VISUALIZATION AND RESEARCH PORTFOLIO

SEAN FISCHER

I. VISUALIZATION PORTFOLIO

II. APPLIED RESEARCH PORTFOLIO

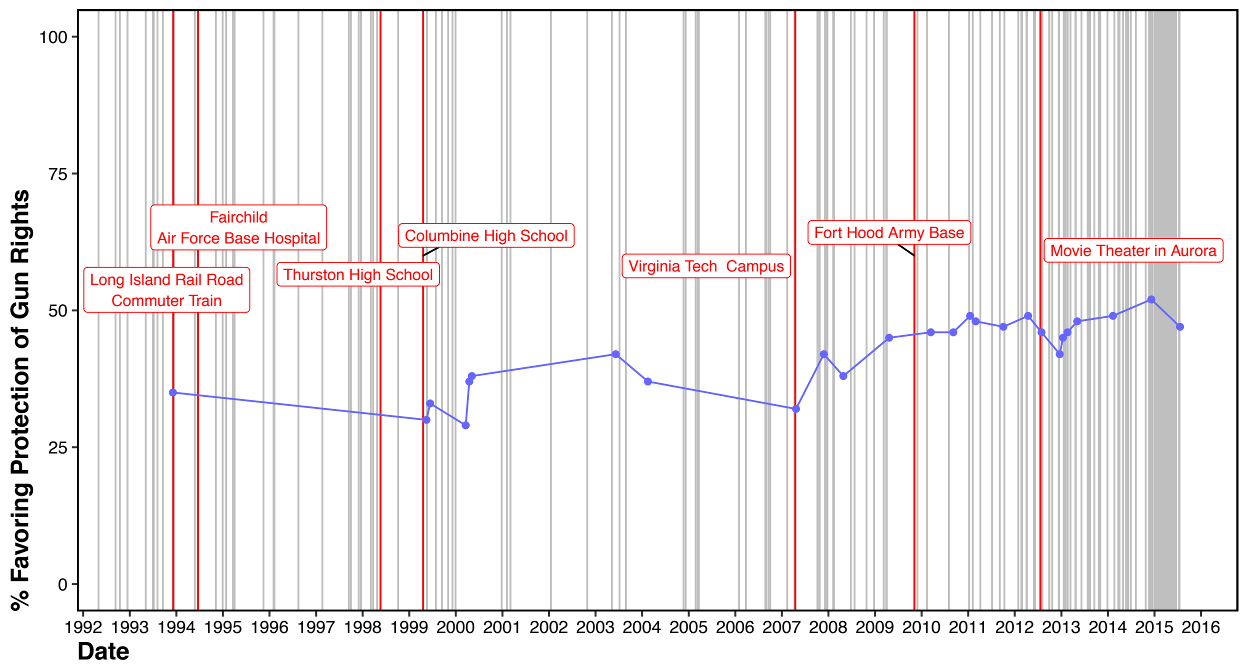
VISUALIZATION PORTFOLIO

SEAN FISCHER

This portfolio presents a selection of data visualizations that I believe represent my skills and successes so far in my career. These are pulled from coursework, original research projects, and side projects. Each entry includes a brief comment on the history behind the figure. The online version of this portfolio includes the R code used to generate each figure and can be found here.

GUN VIOLENCE IN THE UNITED STATES

PLOT



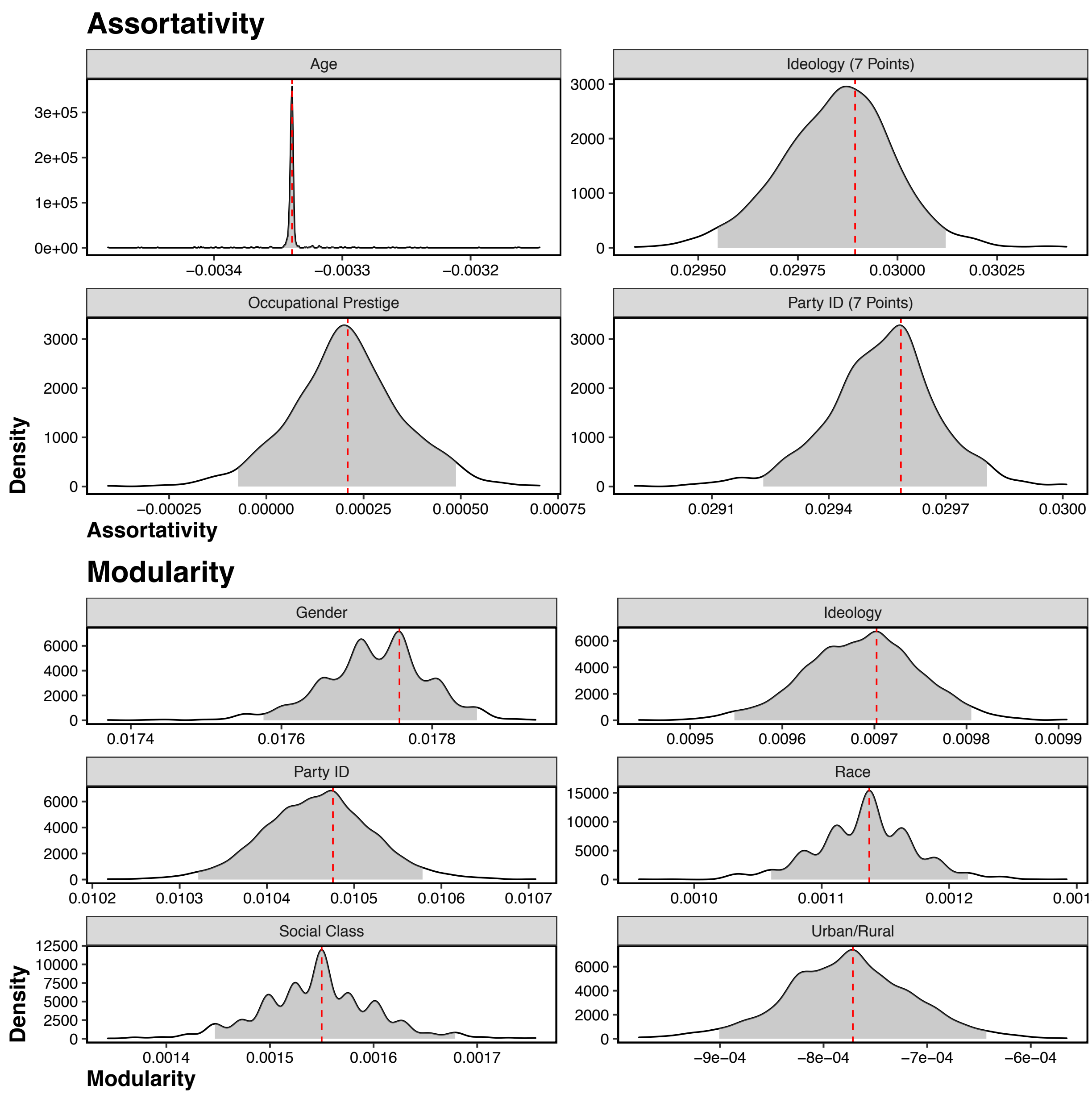
Mass shooting data from Stanford and attitude data from Pew Research.
Vertical lines mark instances of a mass shooting on a given date.
Red lines indicate shootings that had at least 50% of the maximum victims at the time of the shooting.

BACKGROUND

This figure was originally created as part of a graduate course on data visualization. We were tasked to recreate and improve upon a plot created by the Pew Research Center visualizing the trend in the percentage of Americans favoring protections of gun rights over making firearm regulations stricter. My project partner and I decided to plot the trend line over time as seen on Pew Research's website, but with markers behind the line denoting instances of a mass shooting. By marking these instances with thin gray lines, we were able to show how the volume of such shootings varied over time and potentially impacted public opinion. We also chose to highlight particularly large shootings by visualizing shootings that had at least 50% of the total victims of the largest shooting up to that point in time with red lines and labels. The effect is striking, as these particularly salient events, including the Columbine, Virginia Tech, Fort Hood, and Aurora-movie-theater shootings are all highlighted. Finally, we chose to visualize the trend on a y-axis that ranges from 0% to 100% in order to demonstrate the relative stability of mass opinion in this regard. From this view, we can see that while the overall trend has followed an increase in the percentage of Americans favoring the protection of gun rights, the change has been small, with few events leading to any noticeable interruption of this stability.

