2 Background

Engagement as attention. A Facebook interaction is a like, a comment, a share or a reaction to a post. Parties and leaders post on their pages, and their followers, opponents and passers-by respond. The total each page receives depends on the size of its audience, how much the page posts, what it posts and what is happening in the world. Studies of election prediction from social media data found that counts of mentions or followers sometimes lined up with results but did not do so reliably (Gayo-Avello 2013). Jungherr et al. (2017) argue, from German data, that such traces are better read as indicators of attention toward politics than of political support. That reading fits my own findings that engagement is badly calibrated across parties (Hotham 2026c,b). It also implies a testable expectation: if engagement measures attention, it should move with other measures of attention.

Wikipedia and Google as attention measures. Wikipedia pageviews record how often an article is read. They have been used to predict elections, with mixed results: Yasseri and Bright (2016) found that pageviews of party articles before European elections carried information about turnout and results but needed to be combined with theory to be useful; Smith and Gustafson (2017) found that views of candidates' pages helped to predict United States election outcomes; and Salem and Stephany (2020) found that information-seeking on Wikipedia was especially informative about challengers. Google Trends offers an index of search volume for a term in a place and time. Reilly et al. (2012) showed that search data tracked roll-off in American state ballot measures, and Mellon (2013, 2014) showed that searches can measure issue salience in some settings but not in others, depending on whether people search for the issue in a consistent way. Search data also carry warnings. Google Trends draws a sample of searches, so repeated downloads of the same query differ (Eichenauer et al. 2022; Behnen et al. 2020), and the failure of search-based influenza estimates is a reminder that relationships found in search data can drift (Lazer et al. 2014).

Who leads, who follows. Agenda-setting research asks whose attention moves first. Using social media and other online sources, Neuman et al. (2014) found that the relationship between traditional media and social media attention runs in both directions and differs by issue. Barberá et al. (2019) found that American legislators were more likely to follow the issue attention of the public and their supporters on Twitter than to lead it. Murthy (2015) argued that election tweets were mostly reactive, responding to events rather than anticipating them. For party and leader pages, one could expect either order. Pages may anticipate attention because many political moments are scheduled: parties post heavily before a debate, a manifesto launch or polling day, while the public searches when the event happens or when the result is known. Or pages may follow attention, because what draws engagement is usually news that has already broken, and followers arrive at a page after hearing a name elsewhere.

Expectations. I state these as descriptive expectations, not causal hypotheses. **E1:** within each actor, Facebook engagement is positively correlated with Wikipedia pageviews and Google searches, but less closely than the two information-seeking measures are with each other, because engagement also reflects the page's own posting. **E2:** the strongest association is on the same day or in the same week. I have no firm expectation about the direction of any lead or lag, and I report the evidence for both. **E3:** because all three measures capture attention rather than support, none will predict vote shares well, and none will

approach the accuracy of polls.

3 Data

3.1 Facebook pages

The Facebook data are two CrowdTangle exports ([CrowdTangle Team 2020](#)) I made in October 2020 for my doctoral research ([Hotham 2021](#)): one of British party pages and one of British parties and leaders. Each record is a post with its date and time, the counts of likes, comments, shares and, from 2016, the reactions love, wow, haha, sad, angry and care. I define *interactions* as the sum of all of these. After removing posts that appear in both exports, the two lists contain 139,113 posts from 2010 to 2020. I drop one page, Gordon Brown’s, which posted only 15 times. CrowdTangle gives the time of each post in British time; I convert it to Coordinated Universal Time so that days match the Wikipedia data, and I attribute all of a post’s interactions to the day it was posted. This is the main limitation of the timing analysis, since most interactions arrive within hours of posting but some arrive on following days. It will tend to make Facebook look slightly earlier than it is. I return to this below.

I keep 32 pages (Table 1). Thirteen are party pages: the Conservatives, Labour, the Liberal Democrats, the Scottish National Party (SNP), UKIP, the Green Party of England and Wales, the Brexit Party, Plaid Cymru, Sinn Féin, and the Alliance, Democratic Unionist, Social Democratic and Labour, and Ulster Unionist parties of Northern Ireland. Eighteen are the pages of politicians who led, had led or would lead one of these parties, such as Jeremy Corbyn, Theresa May, Boris Johnson, Nigel Farage, Nicola Sturgeon and Jo Swinson. Some of them did not lead their party for the whole period. David Cameron and Ed Miliband had stepped down by the time the data begin or soon after, and Keir Starmer became Labour leader only in April 2020. I call this group politicians rather than leaders. The last page is Momentum, a campaigning organisation linked to the Labour Party, which I include in the pooled analyses but not in the comparison of parties and politicians. For each page I build a daily series of total interactions and number of posts, covering the days from the page’s first to its last post within the study period. Many politicians’ pages did not post every day: for half of the 32 pages, there was no post on at least half of the days. On those days the page’s interactions are zero.

3.2 Wikipedia pageviews

For each page I take the daily views of the English Wikipedia article on the same party or person from the Wikimedia pageviews interface ([Wikimedia Foundation 2026](#)), counting all access methods and only views classified as made by people rather than automated agents. The data run from 1 July 2015, the first day available, to 31 October 2020. I match pages to articles by hand: for example, the page called The Labour Party to the article `Labour_Party_(UK)`, the page of Natalie Bennett to `Natalie_Bennett`, and Momentum to `Momentum_(organisation)`. The Brexit Party article begins in January 2019 and the Momentum article in October 2015, so those series start then. These views are global: English Wikipedia is read throughout the world, and the views cannot be restricted to Britain. This matters most for Sinn Féin, which organises in both parts of Ireland, and for prominent figures such as Boris Johnson and Theresa May, whose articles are read widely abroad. The panel combines the two series on the days that both cover, giving 58,543 actor-days between 1 July 2015 and 27 October 2020, with 93,567 posts, 244.7 million interactions and 125.6 million pageviews.

Table 1. Actors, Facebook pages, Wikipedia articles and Google search terms, July 2015 to October 2020. Posts and interactions are for the days in each actor’s series. No-post days: share of days on which the page did not post. Views: English Wikipedia pageviews, all access methods, user agents. The last column gives the share of weeks in which the term’s Google Trends value was below 1 within its download.