ASSESSING NETWORK STATISTICS

PLOT

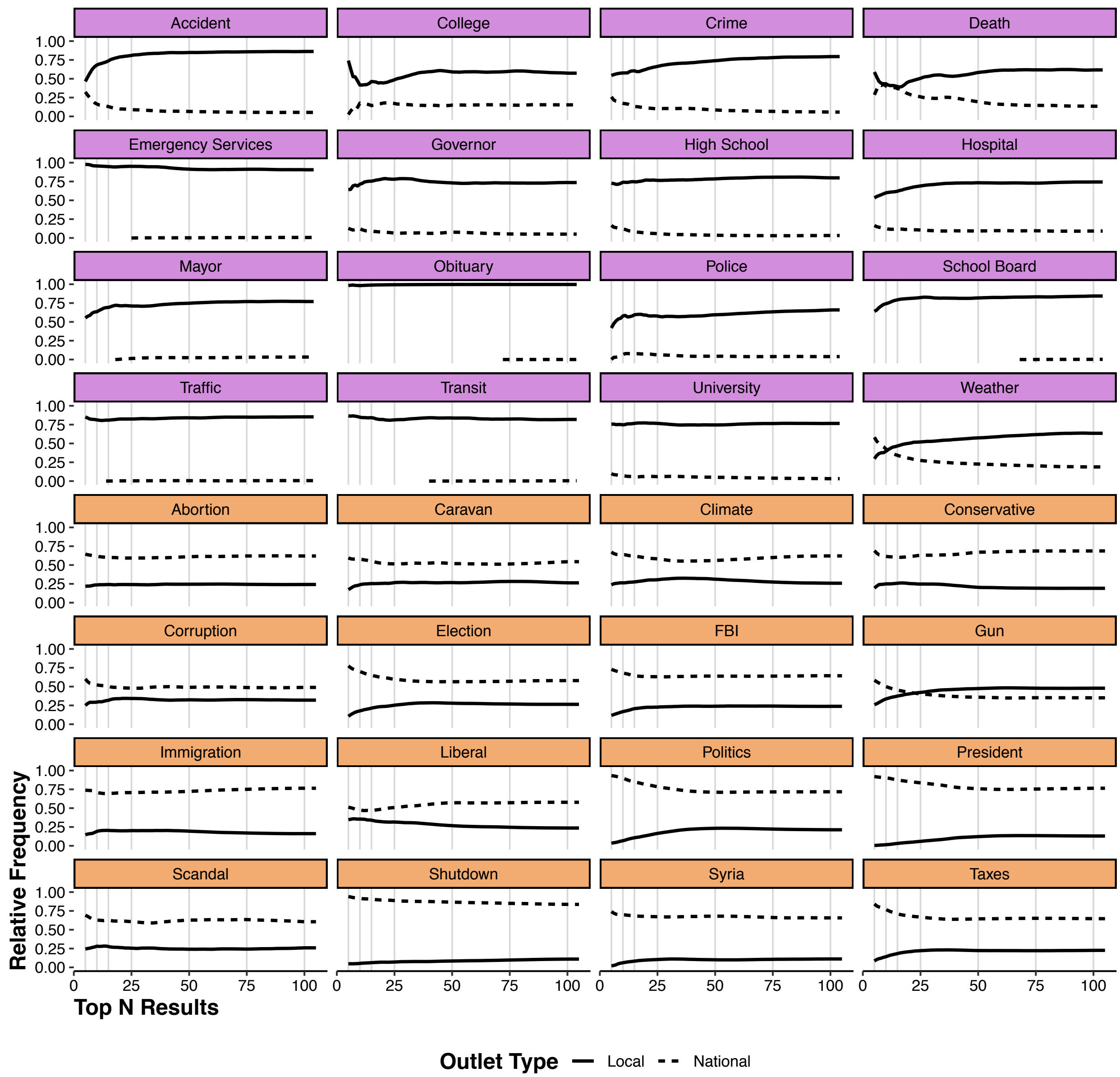


BACKGROUND

This figure is featured in the second empirical chapter of my dissertation studying the musical preferences of American partisans. In this study, I build networks linking partisans together if they share most-listened-to artists on Spotify and calculate two important statistics, the network assortativity and the network modularity, in order to assess whether any individual-level features are associated with an increased probability of connections being made in the network. To evaluate whether the observed statistics are statistically significant, I compared them to the values drawn from 1000 random networks with the same degree distribution. The figure plots the observed value as a dashed red line over the distribution of values observed from the random networks. The middle 95% of the distributions are shaded in gray because if the observed value falls in this region, it is not statistically significant.

PREVALENCE OF LOCAL NEWS

PLOT



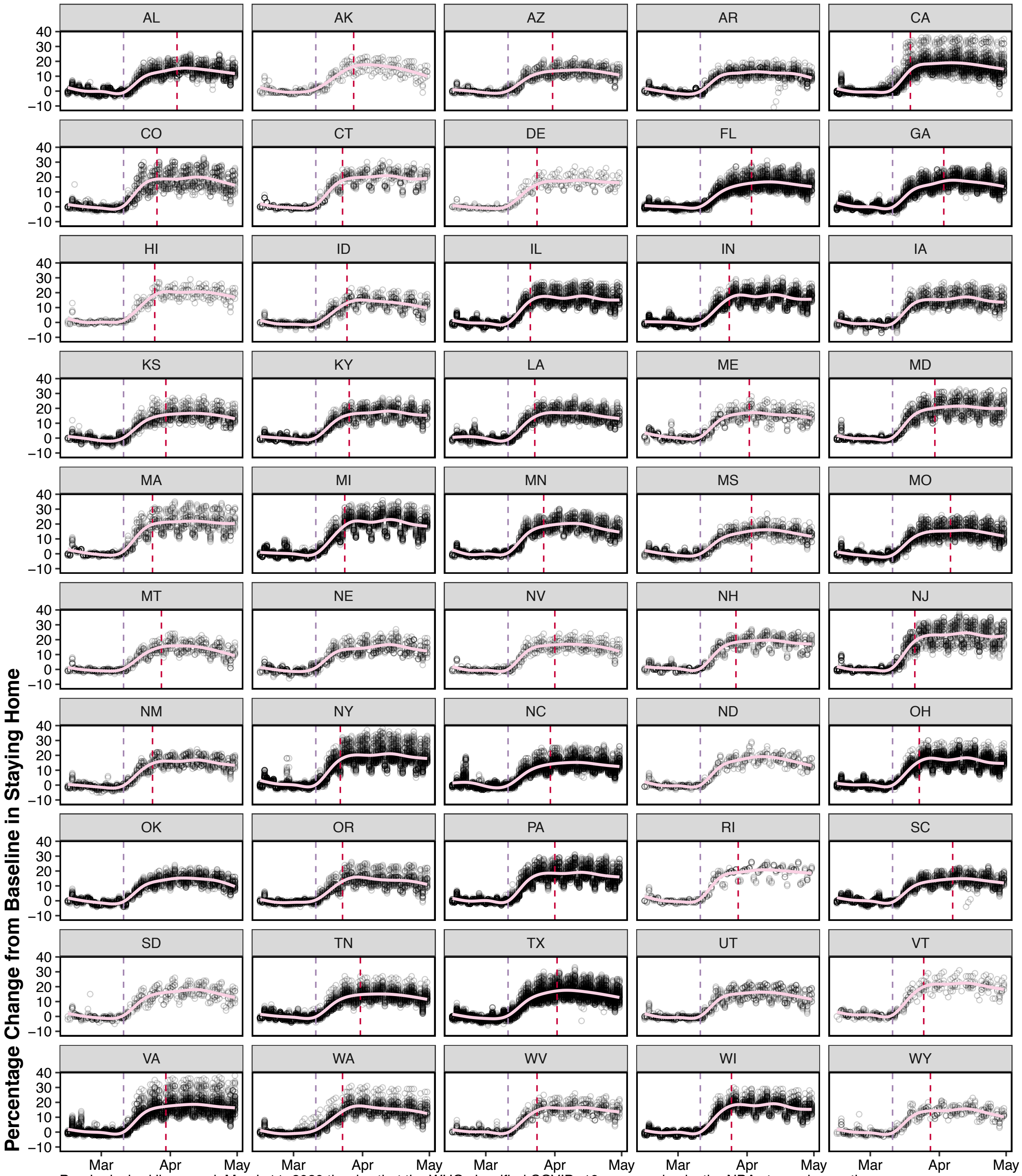
The first 16 purple facets represent locally oriented queries.
The second 16 orange facets represent generally oriented queries.

BACKGROUND

This visualization was designed for my journal article with Kokil Jaidka and Yph Lelkes in Nature Human Behaviour. Our research showed that the rate of local and national news outlets in Google News search results varied depending on how deep into the results you scrolled. To better communicate this point, we needed a visualization that showed how the rates changed based on how many results we considered for each of 32 queries we examined. The final figure uses a 32-facet design that allowed us to color code the facet titles to more easily indicate which of the terms were locally oriented and which were generally oriented. The x-axis, as it runs left to right, reflects looking deeper into the results, a natural extension of English-speakers intuitive notion of reading.

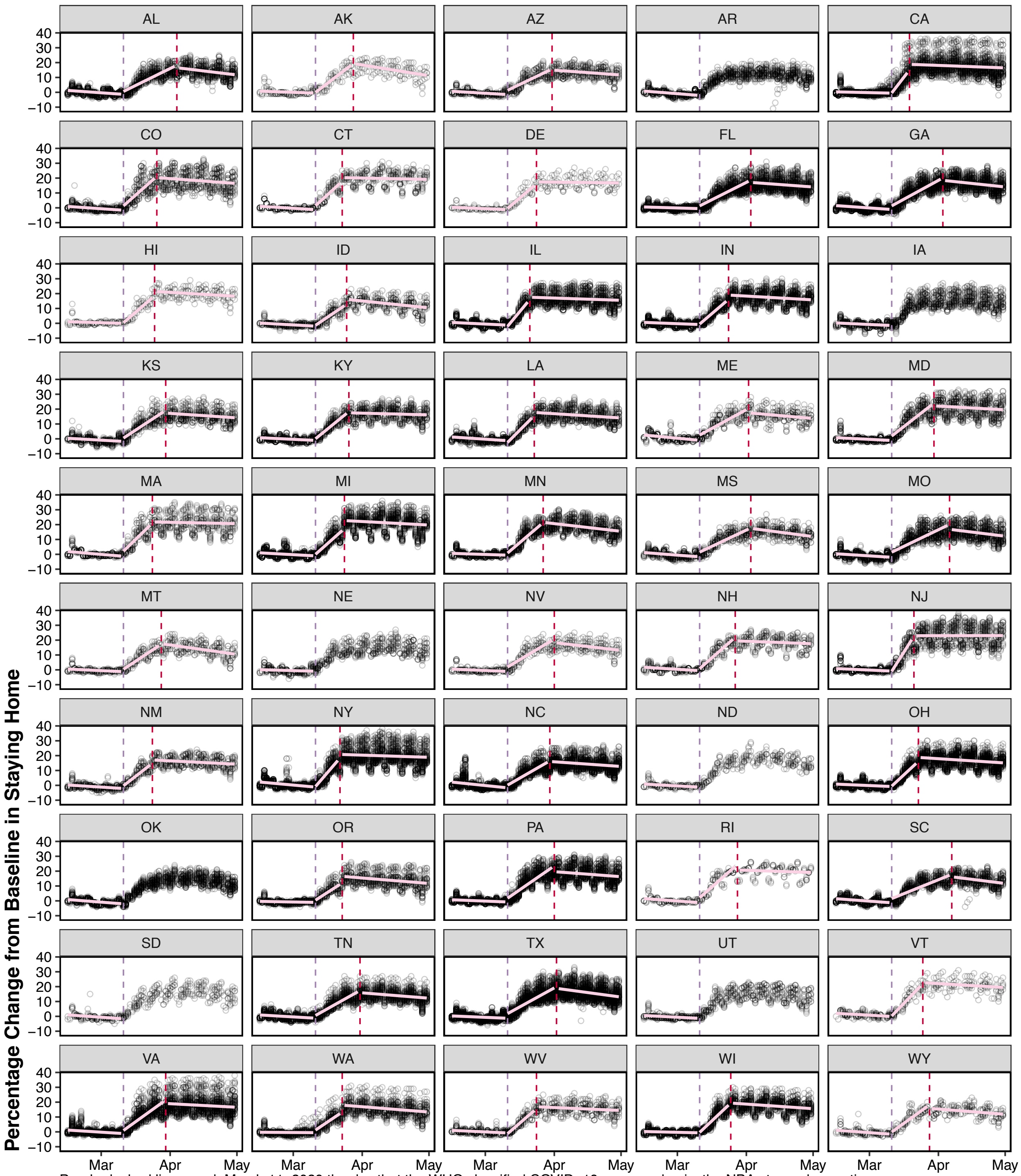
Changes in Mobility by State

Plot 1



Purple dashed lines mark March 11, 2020 the day that the WHO classified COVID−19 as a pandemic, the NBA stopped operations, and Tom Hanks announced he had COVID−19. Red dashed lines mark the dates that states enacted stay−at−home orders. (Not all states enacted orders during this window.)

PLOT 2



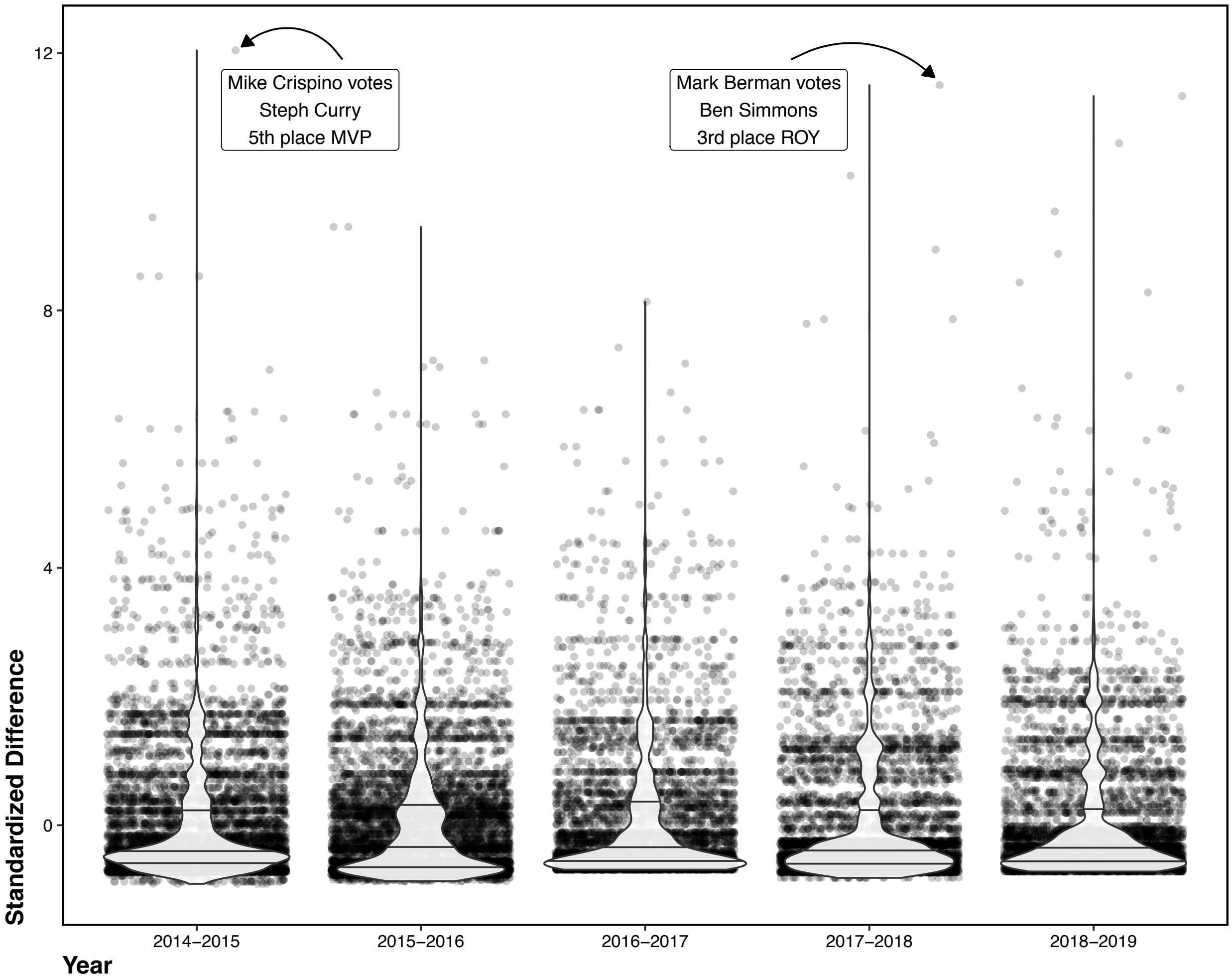
Purple dashed lines mark March 11, 2020 the day that the WHO classified COVID−19 as a pandemic, the NBA stopped operations, and Tom Hanks announced he had COVID−19. Red dashed lines mark the dates that states enacted stay−at−home orders. (Not all states enacted orders during this window.)

BACKGROUND

I have included two plots for this entry because, while similar, they serve slightly different purposes. The first plot, with the smoothed trend line generated by a generalized additive model (gam), shows us how the increase in time spent at home happened rapidly before leveling off. The smoothed curve makes this asymptotic feature quickly recognizable. The second plot, with three straight lines added to (almost all of) the plots shows us the linear trend before March 11th, between March 11th and the implementation of each state's stay-at-home orders (if any were enacted), and after the implementation of the state's stay-at-home orders. This visual represents a more concrete analytic strategy of comparing the slopes of the lines in each time period. The linear trend lines visually capture what we might learn from a standard regression model with interaction between continuous time and the given window. You can learn more about this project here.

NBA AWARDS VOTING

PLOT



BACKGROUND

This plot was generated for a side project examining the recent history of NBA-Awards voting. Using the publicly released results, I calculated how much each vote for a player diverged from the average vote for the given player. This plot visualizes the distribution of the within-year standardized squared differences broken out by year. Each individual vote is represented by gray point. Violin plots are included over each set of points to visualize the shape of each distribution and mark the 25th, 50th, and 75th quantiles. Two particularly notable divergent votes are labeled.

APPLIED RESEARCH PORTFOLIO

SEAN FISCHER

This portfolio presents research projects I have either published in academic journals or as preprints. These projects reflect my abilities as a researcher and scientist, particularly in regard to my ability to perform a variety of data analyses. The methods applied include traditional statistical analyses, network methods, and natural language processing.

AUDITING GOOGLE NEWS

BACKGROUND

The article below presents the results of an audit of Google News. My collaborators and I evaluated whether local news outlets were as accessible as national news outlets on the platform, controlling for a variety of features including the type of query searched for and local economic conditions. We found that local news outlets often appeared deeper into search results, meaning they would be less likely to be accessed by users. This pattern is true even for counties with healthy local news indicators. A subsequent analysis showed that outlets that already had strong followings were returned more than those with smaller offline circulations.

The audit and the analysis of the data generated by the audit were two different challenges. We tackled the first by writing code to replicate and expand a process used in other digital audits, where in browser conditions are manipulated so that websites believe the browser is located in a different geographic location. This auditing process generated millions of search results, which made analysis difficult. Ultimately, I organized our analysis on a remote server using efficient techniques for modeling big data.