Actor	Wikipedia article	Posts	Interactions (m)	No-post days (%)	Views (m)	Google term	<1 (%)
<i>Party pages</i>							
Labour	Labour_Party_(UK)	5,782	19.8	14	6.99	Labour Party	0
Conservatives	Conservative_Party_(UK)	4,623	17.7	26	7.18	Conservative Party	86
UKIP	UK_Independence_Party	4,631	11.4	27	3.27	UKIP	0
SNP	Scottish_National_Party	5,127	9.6	16	2.36	Scottish National Party	98
Brexit Party	Brexit_Party	1,405	5.8	34	1.60	Brexit Party	7
Sinn Féin	Sinn_Féin	4,370	4.1	14	4.91		
Green Party (E&W)	Green_Party_of_England_and_Wales	3,875	4.0	16	1.24	Green Party ^a	0
Liberal Democrats	Liberal_Democrats_(UK)	5,497	3.0	20	3.02	Liberal Democrats	92
Plaid Cymru	Plaid_Cymru	3,817	0.7	18	1.56	Plaid Cymru	89
Alliance	Alliance_Party_of_Northern_Ireland	4,142	0.3	26	0.68		
DUP	Democratic_Unionist_Party	1,081	0.2	64	3.22		
SDLP	Social_Democratic_and_Labour_Party	2,334	0.2	45	0.96		
UUP	Ulster_Unionist_Party	1,149	0.1	70	0.96		
<i>Campaign organisation</i>							
Momentum	Momentum_(organisation)	8,803	20.7	3	0.69	Momentum ^a	0
<i>Politicians’ pages</i>							
Jeremy Corbyn	Jeremy_Corbyn	5,348	55.2	13	12.11	Jeremy Corbyn	14
Nigel Farage	Nigel_Farage	3,436	43.0	16	5.77	Nigel Farage	0
Boris Johnson	Boris_Johnson	2,327	24.2	55	24.46	Boris Johnson	35
Nicola Sturgeon	Nicola_Sturgeon	1,217	6.9	58	3.23	Nicola Sturgeon	9
Theresa May	Theresa_May	1,070	4.3	63	16.15	Theresa May	0
David Cameron	David_Cameron	469	4.0	82	10.07	David Cameron	0
Keir Starmer	Keir_Starmer	1,299	2.4	65	5.57	Keir Starmer	41
Leanne Wood	Leanne_Wood	4,710	2.3	12	0.33		
Natalie Bennett	Natalie_Bennett	7,894	1.4	22	0.25		
Caroline Lucas	Caroline_Lucas	1,041	1.3	63	0.77	Caroline Lucas	68
Alex Salmond	Alex_Salmond	1,159	0.8	72	1.09		
Tim Farron	Tim_Farron	1,684	0.4	52	1.30	Tim Farron	72
Vince Cable	Vince_Cable	2,030	0.3	51	1.03	Vince Cable	54
Ed Miliband	Ed_Miliband	405	0.2	83	2.04	Ed Miliband	52
Jo Swinson	Jo_Swinson	634	0.1	64	2.01	Jo Swinson	81
Siân Berry	Siân_Berry	968	0.1	69	0.33		
Jonathan Bartley	Jonathan_Bartley	600	0.1	72	0.25		
Adam Price	Adam_Price	640	0.1	76	0.21		

^a Ambiguous search term: excluded in robustness checks. Google values for Labour come from the batch in which Labour had the highest values; the term appears in all five batches.

3.3 Google searches

Google Trends (Google 2026) reports, for up to five search terms at a time, an index of weekly search interest scaled so that the highest week for any of the five terms is 100. Values are integers, and weeks with some but very little interest are shown as below 1. I downloaded five batches of weekly data for the United Kingdom, from the week beginning Sunday 27 December 2015 to October 2020, each including the term Labour Party as a common anchor. The batches cover 21 actors, using plain search terms rather than Google’s topic entities (Table 1). I treat values shown as below 1 as 0.5. To put all terms on one scale, I multiply each batch by the ratio of the anchor’s total in the reference batch to its total in that batch, taking as the reference the batch in which Labour Party had its highest values. This rescaling is only needed to compare actors with each other, as in the election analysis; the time-series analysis uses each term’s values within its own batch, where changes are unaffected by the scale.

Google data have three weaknesses here. First, precision: within a batch the largest term sets the scale, so terms with much less interest spend most weeks near the floor. In the batch that included Boris Johnson, the anchor Labour Party itself was below 1 in 60% of weeks, so the rescaling of that batch is coarse, and the search terms Conservative Party and Liberal Democrats were below 1 in 86% and 92% of weeks.

The term Scottish National Party was below 1 in 98% of weeks, probably because people search for SNP. For the time-series analysis I therefore keep the 12 terms that were below 1 in fewer than half of the weeks in which their actor is observed. Second, ambiguity: Momentum is an ordinary word, and Green Party matches searches for green parties other than the one in England and Wales. I flag both and repeat the analyses without them, leaving ten terms. Third, sampling: Google computes the index from a sample of searches, so downloads made on different days give slightly different values (Eichenauer et al. 2022; Behnen et al. 2020). I use a single download of each batch and cannot measure this noise.

3.4 Elections and polls

For the election comparison I use the official results compiled by the House of Commons Library for the general elections of 2015, 2017 and 2019 (vote shares for the United Kingdom) and for the 2019 European Parliament election (shares for Great Britain) (House of Commons Library 2015, 2017, 2020, 2019). The 2016 referendum was not a contest between parties and I leave it out, as I do the 2015 general election, which falls before the Wikipedia and Google data begin. For the general elections, the parties compared are those for which my forecasting working paper has averages of the final polls, the Conservatives, Labour, the Liberal Democrats, the SNP, the Greens and, in 2017, UKIP or, in 2019, the Brexit Party (Hotham 2026b). Those averages cover polls with fieldwork ending in the 14 days before polling day. For the European election I compare the Brexit Party, the Liberal Democrats, Labour, the Greens, the Conservatives, the SNP and UKIP, without polls. Change UK has no page in the data. Plaid Cymru is added in a robustness check.