The final publication has been published in *Nature Human Behaviour*.

nature human behaviour

ARTICLES

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Check for updates

Auditing local news presence on Google News

Sean Fischer [1], Kokil Jaidka [2] and Yphtach Lelkes [1] ✉

Local news outlets have struggled to stay open in the more competitive market of digital media. Some have noted that this decline may be due to the ways in which digital platforms direct attention to some news outlets and not others. To test this theory, we collected 12.29 million responses to Google News searches within all US counties for a set of keywords. We compared the number of local outlets reported in the results against the number of national outlets. We find that, unless consumers are searching specifically for topics of local interest, national outlets dominate search results. Features correlated with local supply and demand, such as the number of local outlets and demographics associated with local news consumption, are not related to the likelihood of finding a local news outlet. Our findings imply that platforms may be diverting web traffic and desperately needed advertising dollars away from local news.

Local news in the United States is disappearing, leaving citizens with less access to the information necessary to participate in the civic and political life of their communities. From 2003–2018, one in five newspapers in America ceased publishing. These closures have left about half of the 3,143 counties in the United States with only a single paper and about 200 counties without any local paper[1].

The widespread decline of local news has been associated with changes in the advertising business brought about by online news consumption[2]. Almost 90% of Americans obtain some of their local news digitally, with almost half of local news consumption occurring on mobile devices. Digital consumption has also nearly surpassed television as the preferred medium for accessing local news (37 versus 41%)[3]. Because the Internet offers a broad set of media options, individuals rely on curation by search engines and other online platforms, which are now central conduits through which individuals access news on the Internet. Almost one-quarter of traffic to online news sites comes from search engines[4], and it falls on them to rank and prioritize news outlets to help users determine what content to consume[5]. By highlighting specific stories and outlets over others, these platforms can operate as gatekeepers to advertising dollars.

Because of rising concerns that automatic algorithms reinforce existing social and economic inequalities that undermine private and public welfare[6], researchers have audited specific platforms in order to document platform behaviour and to estimate the relationships between information fed to the platforms and the information the platforms present to users[7–10]. While a few studies indicate that online platforms may over-represent certain news outlets, algorithms appear to be relatively insensitive to the ideological preferences of consumers[11–13]. Google does appear to alter its results based on user location[8]; however, there has been little work done to assess the relationship between news aggregators' algorithmic behaviour and the curation of local news.

In this paper, we assess whether a major online news aggregator, Google News, might contribute to the observed declines in local news in the United States. Google News is used by about 15% of Americans, a level of reach similar to that of *The Washington Post* but about half the percentage of Americans using Facebook to seek out news (39%)[14]. To systematically audit whether (the decline in) local news' online traffic can be attributed to Google News, we must show that Google News is more likely to feature national news outlets than local news outlets (hypothesis 1). If Google's selection of news outlets overwhelmingly favours national newspapers, we have evidence that Google could be reducing the traffic to local news sites, and potentially reducing the likelihood that readers would be exposed to local outlets.

However, Google may stratify results by search term, privileging national outlets for general interest topics and local outlets for city-specific topics (pages 79–82 of ref. [2]), such as accidents and local governance. Hence, we examine whether Google News prioritizes national news outlets for topics of general interest and local news outlets for locally oriented issues (hypothesis 2).

We also expect that Google News is sensitive to local supply and demand (hypothesis 3). From a supply perspective, we expect that Google News would offer more local news when there are more local outlets in an area. From a demand perspective, we expect that Google News would offer more local news when the population is less white, less educated and older: demographic groups that generally say they follow local news closely[15]. Greater local news coverage in Google News results is expected to benefit minority and under-represented populations. However, empirical findings from a study of local TV news reporting suggest that such generalizations may be misguided[16].

To prepare for our audit, we selected a set of keywords based on other recent audits[8]. Depending on their relevance to the local governance, we labelled the keywords as either locally oriented or more general. We audited the location-specific news results for these keywords in over 3,000 US counties, which were collected using automatic scripts running on an internet browser's private-browsing mode. In this manner, we scraped 12,290,428 research results, and classified its 8,740 news sources as either local, regional, national or international outlets.

To test hypothesis 1, we calculated descriptive statistics about the outlet frequencies across all of the news search terms. We also measured the Gini Index for the distributions of local and national news outlets. The Gini Index tells us whether a few outlets dominate search results or whether outlets appear at similar levels. As a first test of hypothesis 2, we assessed whether our findings were driven by the nature of the search keyword chosen by measuring the Gini Index in the subsets of results from general versus locally oriented keywords.

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Next, we tested hypothesis 3 about the role of geographic associations by considering the county-level variation of the proportion of local or regional to national outlets in news results across the United States. We further estimated a set of linear models. The first pair regressed the presence of local news on its rank in the search results, the number of local newspapers in a county and the county-level demographics we hypothesized to be related to local news demand. The second pair allowed us to test associations between local demand conditions and the number of times Google News returned an outlet, by regressing the number of times a print-based outlet was returned on its circulation and a similar selection of county-level demographics.

Finally, to understand whether Google News merely responds to user disinterest in local news, we compared relative interest in locally oriented terms with interest in general terms. We did this by collecting and analysing Google Trends data for each term in our query list.

Our findings suggest that Google News users are exposed to far more national news outlets than local outlets. This relationship is driven by the fact that readers who search for general policy issues are almost exclusively directed to reports by national newspapers. Only the readers who explicitly search for keywords related to local governance and public services are directed to local and regional newspapers, and only if they look past the first few results—an unlikely phenomenon. Furthermore, county-level predictors of both local news supply and demand, such as the number of newspapers in a county and their circulation, are not related to the likelihood of receiving a local news outlet as a result nor the number of times a local news outlet is returned. These results indicate that there is sparse evidence that Google News' algorithms are sensitive to local supply or demand. However, the analysis of Google Trends data suggests that users have more interest in locally oriented terms than general ones, which indicates that user interests may moderate the negative relationships between the platform and local news exposure.

Results

Distribution of returned outlets. The distribution of the number of times each outlet was returned is particularly long tailed, with the three most common outlets making up 16.4% of the returned results (Supplementary Fig. 1). While descriptive statistics offer some sense of the level of inequality in the distribution, we also consider a more robust measure of inequality: the Gini Index. The Gini Index is a measure of inequality that ranges between 0 and 1, with low levels indicating equal distribution across outlets and high levels indicating more inequality between outlets. In the context of digital platform audits, high Gini Index values indicate that a few outlets are returned much more frequently than all others in a set of results.

For the whole set of aggregated results, we find that the Gini Index signals a very high level of inequality ($G=0.82$). This value is in line with the highest levels of concentration observed in other search audits[9]. To put this value in context, the Gini Index for income inequality in the United States was 0.49 in 2018. Importantly, this level of inequality in the returned results exceeds the inequality in total circulation for papers captured in University of North Carolina Center for Innovation and Sustainability in Local Media's Database of Newspapers ($G=0.65$)[1]. These results provide evidence in support of hypothesis 1, that Google News is favouring national outlets at the expense of local outlets, as we see a high degree of concentration in which outlets are commonly returned.

The variation across terms is minimal (Fig. 1). The set of locally oriented terms appears to produce a lower level of inequality, on average, than the set of general terms. This intuition was confirmed via a one-tailed Wilcoxon test ($W=242$; $P<0.001$). However, it is not obvious from these results whether the levels of concentration are substantively different between locally oriented and general terms, leaving us with inconclusive initial evidence for hypothesis 2.

Composition of search results by query. While the level of inequality in the number of times an outlet is returned may not be substantively different between sets of queries, queries may produce sets of results that vary quite a bit in the volume of local news outlets returned, even if the same few national outlets appear across all sets of results, producing the observed levels of inequality. Based on previous audits of Google's search platform, we expected Google News to return more local media outlets when users search for news about topics of local interest and more national media outlets when users search for news about general interest issues[9,17]. We show in Supplementary Fig. 2 that this is the case.

However, considering the whole set of returned results reflects unrealistic user behaviour. A majority of search engine users do not look past the first page of results and about one-third stop looking at results after the first link[18–20]. Eye-tracking studies have suggested that search engine users generally consider only the first ten results of a search, with most of their attention reserved for the top results[21]. Therefore, the composition of results may only matter for some subset of those that we collected. To see whether looking at only the top results changed the composition of our results sets, we iteratively filtered each and calculated the relative frequency of local and national outlets at every step. These frequencies are reported in Fig. 2.

We can see that for locally oriented terms (top 16 panels), the relative frequency of local outlets declines as we isolate only the top results for many terms in the set. Even for topics as contextually dependent as weather, the share of local news outlets in the first ten hits is lower than that for national outlets, and the trend changes only after the tenth result. A similar pattern is observed for the set of general terms (bottom 16 panels). Local news is available on Google News, but users need to scroll through the results to find it.

Together, these results provide credible support for our second prediction that the scope of the query is associated with the composition of results. We can see that the composition of results, with regard to the volume of local and national news outlets, changes in dramatic and substantive ways with the type of query we searched.

Modelling supply and demand. While we find little evidence of a geospatial relationship between the composition of search results and the location of our searches (Supplementary Fig. 3), we also tested whether Google News search results are responsive to local supply and demand.