4 Methods

4.1 Series

For each actor I take the natural logarithm of one plus daily interactions, and of one plus daily pageviews. To remove slow trends, such as the growth of a page’s audience or the decline of interest in a former leader, I subtract from each value the centred 29-day moving average of the series, and then subtract the actor’s average deviation for each day of the week, because parties post less at weekends and Wikipedia is read differently on different days. I call the result the *detrended* series; it measures how far a day is above or below its local level. I also use first differences of the log series. For weekly analyses I sum days into Sunday-to-Saturday weeks to match Google’s weeks, use the logarithm of one plus the Google index, and detrend with a centred nine-week moving average.

4.2 Correlation and timing

For RQ1 I compute, for each actor, the correlation between Facebook and each attention measure in log levels, detrended values and first differences, and average the correlations across actors using Fisher’s transformation, with 95% intervals from resampling actors. For RQ2 I use four approaches, each with its own strengths.

Cross-correlations. For each actor I compute the correlation between Facebook on day t and Wikipedia on day $t + k$, for k from -14 to 14 days, and average across actors. A positive k means Wikipedia after Facebook. If Facebook led, the correlations would peak at positive k ; if it followed, at negative k . The cross-correlation function has a known weakness: it cannot separate a lead from a difference

in persistence. If both series jump on the same day but one decays more slowly, the correlations will be higher on that side of zero even though neither moved first. I therefore also report an asymmetry measure, the average correlation at lags one to three minus the average at leads one to three, and treat it as descriptive.

Lead-lag regressions. I regress each actor's standardised detrended Wikipedia series on Facebook three days before, on the same day and three days after, with fixed effects for actor and date. The date effects absorb shocks common to all actors, such as election nights. Standard errors are clustered by actor and, as an alternative, follow [Driscoll and Kraay \(1998\)](#), which allows for correlation across actors and over time.

Panel Granger tests. Following [Granger \(1969\)](#), I ask whether past changes in one series help to predict changes in the other once the other's own past is known. For the daily data I regress the standardised first difference of log Wikipedia views on seven of its own lags and seven lags of the standardised first difference of log Facebook interactions, with actor and date fixed effects, and test whether the Facebook lags are jointly zero. I then reverse the roles. For the weekly data I use four lags and repeat the tests between Facebook and Google, between Facebook and Wikipedia, and between Wikipedia and Google. I report the joint Wald test and the sum of the lag coefficients, which measures, in standard deviations, how much a one standard deviation change in one series is followed by change in the other over the following period. With 32 actors, and only 12 for Google, tests based on clustered errors can be too ready to reject, so I also report Driscoll-Kraay errors and treat isolated significant results with caution. I also run the daily tests separately for each actor using ordinary least squares with heteroskedasticity and autocorrelation consistent errors.

Spikes. The averages above weigh every day equally. To focus on the moments that matter most for attention, I identify for each actor the ten largest daily spikes in the detrended Wikipedia series, at least 15 days apart, and find the day within seven days either side on which detrended Facebook engagement peaked. I record the offset, negative if Facebook peaked before the Wikipedia spike and positive if after, and repeat the exercise in the other direction, starting from Facebook spikes. As a benchmark I apply the same procedure to random days. At the weekly scale I use the five largest Google spikes per actor and a window of two weeks either side.

4.3 Elections

For RQ3 I sum each party's Facebook interactions and Wikipedia views over the 30 days before polling day, and its rescaled Google index over the four complete weeks before the week of polling day. I convert each measure to shares of the total for the parties compared and compare them with each party's share of the votes cast for the same parties. I summarise accuracy by the mean absolute error in percentage points, and compare it with the final polls and with the previous general election result, both renormalised in the same way. With three elections and six or seven parties in each, this comparison is descriptive.

5 Results

5.1 Facebook tracks attention, but loosely

Figure 1 shows the three measures for three actors over 2019 and early 2020, each scaled to its own peak. They share the large moments: the general election in December 2019 for Labour, the Conservative

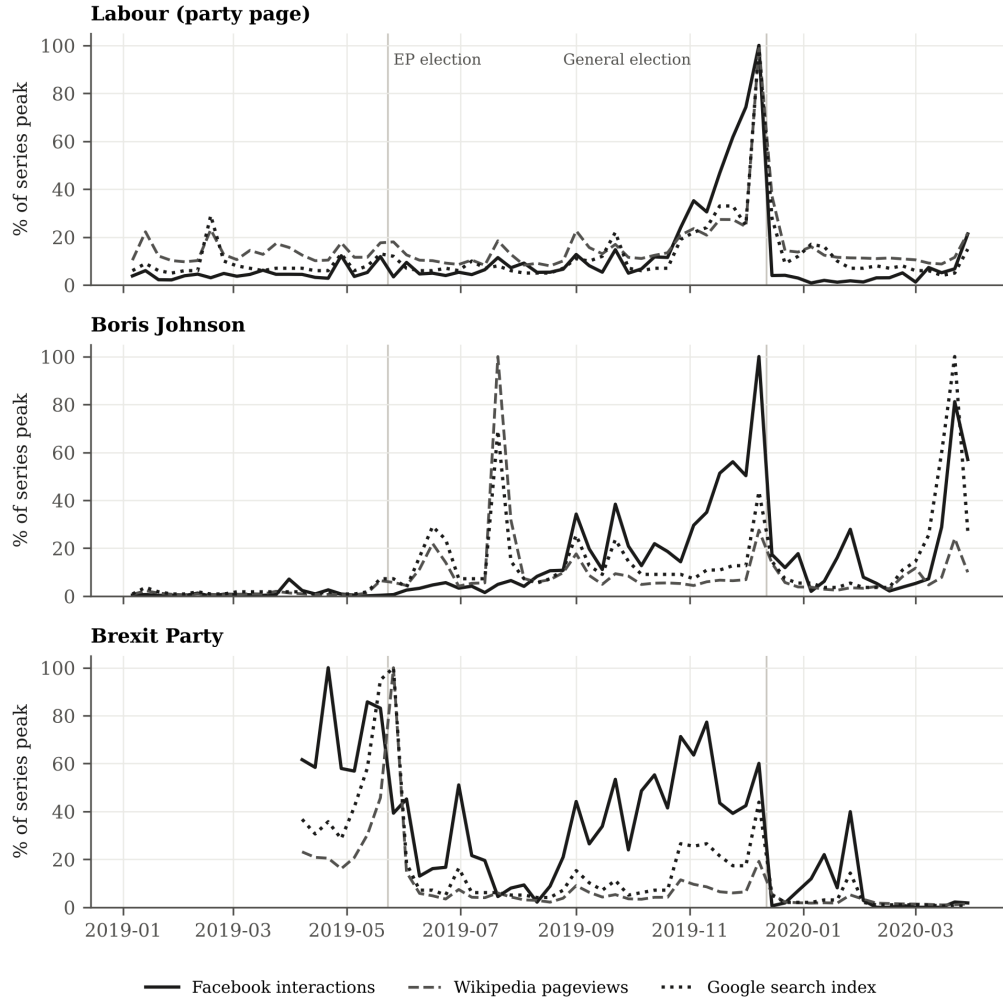


Figure 1. Weekly Facebook interactions, Wikipedia pageviews and Google search index for three actors, January 2019 to March 2020, each as a percentage of its own peak in this period. Vertical lines: European Parliament election (23 May 2019) and general election (12 December 2019).

leadership contest in July 2019 and the first Covid-19 lockdown in March 2020 for Boris Johnson, and the European Parliament election in May 2019 for the Brexit Party. But Facebook also has its own rhythm. Engagement on the Labour and Boris Johnson pages built up over the weeks of the 2019 campaign, while Wikipedia and Google attention stayed low until the final week. The Brexit Party’s page drew high engagement through the autumn of 2019, when searches and pageviews were modest.

Table 2 summarises the correlations within each actor. For daily data, the average correlation between log Facebook interactions and log Wikipedia views was 0.27. Once slow trends and weekly cycles are removed, it fell to 0.12 (95% interval 0.10 to 0.14), and it was positive for all 32 actors. Weekly series correlated more closely: 0.25 for detrended Facebook and Wikipedia, and 0.24 for detrended Facebook and Google among the 12 actors with usable Google data. By contrast, Wikipedia and Google, the two information-seeking measures, correlated at 0.83 in the same weekly detrended series. On this evidence Facebook engagement shares some of the movement of public attention, but most of its day-to-day and week-to-week variation is its own.

The fit differs a lot between actors (Figure 2). Weekly detrended correlations between Facebook and Wikipedia ranged from 0.04 for Ed Miliband, whose page rarely posted after he stepped down as leader,

Table 2. Average within-actor correlations between Facebook engagement and attention measures. Averages across actors use Fisher’s transformation; 95% intervals in brackets from resampling actors. Google rows use the 12 actors whose search terms had adequate precision. The party and politician rows exclude Momentum.

Pair	Scale	Actors	Log levels	Detrended	First differences
Facebook, Wikipedia	daily	32	0.27 [0.21, 0.32]	0.12 [0.10, 0.14]	0.13 [0.11, 0.14]
parties		13	0.27	0.12	0.14
politicians		18	0.26	0.12	0.12
Facebook, Wikipedia	weekly	32	0.41 [0.34, 0.47]	0.25 [0.20, 0.30]	0.22 [0.17, 0.26]
parties		13	0.46	0.32	0.28
politicians		18	0.36	0.21	0.18
Facebook, Google	weekly	12	0.45 [0.34, 0.54]	0.24 [0.19, 0.31]	0.20 [0.14, 0.26]
parties		4	0.45	0.26	0.21
politicians		7	0.52	0.26	0.21
Wikipedia, Google	weekly	12	0.87 [0.81, 0.92]	0.83 [0.79, 0.85]	0.81 [0.76, 0.84]
parties		4	0.89	0.82	0.82
politicians		7	0.89	0.84	0.82

to 0.62 for the SNP. Party pages matched more closely than politicians’ pages, at 0.32 against 0.21 on average. One reason is posting: many politicians’ pages posted on fewer than half of the days, so their engagement depended heavily on when they chose to post. The correlation between the number of posts and Wikipedia views (0.12 for detrended daily series) was as large as that for interactions, a reminder that pages tend to post more when there is more to talk about.

5.2 Timing: mostly together

Figure 3 shows the average cross-correlations. In daily data the peak is on the same day, for parties and for politicians alike, and for 24 of the 32 actors individually. The function is not symmetric. The correlation between Facebook on one day and Wikipedia on the next (0.087) was higher than between Facebook on one day and Wikipedia on the day before (0.029), and the correlations stay positive for about a week on the side where Wikipedia comes after Facebook. Weekly data show the same shape: the correlation between Facebook in one week and Wikipedia in the next was 0.16, against -0.02 for the week before, and the pattern for Google was almost identical.

This asymmetry could mean that Facebook engagement comes first, but there is a simpler reading. Wikipedia attention fades slowly after a news event, as people continue to read about a person or party for days, while engagement on a page is concentrated on the day of the posts. Two series that jump together but decay at different speeds produce exactly this shape. The comparison between Wikipedia and Google supports this reading: the correlation between Wikipedia in one week and Google in the week before (0.30) was higher than with Google in the week after (0.15), even though Google and Wikipedia measure very similar behaviour and there is no reason to think searches cause pageviews a week later. When I use first differences, which remove most of the persistence, the daily asymmetry disappears (0.003, interval -0.003 to 0.008) and the peak for 31 of 32 actors is on the same day.