To do so, we estimated a linear model regressing an indicator for whether a result came from a local or regional outlet (coded 1) or a national outlet (coded 0) on search rank, query type and a set of measures that capture local supply and demand. We controlled for a set of census measures for each county (population, median age, poverty level, racial composition, educational composition and internet access), an indicator for whether a county contains a state capital, an estimate of county-level turnout in the relevant state governor's race between 2013 and 2016, and the estimated time in hours since a story was published.

We include these demographic variables because previous research has linked all three features to interest in local news[3,15]. Similarly, we include the indicator for the presence of a state capital because past results have shown that news outlets located in state capitals provide increased coverage of state politics, which could lead to more relevant stories being published on broad political topics[22]. The inclusion of a term for county turnout for a state election is a proxy for civic engagement, another predictor of local news interest. As an indicator of local supply, we include the log of the number of papers available in a county. This model was estimated with ordinary least squares (OLS) and standard errors clustered at the county level. The results in Supplementary Table 4 show that OLS results are similar to those for probit models. The decision to use the collapsed measure of local–regional status was made to reduce any noise introduced during our classification task.

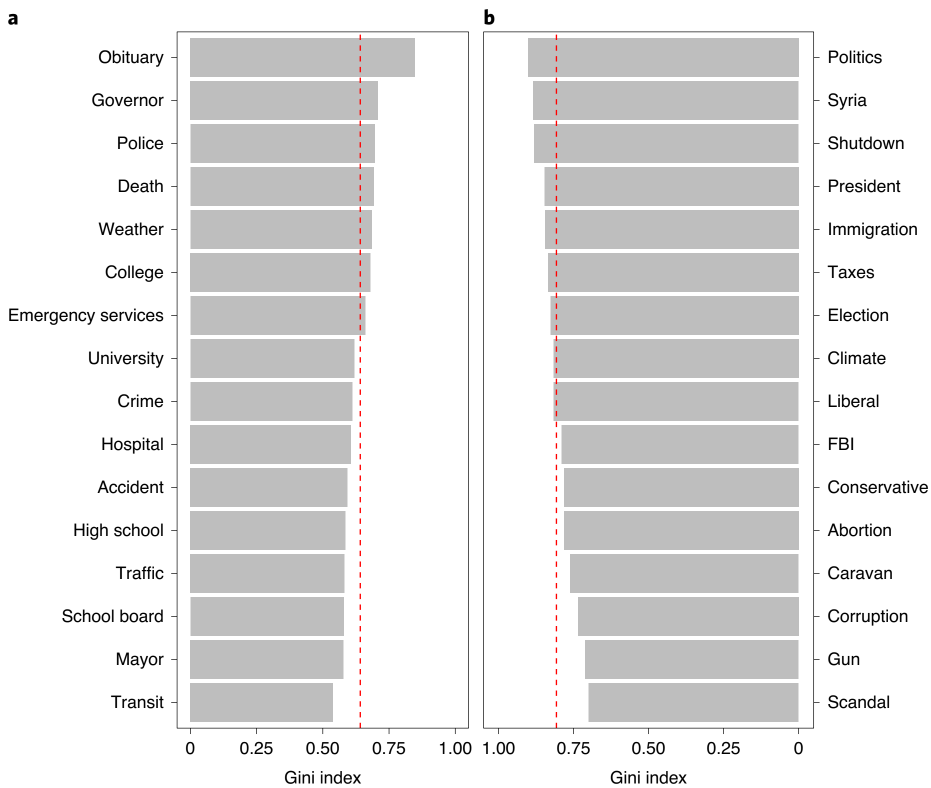

Fig. 1 | Gini index for individual searches. a, Gini index for locally oriented search terms: accident (n=221,830, $n_{outlets}$=225), college (n=66,047; $n_{outlets}$=115), crime (n=158,239; $n_{outlets}$=196), death (n=168,537; $n_{outlets}$=191), emergency services (n=420,541; $n_{outlets}$=153), governor (n=168,142; $N_{outlets}$=206), high school (n=223,591; $n_{outlets}$=316), hospital (n=342,145; $n_{outlets}$=322), mayor (n=118,767; $n_{outlets}$=192), obituary (n=282,238; $n_{outlets}$=56), police (n=177,888; $n_{outlets}$=241), school board (n=295,003; $n_{outlets}$=262), traffic (n=331,774; $n_{outlets}$=323), transit (n=319,032; $n_{outlets}$=145), university (n=308,847; $n_{outlets}$=255) and weather (n=315,599; $n_{outlets}$=228). **b**, Gini index for general search terms: abortion (n=558,480; $n_{outlets}$=356), caravan (n=506,905; $n_{outlets}$=245), climate (n=500,082; $n_{outlets}$=350), conservative (n=547,160; $n_{outlets}$=270), corruption (n=289,901; $n_{outlets}$=187), election (n=629,307; $N_{outlets}$=460), FBI (n=532,117; $n_{outlets}$=339), gun (n=503,604; $n_{outlets}$=502), immigration (n=640,117; $n_{outlets}$=354), liberal (n=385,714; $n_{outlets}$=189), politics (n=664,457; $n_{outlets}$=293), president (n=662,253; $n_{outlets}$=398), scandal (n=149,270; $n_{outlets}$=155), shutdown (n=695,655; $n_{outlets}$=359), Syria (n=578,667; $n_{outlets}$=166) and taxes (n=528,519; $n_{outlets}$=478). In **a** and **b**, the dashed red line marks the mean value.

As we can see in Fig. 3, most of our features of interest are not significantly associated with the probability of observing a local or regional outlet versus a national outlet. The only features that are significantly and substantively related to the outcome are the rank of the results and the type of term queried. As expected, searching for one of our general queries is negatively associated with the chance of seeing a local or regional outlet ($b = -0.629$; $P < 0.001$; 95% confidence interval (CI) = −0.629 to −0.628). Alternatively, the farther into the results we go and the rank increases, the more likely we are to observe a local or regional outlet ($b = 0.00050$; $P < 0.001$; 95% CI = 0.00049 to 0.00051). There is also a significant, but not substantial, negative relationship between a county's population and the likelihood a local or regional outlet is returned ($b = -0.00029$; $P = 0.014$; 95% CI = −0.00053 to −0.000060). However, moving from the smallest county to the largest county would only be associated with a 0.34 percentage-point decrease in the probability of observing a local or regional outlet. Time since publication also has a significant and negative relationship with the likelihood of observing local news, as we would expect ($b = -0.00024$; $P < 0.001$; 95% CI = −0.00024 to −0.00024).

Given the importance of search terms, supply and demand relationships may reasonably vary between general and locally oriented queries. As such, we re-estimated our model including interactions between each term and the indicator variable for a query being for a general interest search term (see Supplementary Table 5 for the full results of this specification). The noteworthy findings are that the probability of observing a national news outlet is associated with the interaction of the type of term with the (higher) rank of the result ($b = 0.00073$; $P < 0.001$; 95% CI = 0.00071 to 0.00074) and with the (higher) number (logged) of papers in a county ($b = 0.00083$; $P = 0.041$; 95% CI = 0.000035 to 0.0016).

As an alternative test of supply sensitivity, we used local newspaper circulation as our operationalization of local demand. In this case, we used OLS to fit linear models that regressed the number of times an outlet was returned in our results on its total circulation reported in the University of North Carolina Center for Innovation and Sustainability in Local Media's Database of Newspapers[1], reported as a percentage of the total population of the county where it is headquartered. As with our earlier models, we controlled for the same variety of county demographic features, but for each paper's home county. Standard errors were again clustered at the county level. Supplementary Table 6 shows that the results we report from these models are similar to those from models estimated via Poisson regression.

As we can see in Fig. 4, while controlling for county demographics, state capital status and civic engagement, an increase in newspaper circulation, in both absolute and relative numbers, is associated with an increase in the number of times an outlet appeared in our results. The magnitude of the relationship for both measures is an increase of about 2,800 more appearances per a one-standard

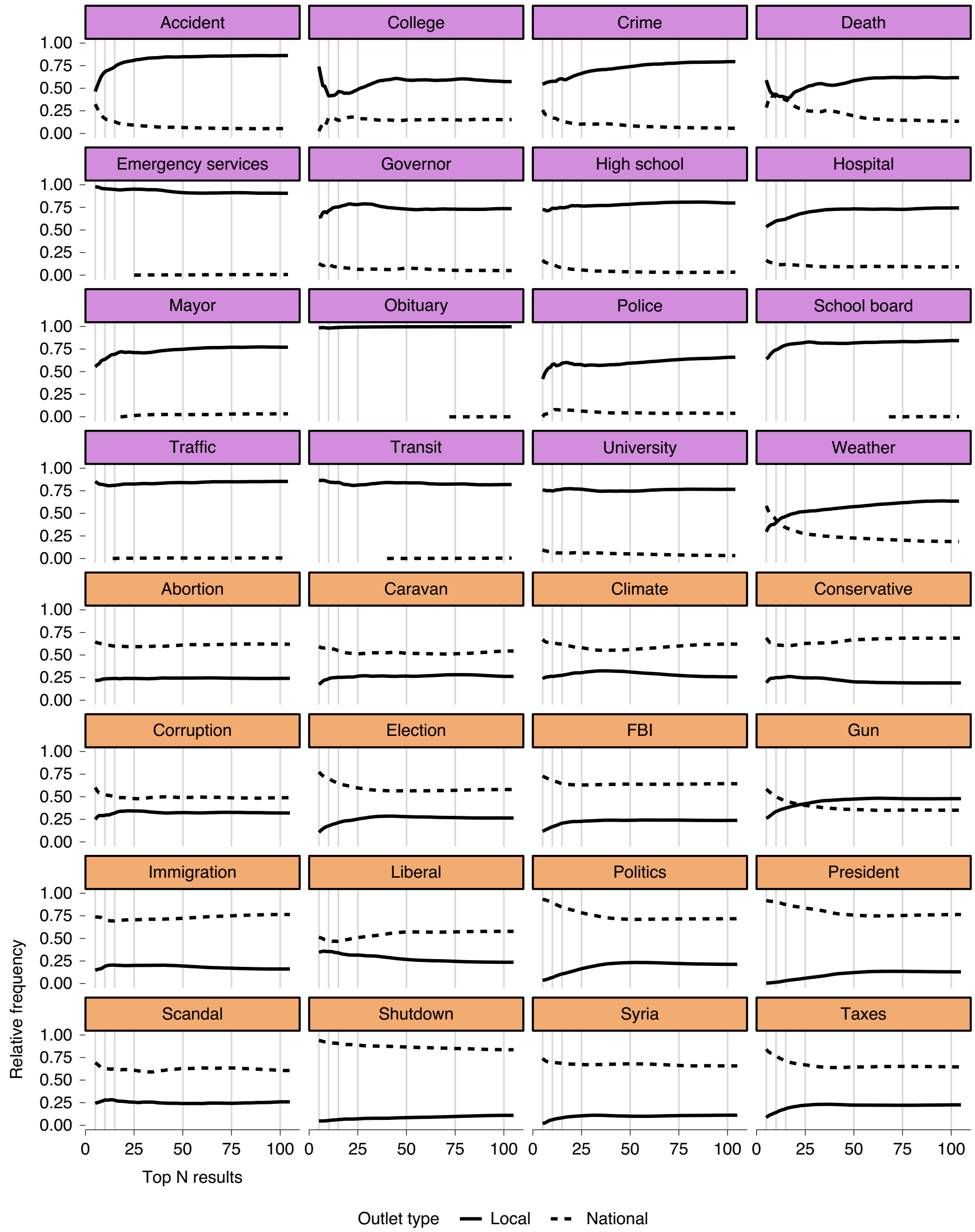

Fig. 2 | Relative frequency of local and national outlets for the top-*n* results of each search query. The top 16 purple-labelled terms are locally oriented terms. The bottom 16 orange labelled terms are general terms.

deviation increase in circulation ($b_{\text{total circulation}} = 2{,}876.35$; $P < 0.001$; 95% CI = 1,974.18 to 3,778.52; $b_{\text{circulation share}} = 2{,}833.82$; $P = 0.0059$; 95% CI = 818.43 to 4,849.22).

Unlike our earlier models, some county features were significantly associated with the number of times an outlet was returned. These include the median age and educational attainment of county residents. Older county populations are associated with lower outlet frequency, with the magnitude of this drop ranging between about 3,000 occurrences ($b_{\text{total circulation}} = -2{,}996.64$; $P = 0.0045$; 95% CI = −5,057.57 to −935.71) and about 4,000 occurrences ($b_{\text{circulation share}} = -4{,}271.12$; $P < 0.001$; 95% CI = −6,584.86 to −1,957.37) per a one-standard deviation increase in a county's median age. Alternatively, we see that higher levels of education are positively associated with outlet frequency, especially with regard to the share of residents with high school degrees or general educational development (GED) qualifications and higher levels of attainment.

These models tell us that Google News' algorithm reinforces existing inequalities in the media marketplace. The platform rewards outlets that already have strong consumer bases and, in turn, makes it more difficult for readers to find news from less frequented local outlets. As we see in Supplementary Table 7, these results are robust to the exclusion of papers from Los Angeles, Washington DC, New York City and Chicago, which could have confounded our findings because of their large papers with national circulation.

Together, the results from both sets of models present mixed evidence for and against our hypothesis 3 that Google News is responsive to local demand and supply. On the one hand, one's community features, including the number of local media outlets in the area, have only weak relationships with the likelihood that one sees local news outlets in Google News search results. At the same time, Google News is sensitive to the existing off-platform reach

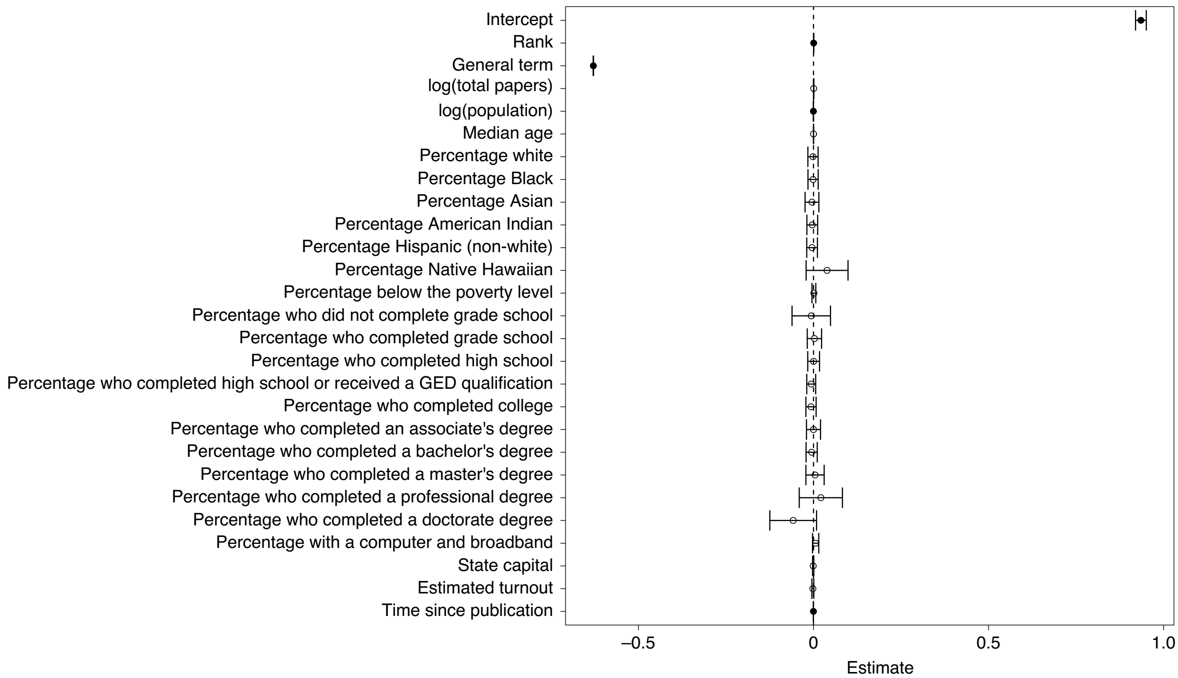

Fig. 3 | Estimated coefficients from the model with no interactions and standard errors clustered by county. Bars represent 95% CIs. Filled points indicate statistical significance at the $\alpha=0.05$ level ($n=12,340,560$). GED, general educational development.

of outlets, returning local newspapers more when they have more subscribers. The combination, though, reinforces current market inequalities and the strength of outlets that have established audiences without supporting interventions to support struggling or fledgling local and regional news outlets.

Search interest. The type of query a Google News user searches for is strongly related to how likely they are to be exposed to local news. Accordingly, we compared the frequencies of news queries in the United States for more locally oriented terms or more general terms. Our findings illuminate whether users are more or less likely to be exposed to local news outlets.

To compare user interest, we collected the Google News trends for each term. We depict these trends relative to the trend for "corruption", which was an appropriate baseline value because interest in the topic was consistent across the entire time window, with weekly unadjusted values ranging from 2–6 on the 100-point scale. Adjusted values range between 0 (not inclusive) and 100 (inclusive),

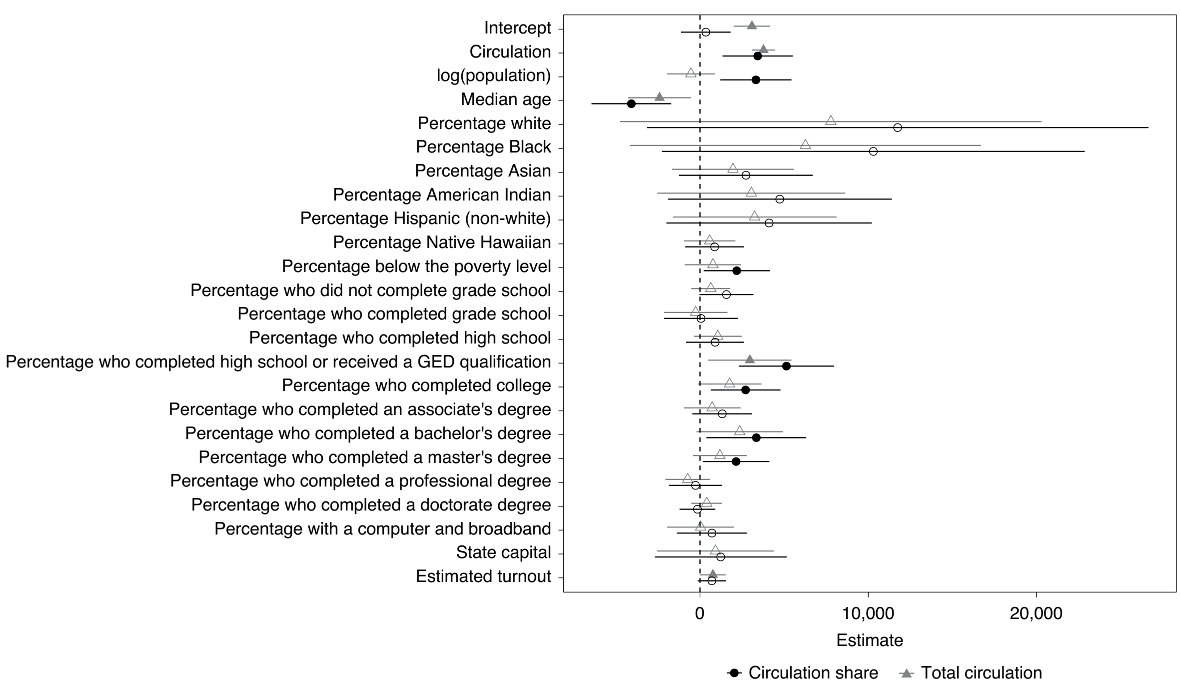

Fig. 4 | Estimated effects on the number of appearances in scraped results with standard errors clustered by county. Bars represent 95% CIs. Filled points indicate statistical significance at the $\alpha=0.05$ level. Independent variables are standardized ($n=588$).