The lead-lag regressions, which compare each actor with itself and remove shocks common to all actors on the same day, tell the same story. A one standard deviation rise in detrended Facebook engagement went with a rise in Wikipedia views of 0.076 standard deviations on the same day, 0.047 the next day and 0.027 two days later, against 0.016 for Facebook engagement the day after the Wikipedia rise. In

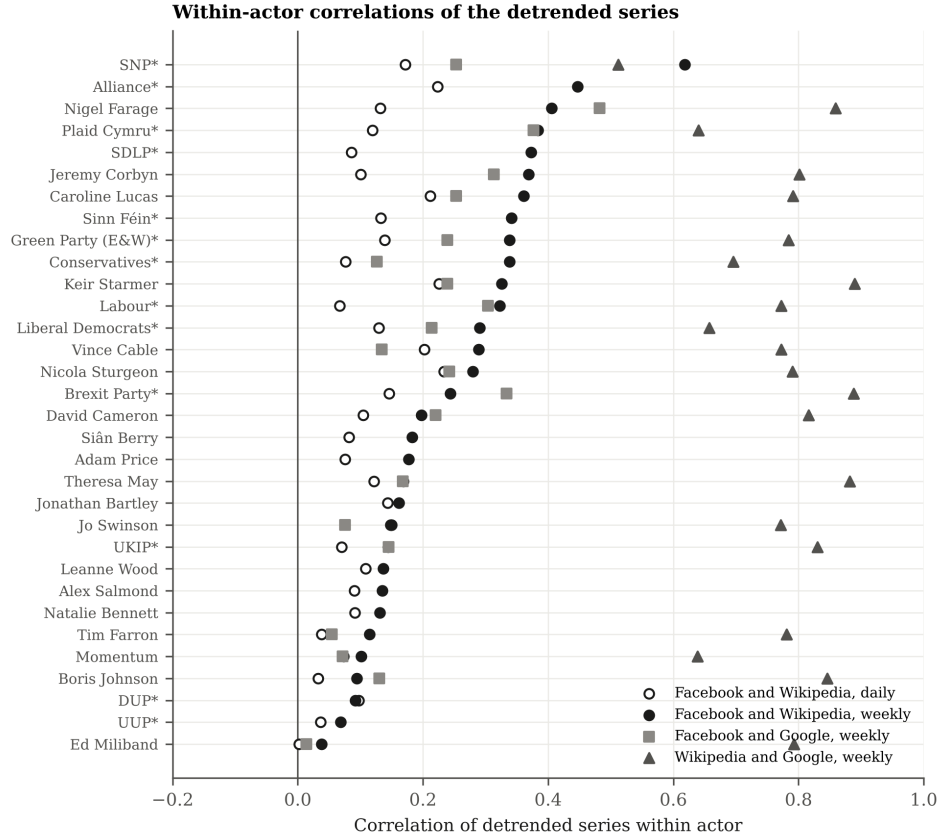


Figure 2. Within-actor correlations of detrended series, by actor. Party pages are marked with an asterisk. Google correlations are shown for the 21 actors with a search term; the main analyses use the 12 with adequate precision. Actors are ordered by the weekly Facebook and Wikipedia correlation.

weekly data the same-week coefficient was 0.105 and the coefficient for the following week 0.046.

The Granger tests in Table 3 ask a stricter question: whether the past of one series helps to predict the other beyond the other’s own past. At the daily scale, both directions pass the joint test with clustered errors: past Facebook changes help to predict Wikipedia changes ($p = 0.016$), and past Wikipedia changes help to predict Facebook changes ($p < 0.001$). The summed effects are small, 0.05 and 0.03 standard deviations, and neither is statistically distinguishable from zero on its own. Among party pages, past Facebook changes went with a summed rise in Wikipedia changes of 0.11 standard deviations ($p = 0.03$ for the sum). When I test each actor separately, past Wikipedia changes helped to predict Facebook changes for 14 of the 32 actors at the 5% level, and past Facebook changes helped to predict Wikipedia for 2. At the daily scale, then, if anything follows, it is more often Facebook.

At the weekly scale the picture tilts the other way. A rise in Facebook engagement was followed by somewhat higher Wikipedia attention over the next four weeks (summed effect 0.15 standard deviations, $p = 0.001$), and the reverse link was not significant. The result held outside the campaign periods around the four national votes (0.12, $p = 0.003$). For Google, the corresponding summed effect was 0.18 standard deviations, but the joint test was not significant with Driscoll-Kraay errors ($p = 0.15$), and outside campaign periods the effect was smaller and the joint test not significant (0.10, $p = 0.39$). Without the two ambiguous search terms, both directions were significant in the joint test. Testing actor by actor in weekly data, Facebook helped to predict Wikipedia for 11 actors and Wikipedia helped to predict Facebook for 9; for Google, the numbers were 4 and 3 of 12. I read these weekly results as a

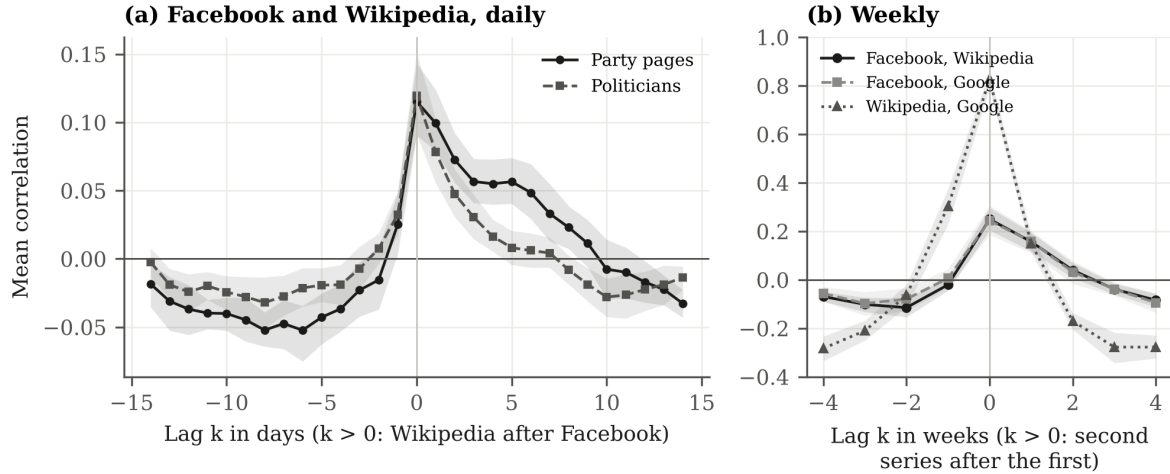


Figure 3. Average cross-correlations of detrended series within actors, with 95% intervals from resampling actors. (a) Daily Facebook interactions and Wikipedia pageviews for party pages (13) and politicians' pages (18). (b) Weekly series: Facebook and Wikipedia (32 actors), Facebook and Google, and Wikipedia and Google (12 actors). Positive lags mean the second series after the first; in panel (b), Google is the second series for the Wikipedia and Google pair.

modest and fragile tendency for engagement to rise slightly ahead of wider attention, not as a stable lead. Part of it may come from how the Facebook data are dated: interactions with a post published late on a Saturday are counted in that week, though many arrive the next day, in the next Google week.

5.3 Spikes

The largest attention spikes are where a lead or lag would matter most. Figure 4 shows, for the 320 largest Wikipedia spikes (ten per actor), the day on which Facebook engagement peaked within a week either side. In 22% of cases Facebook peaked on the same day, against 5% for random days, and in 42% within a day either side, against 18% for random days. Facebook peaked before the Wikipedia spike in 40% of cases and after it in 38%. Among peaks on different days, 129 of 249 came before, a split close to even ($p = 0.61$ in a sign test). The same holds when I start from the 316 largest Facebook spikes: Wikipedia peaked on the same day in 14% of cases, against 6% for random days, and the remaining peaks were spread on both sides. Within two days either side, Wikipedia peaked after the Facebook spike in 49 cases and before it in 33 ($p = 0.10$). In about three quarters of the Wikipedia spikes (73%), Facebook engagement in the window rose above its own 90th percentile, so most big moments of public attention registered on the pages.

The largest Wikipedia spikes are mostly the obvious ones: the days after the 2017 and 2019 general elections and the 2016 referendum, leadership contests and resignations. Many fall on the day after a vote, when results are announced overnight and people read about the winners, while party pages had posted most heavily on polling day itself. Without detrending, which keeps these scheduled peaks dominant, Facebook peaked before the Wikipedia spike in 63 of the 87 cases within two days ($p < 0.001$). This is the clearest form of Facebook coming first in the data, and it reflects the calendar: pages mobilise before a scheduled event and the public reads up after it.

At the weekly scale, around the largest Google spikes, Facebook engagement peaked in the same week in 56% of the 59 spikes, against 18% for random weeks, before in 24% and after in 20%. Wikipedia peaked in the same week as Google in 86% of cases.

Table 3. Panel Granger tests. Each row regresses the standardised first difference of the outcome on its own lags and lags of the other series (seven daily or four weekly), with actor and date fixed effects. Sum of lags: summed coefficients on the other series, in standard deviations. Wald: joint test that those coefficients are zero. Standard errors clustered by actor unless marked Driscoll-Kraay. Campaign periods: the 35 days before and seven days after each of the four national votes.

Sample	Facebook → attention			Attention → Facebook		
	Sum of lags (SE)	Wald	<i>p</i>	Sum of lags (SE)	Wald	<i>p</i>
<i>Attention measure: Wikipedia</i>						
Daily, all actors (32)	0.054 (0.035)	17.3	0.016	0.030 (0.017)	33.8	0.000
Daily, parties (13)	0.108 (0.051)	20.3	0.005	0.024 (0.033)	69.9	0.000
Daily, politicians (18)	0.012 (0.052)	16.6	0.020	0.047 (0.025)	18.7	0.009
Daily, all, Driscoll-Kraay	0.054 (0.034)	13.4	0.064	0.030 (0.025)	27.0	0.000
Weekly, all actors (32)	0.146 (0.042)	13.6	0.009	-0.056 (0.041)	7.9	0.096
Weekly, outside campaigns	0.117 (0.039)	20.8	0.000	-0.033 (0.045)	2.1	0.726
<i>Attention measure: Google</i>						
Weekly, Google set (12)	0.181 (0.064)	10.4	0.035	0.010 (0.096)	4.5	0.338
Weekly, Google set, Driscoll-Kraay	0.181 (0.081)	6.8	0.147	0.010 (0.076)	3.2	0.524
Weekly, Google set without ambiguous terms (10)	0.201 (0.088)	16.2	0.003	0.066 (0.092)	11.6	0.021
Weekly, Google set, outside campaigns	0.102 (0.070)	4.1	0.387	-0.049 (0.085)	5.9	0.204

5.4 Parties and politicians

Party pages and politicians' pages behaved similarly. Detrended daily correlations with Wikipedia averaged 0.12 for both types (Table 2). Weekly correlations were higher for parties, 0.32 against 0.21, which fits the steadier posting of party pages. The asymmetry in the cross-correlations was somewhat larger for parties (0.081, interval 0.058 to 0.102) than for politicians (0.041, interval 0.022 to 0.061). In the daily Granger tests, past Facebook changes predicted Wikipedia changes for parties with a summed effect of 0.11 standard deviations, but not for politicians (0.01), while past Wikipedia changes predicted Facebook changes for both in the joint tests. Among individual actors, Wikipedia helped to predict Facebook for 7 of 13 parties and 7 of 18 politicians, and Facebook helped to predict Wikipedia for 2 parties and no politicians. The differences between the types are small next to the differences between individual actors.

5.5 Elections

Figure 5 and Table 4 compare the three attention measures with the results of the 2017 and 2019 general elections and the 2019 European Parliament election. None is close to the result. Across the 19 party-elections, the mean absolute error was 8.0 points for Facebook shares, 7.4 for Wikipedia shares and 11.2 for Google shares. For the two general elections, where the comparison can include the final polls and the previous result, the errors were 7.0 points for Facebook, 9.1 for Wikipedia, 13.4 for Google, 4.1 for repeating the previous general election and 1.1 for the polls. The Facebook errors are close to those for the same elections in my forecasting working paper (7.6 points in 2017 and 6.4 in 2019 there, against 7.5 and 6.5 here), which used a slightly different set of parties (Hotham 2026b).