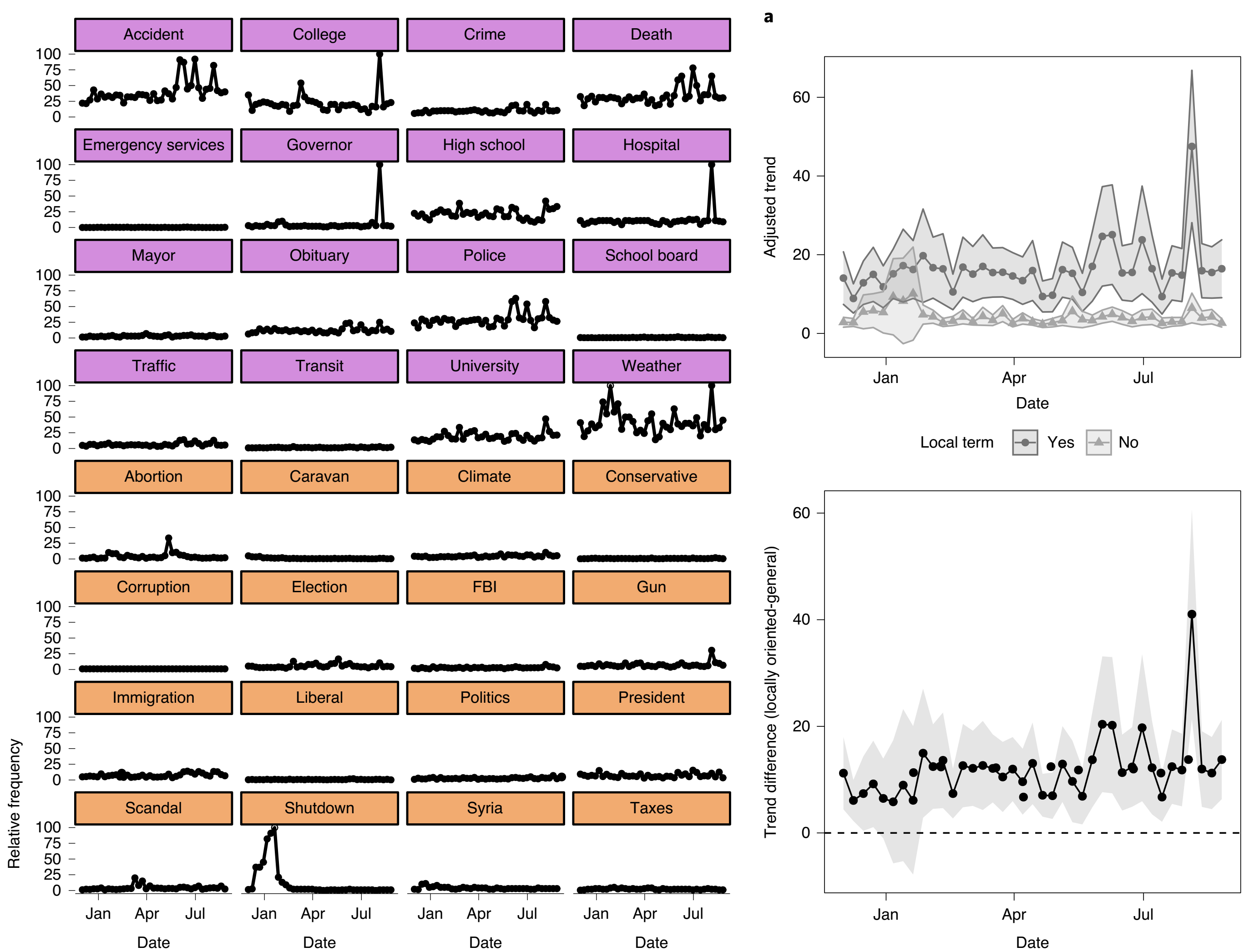

Fig. 5 | Google trends for locally oriented and general terms over time. a, Time series of the trend (relative to "corruption") for each term queried. **b**, Time series of the average trend (relative to corruption) for locally oriented and general search terms. Shaded regions denote 95% CIs. **c**, Time series of the difference in the average Google News trend (relative to corruption) between locally oriented and general terms. Shaded regions denote 95% CIs. The observed difference is statistically significant (W=290,387; P<0.001).

with values higher than 1 indicating more interest in a given term than in corruption in a given week. Values less than 1 indicate less interest in a term than in corruption for a given week.

Figure 5a visualizes interest in each term (measured in relative trend units) from December 2018 to August 2019—the time window over which we collected our data. As we can see, interest in most terms is stable, with only a few cases of any substantial variation from the term average. We can also infer from these time series that locally oriented terms appear to generate more interest than general terms, which we see confirmed in Fig. 5b,c.

In Fig. 5b, we see the time series of the aggregated average and associated 95% CI for each set of terms, making it evident that locally oriented terms produce more interest than general terms, but that the dynamics of the two series are similar. In Fig. 5c, we see the difference between the two group averages and the associated 95% CI plotted over time. Here, we see that in most weeks the two groups are statistically distinct as their difference is distinct from 0. Collapsing over the entire time window, we find that this difference is statistically significant (one-tailed Wilcoxon test; $W=290{,}387$; $P<0.001$), providing more evidence that individuals are more interested in local topics than general ones.

To provide a more informative estimate of the difference between the two groups, taking into account the potential outlier terms "accident" and "weather", we regressed the relative trend value on binary indicators for general terms with controls for these two terms. We find that even when controlling for these potential outliers, the average difference is still 8.41 ($P<0.001$; 95% CI $=7.09$ to 9.72).

These results indicate that Google News users search for local and general topics at different rates, with locally oriented topics being slightly more popular searches. The popularity of locally oriented search terms suggests that users are interested in learning about locally relevant information most of the time; interest in national politics spikes when major news events occur, such as the government shutdown from January 2019 to February 2019.

Discussion

Our findings offer insights into the relationship between Google News and local news. There was a large disparity in the number of times national versus local outlets appeared in our audit, and it went beyond simply differences in newspaper circulation. Together with our regression analyses, these results support our hypothesis 1 that Google News skews results in favour of large national outlets. The local–national outlet disparity was lower in queries about locally oriented topics than for general topics. This disparity lends credence to our hypothesis 2 that the composition of results would vary depending on the scope of the query.

Our hypothesis 3 that Google News would be sensitive to supply and demand in local media economies had mixed support. The first challenge to this hypothesis came from a lack of spatial autocorrelation in the relative frequency of local and regional outlets across counties. Instead, we found that geospatial variation in this measure was low, with all counties falling in a small band. Additionally, when we modelled the probability of Google News returning a local or regional news outlet for a given result within the broader set of results for a query in a given county, we found that the only substantial association was with the type of term for which we searched. Again, topics that are locally oriented generate results that include more local outlets, while topics that are generally oriented generate results that include more national outlets. At the same time, media supply and audience demand in the county were not significantly or substantially related to local news exposure. However, outlets' off-platform reach was associated with the number of times outlets appeared in our results; local news outlets appeared more frequently when they had more subscribers. Yet, this association has the possibility of reinforcing existing inequalities in media industries.

These results align with those from audits of the core Google Search platform, which identified the search query as the source of the most variance in the results returned to users[7–9,17]. However, in contrast with the audits assessing how Google promotes echo chambers[7], the outcomes here are not generally normatively positive. There is a great deal of opacity that goes into determining how stories are selected to be included in search results. Is there a general platform preference for large national outlets, with local outlets being included when there are no more national outlet stories to include? Depending on the answer, Google News may be directing individuals away from crucial local reporting and, as such, reducing the viability of these local news operations.

The strength of local news markets does not substantially influence the likelihood of local news being included in any set of results. If robust local news offerings do not lead to more attention being directed back to local media, the value of such investments—and the algorithms that curate them—may need to be questioned. The greater implication of declining traffic to local news is the potential exacerbation of America's news deserts, and the increasing social and economic inequalities between those who are and are not in the news[1,6]. A recent content analysis of media outlets conducted by researchers at Duke University reported that while local newspapers accounted for only one-quarter of the total media outlets in a random sample, they produced 50% of all original news stories reporting local news[23].