The measures erred in different ways. Facebook overstated Labour by 14 points in 2017 and 9 in 2019, and understated the Conservatives by 19 and 8 points. In the European election it overstated UKIP by 18 points and the Brexit Party by 12, and understated the Liberal Democrats by 18. Wikipedia understated the Conservatives by 17 and 20 points at the two general elections, probably because a governing party's article draws less attention than those of its rivals in a campaign, and overstated smaller parties such

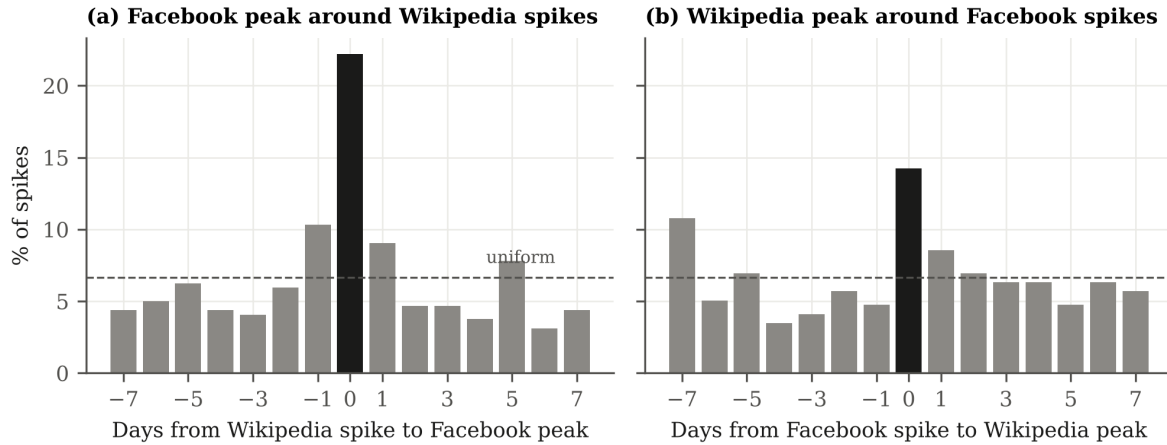


Figure 4. Timing of peaks around the largest spikes. (a) For the ten largest detrended Wikipedia spikes per actor (320), the day within seven days on which detrended Facebook engagement peaked. (b) The same, starting from the ten largest Facebook spikes per actor (316). Dashed line: the share expected if the peak day were random within the window.

Table 4. Mean absolute error of each measure against the vote, in percentage points of the shares of the parties compared.

Election	Parties	Facebook	Wikipedia	Google	Facebook and Wikipedia ^a	Final polls	Previous result
General election 2017	6	7.5	9.5	14.0	5.9	1.6	5.2
European Parliament 2019	7	9.6	4.7	7.5	6.7	n/a	n/a
General election 2019	6	6.5	8.6	12.8	4.7	0.7	3.0
All party-elections	19	8.0	7.4	11.2	5.8	1.1 ^b	4.1 ^b
General elections only	12	7.0	9.1	13.4	5.3	1.1	4.1

^a Average of the Facebook and Wikipedia shares. ^b General elections only (12 party-elections).

as the Liberal Democrats, UKIP and the Brexit Party. Wikipedia did best at the European election (4.7 points), the only one where the party with the most views, the Brexit Party, also won the most votes by a wide margin.

Google shares were the least accurate, and much of their error comes from the search terms rather than from attention. People searching for the Conservatives may type Tories, Conservatives or the name of the leader, and the term Conservative Party drew only 12% of the search index for the six parties at both general elections, against vote shares of 44% and 46%. The SNP term had almost no measured interest, and Green Party and UKIP drew large shares. Search terms are not equivalent across parties, and this is a reason for caution in comparing parties with Google data, as [Mellon \(2014\)](#) warned for issues.

Did the measures add anything to each other? Their errors partly offset. Averaging the Facebook and Wikipedia shares gave a mean absolute error of 5.8 points across the 19 party-elections, lower than either alone, and 5.3 points at the two general elections. Even so, the average was less accurate than simply repeating the previous result (4.1 points) and far less accurate than the polls. Changes between 2017 and 2019 tell a similar story, though with five parties they can only illustrate: the correlation between each measure's change and the change in vote share was 0.48 for Facebook, 0.72 for Wikipedia, 0.44 for Google and 0.85 for the polls. With two general elections and one European election, these comparisons cannot show that any measure is better than another in general.

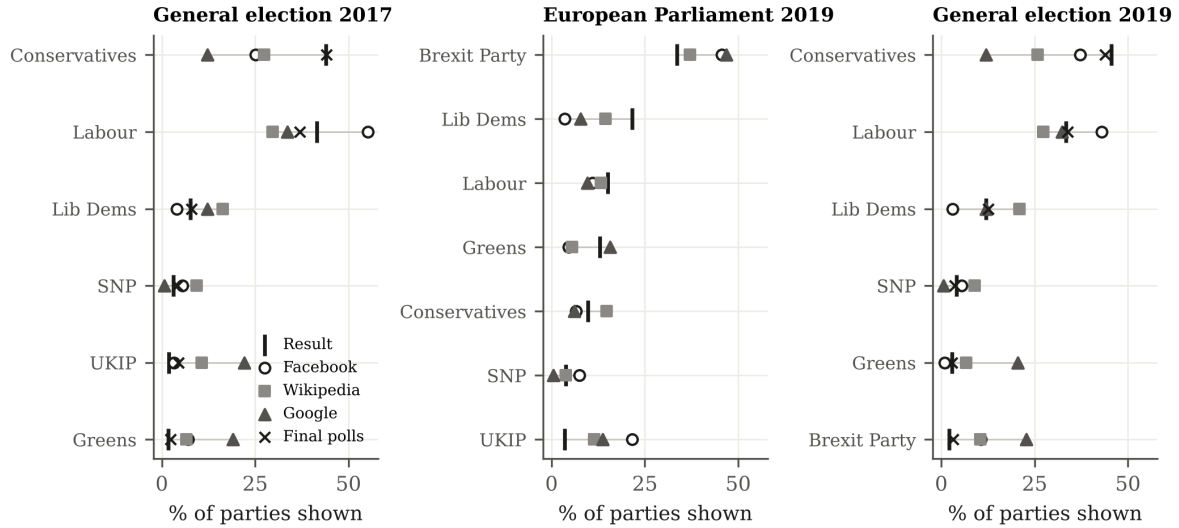


Figure 5. Shares of the parties shown, by measure, at three elections. Result: share of the votes cast for the parties shown. Facebook: interactions on party pages in the 30 days before polling day. Wikipedia: views of party articles in the same days. Google: rescaled search index in the four weeks before the week of polling day. Final polls (general elections only): average of polls in the final 14 days, from the author’s forecasting working paper.

5.6 Robustness

The main patterns hold across a range of checks, reported in the replication output. Restricting the daily analysis to the 16 pages that posted on at least half of the days gives the same same-day peak and a similar asymmetry (0.065). Dropping the five Northern Ireland and all-island parties, whose Wikipedia views are least likely to come from Britain, changes little (0.053). Removing the campaign periods around the four national votes reduces the asymmetry to 0.037 but leaves it positive, and leaves both daily Granger directions significant in the joint test. Using daily numbers of posts in place of interactions gives a similar cross-correlation (0.116 on the same day). Three or fourteen daily lags in place of seven change the summed Granger effects but not the overall reading that the links are small and run both ways. The election comparison is similar with 14-day or 60-day windows (pooled errors for Facebook of 8.2 and 7.5 points, and for Wikipedia 8.1 and 8.2), with Plaid Cymru added, without the Greens, or without the SNP, and with two alternative factors for rescaling the Google batch that contains Labour, the Conservatives and the Liberal Democrats (Google errors of 11.0 points in both).

6 Discussion

The question in the title has a plain answer for these pages and years: Facebook engagement mostly neither led nor followed public attention, it moved with it. When a party or politician became the subject of national attention, engagement on their page usually rose on the same day or in the same week as searches and pageviews. The leads and lags around that shared movement were small, ran in both directions and depended on the time scale and the sample. At the daily scale, Wikipedia changes predicted later Facebook changes for more actors than the reverse. At the weekly scale, Facebook engagement rose slightly ahead of Wikipedia attention, including outside election campaigns, while the link with Google was less robust. Around scheduled events such as elections, pages mobilised before the moment and the public read up after it.

That combination is what one would expect if engagement is attention gathered by actors who also control the supply of content. Pages respond to news, which is why engagement follows Wikipedia at the daily scale for many actors. Pages also anticipate the calendar: they post most heavily before the votes, debates and announcements that the public will look up when they happen. Neither pattern makes Facebook a source of public attention. The design cannot say whether a page's engagement ever drew people to search for a party, and the small size of the predictive links suggests that, on average, any such effect was modest. The weak link with Google outside campaigns, and the sensitivity of the weekly results to the choice of errors and search terms, are further reasons not to read the weekly lead as a general rule.

The correlations matter more than the leads. Facebook engagement shared only a modest part of its variation with the two information-seeking measures, which shared most of theirs with each other. Most of what moves engagement from day to day is particular to Facebook: the page's own posting, the content, the size and loyalty of its following, and the platform's ranking of posts. This fits the finding that engagement is badly calibrated across parties (Hotham 2026c,b) and that it rewards some kinds of parties far more than others (Hotham 2026a). It also suggests that when researchers use engagement as a measure of public attention, they should expect it to agree with other measures on the big moments and to differ in between.

The election comparison returns to the forecasting question from a different angle. My earlier work showed that Facebook engagement shares miss vote shares by far more than polls (Hotham 2026b). Here, two measures of attention that do not depend on any party's page did no better. Wikipedia views were about as far from the result as Facebook engagement, and Google searches further, partly because the search terms that people use for parties differ. This supports the view that the problem lies in measuring attention rather than support (Jungherr et al. 2017), not in anything peculiar to Facebook. The earlier Wikipedia studies that found predictive value used pageviews alongside other information or theory (Yasseri and Bright 2016; Smith and Gustafson 2017; Salem and Stephany 2020); my comparison, which uses raw shares on their own, does not contradict them.

The study has several limitations. The first is dating. CrowdTangle records when a post was published, not when its interactions arrived, so a post's interactions are counted on the day it appeared even if they continued into the next day. This tends to shift Facebook engagement slightly earlier and may account for part of the small lead at the weekly scale. The second is geography. Wikipedia views are global English-language views, and some actors, such as Boris Johnson and Sinn Féin, draw large audiences outside Britain, while Google data are for the United Kingdom and Facebook audiences can come from anywhere. The third is the Google data: single downloads of a sampled index, integer values with many weeks near the floor, rescaling through an anchor with limited precision, and search terms that are ambiguous or not the ones people use. The fourth is coverage: the pages come from my own CrowdTangle lists, some leaders lack pages or Google terms, and several politicians did not lead their party for the whole period. The fifth is the design: these are observational time series, and Granger tests describe prediction, not causation. Finally, three elections and a handful of parties are far too few to rank the measures as forecasts.

7 Conclusion

Between 2015 and 2020, engagement on the Facebook pages of British parties and their leaders moved with public attention as measured by Wikipedia and Google, but more loosely than those two moved

with each other, and mostly at the same time rather than before or after them. Wikipedia changes more often predicted later Facebook changes at the daily scale, Facebook rose slightly ahead of Wikipedia at the weekly scale, and around elections the pages mobilised before polling day while the public read up afterwards. At three elections, shares of engagement and of pageviews were about equally far from the result, searches further, and all were far behind the polls. Facebook engagement is best treated as one more partial and noisy measure of attention, shaped by the pages themselves, and not as a sign of where public attention or support is heading. A useful next step would be to date interactions by when they occurred rather than when posts were published, which would allow sharper tests of timing within the day.

Data and code

The posts were exported from CrowdTangle in October 2020. CrowdTangle’s terms do not permit sharing the raw posts. Wikipedia pageviews and Google Trends indices are public and were downloaded in October 2026. The analysis code, the matching of pages to articles and search terms, the daily and weekly aggregate series and a file of all reported results are available from the author.

Provenance and AI use

The Facebook data were exported from CrowdTangle in October 2020 for my doctoral research. This paper builds on my doctoral thesis ([Hotham 2021](#)). The analysis and writing were completed in 2026.

I designed the study and am responsible for the analysis and conclusions. I wrote the text, with drafting and editing assistance from Claude (Anthropic), which also helped prepare the analysis code. I reviewed and checked all text and results.

Ethics

Not applicable: the study involves no human participants. The data are public posts by the official Facebook pages of political parties, party leaders and a campaigning organisation, analysed only as counts of interactions and posts aggregated by page and day or week, together with public aggregate counts of Wikipedia article views and Google Trends search indices. No post content is quoted or reproduced, and no data on individual users are used.

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