This finding is different from a strand of media economics research leveraging the shutdown of Google News in Spain in December 2014. Multiple research teams have shown that the removal of Google News as a pathway to exposure in Spain reduced news consumption, with the largest effects for small outlets[24,25]. In contrast, we focus on the competition between local and national outlets within the Google News platform. Furthermore, as Google regularly introduces algorithmic, technological and design changes to its platform, such as accelerated mobile pages[26,27], it would be difficult to replicate the same study, even if we could suspend Google News for a laboratory experiment.

Looking past the immediate consequences of our findings on local media economies, the extended implications for behaviour and civic life are also not normatively positive. By presenting most stories from national outlets in response to general interest queries, Google News may be exacerbating local information gaps related to these topics. Citizens who are learning about a topic through Google News may not learn how a topic affects their state or local community, forcing them to revert to using less-than-ideal information[22,28] or, in extreme cases, to dropping out of civic life[29–31]. For example, Google News users interested in taxes may not learn about the function of taxes in their community and instead may rely on national party cues to determine whether or not they support a local policy. Reliance on national party cues may intensify partisan polarization[28].

The possibility for any positive downstream implications comes from evidence about user search behaviour. Our analysis of Google News trends indicates that the locally oriented search terms we queried receive more interest on average than those that are more general. Therefore, it seems at least plausible that user behaviour and platform behaviour could interact to increase exposure to local news outlets. However, these results run against previous findings indicating that interest in local news is much less than that for general interest news[2]. Increased interest in general interest news has been identified as a critical factor in declining local news audiences[22]. This discrepancy is substantial because users' search interests provide the frame through which platform gatekeeping is evaluated. When platforms nudge users towards general interest topics (as we show Google News does in the Supplementary Information), they risk failing to meet the needs of their users and the critical information needs of local communities.

One explanation for this difference in interest may be the way we selected our queries. We queried generic terms related to current events so that we could be sure to avoid generating results through hyper-specificity. However, users' actual queries may differ from these generic topical searches. For example, individuals seeking out news about the president may search for that figure by name instead of through a more abstract term. Yet, it should be noted that Google's Knowledge Graph disambiguates such queries before results are retrieved[32], so we anticipate that our queries would still draw from a superset of relevant results. Furthermore, users may not experience any need to search for generally oriented topics since Google News already curates these stories and presents them on the home page. If so, Google Trends would not wholly represent the total user interest in these topics.

Our decision to proxy the strength of a local media market by the number of papers operating within a geographic unit is another potential limitation worth considering. Our data do not take into account the possibility that some papers have become ghost papers; that is, heavily reduced versions of their former operations that provide little original content in their communities[1]. As part of this process, some stories published by local outlets may be from wire services or only function as summaries of reporting done by larger outlets. We know that only about 17% of news stories take place in the community[33]. That being said, our choice of covariates in our models, such as the number of papers in a county and a county's socioeconomic indicators, are similar to those in recent economic analyses of local news markets[2] and are associated with interest in local news[15]. By controlling for all of these likely covariates of the strength of the local news economy, we take into account both demographic and structural market features that could affect the frequency of local news in Google News results.

Additionally, we did not audit the effect of user-specific personalization on the curation of local news; however, we provide a different perspective on how filter bubbles limited to national news outlets may reinforce the existing status quo[13,34,35].

It is also not known whether Google News' algorithms consider trending searches, promoted or sponsored posts, social media shares, paywalls and search engine optimization strategies when they determine the rank order of research results. Other scholars have reported that Google has long acknowledged that commercial interests may compromise the quality of Google's search results[36]. We recommend that a future audit could consider these and other factors by supplementing our sampling strategy with a web crawl.

It is worth considering whether having more transparent curative algorithms for news aggregators could lead to a more informed, digitally literate and responsible citizenry. Moving forward, we have four recommendations for future research that we believe are essential for developing the most accurate understanding of the digital platform's role in the local news economy. First, we recommend that future work consider synchronous audits of both Google News and the major national outlets, such as *The New York Times*, *The Washington Post* and CNN, to account for changes in coverage. Second, the content of stories could also be mined to account for local context. Third, researchers could conduct behavioural audits of Google News users, tracking which stories they choose to read from those presented to them, in order to simulate actual use and search traffic to local news outlets. In this pursuit, it is important to consider that, in 2016, the Pew Research Centre reported that 44% of American users obtain their news from social media sites[37]. Finally, scholars could test whether our findings are replicated in how political content is curated in users' social media newsfeeds on Facebook and Twitter[10,38].

Even though we can already see future directions for research into platform effects on local news, we find strong evidence of a query-driven process of supplying local news to users. The data collected in our audit clearly show that Google News could perpetuate a concerning feedback loop in which attention and resources are diverted away from local news when individuals seek information about many essential political topics. This likely diversion away from local news has the possibility of shrinking the local information environment, which in turn can produce normatively undesirable effects on political and civic behaviour.

Methods

Selection of geographic units and search terms. For this project, we set our geographic area of interest to that of the entire United States. To assess geographic variation, we considered counties as our unit of interest, as was done in previous research[8]. For each county in the United States, we identified the county seat and created a list of latitude–longitude coordinate pairs to be fed to our data collection algorithm.

We wanted our assessment of the variation of Google News search results to cover as many news and policy topics as possible and to be the least biased by the specificity of search terms. To the best of our knowledge, Google does not provide a list of the most popular search terms on the news platform for us to build on, and there has been no substantial analysis of Google News search behaviour.

Furthermore, the Federal Communications Commission (FCC) and partnered scholars have begun to assess the health of local journalism by evaluating how well a community's need for information in these areas is met[33,39,40]. As part of this initiative, the FCC[41] has released a list of critical information needs (that is, emergencies, health, education, transportation, jobs and the local economy, the environment, civic life and politics, and local government), which offer a way to study how well Google News is supporting the central goals of local journalism.

In creating our list of keywords, we referred to the search keywords that have been used in similar audits of search engines[8,9], as well as tallying it with the FCC's recommendations to ensure that it was representative of critical information areas. Finally, our first list referred to general policy issues, or the words were associated with current events of general interest in the United States during the period from January 2019 to February 2019. This list comprised the terms abortion, caravan, climate, conservative, corruption, election, FBI, gun, immigration, liberal, politics, president, scandal, shutdown, Syria and taxes. The second list was aimed at capturing local heterogeneity and was based on the set of locally oriented terms used in previous research[8]. This list comprised the terms accident, college, crime, death, emergency services, governor, high school, hospital, mayor, obituary, police, school board, traffic, transit, university and weather. These data were collected over the course of June 2019. To make our searches location specific, we paired each term with the modifier "near <county seat>".

Data collection. We collected the headline, outlet, URL and time stamp for the first 100 results for every query in every county.

We used the Python package Selenium, which allows users to automate web browser interactions and scrape data from web pages with lower memory overhead compared with previous methods[8,17]. Selenium can preset the browser's location through pre-specified geographical coordinates, which enabled us to simulate independent search sessions from different counties.

We instituted many checks to account for external confounds, such as biases due to temporary cookies, the order of queries, the timing of the search requests or the surge in importance of a keyword. First, every query was instituted on a new browser window opened in incognito mode, and we repeatedly generated and subsequently terminated browser windows with different latitude and longitudinal coordinates. Second, the query order was randomized for each search term, so that time-related biases did not confound the local results for each county. Third, three full sets of results were collected for each search term over the data collection period of 6 months, to adjust for any local maxima in news attention, from January 2019 to June 2019. Fourth, to obtain local search results, we also modified the search query for each keyword in our list (that is, "gun near Orange County, CA"). While ensuring that our results were location specific, this query template also circumvented Google News' possible reliance on IP addresses rather than browser presets to serve local results. We found it to be the recommended method for marketers to test their search engine advertising and optimization results[42–44]. Finally, we instituted a sleep timer to stagger our requests over time.

Some data were returned with corruptions. This meant that for some terms we ended up with fewer than three usable captures. For the terms accident, crime, death, governor, high school, obituary, police, school board and scandal, we only had two usable captures. For the terms college and mayor, we only had one usable capture. The total numbers of observations for each term are reported in Supplementary Table 1.

Coding outlets. We filtered the collected data to retain the outlets and their position in the search results, which we refer to as the rank of the result. We then classified the outlets as being local, regional, national or international media outlets by delineating websites by the scope of their reporting. Outlets covering stories in small finite areas would be classified as local outlets, while those covering stories in larger but still finite areas would be classified as regional outlets. National outlets would be those located in the United States and covering news across multiple areas of the United States.

Many of our outlet classifications came from data provided by the Social Media and Political Participation laboratory at New York University[45], which is sourced from databases maintained by the United States Newspaper Listing and Station Index. This dataset identified local newspapers, magazines and broadcast television stations across the United States. However, given the variety of outlets observed during our searches, the dataset provided minimal coverage of our outlets.

To supplement this existing resource, we performed a classification procedure on Amazon Mechanical Turk for 1,078 additional outlets. As part of our procedure, we showed two Amazon Mechanical Turk workers an unclassified outlet, linked them to a general Google search for the outlet and asked them to decide whether the outlet was local, regional, national or international media. This classification question was split into logical branches so that workers first identified whether the given outlet was located in the United States, and then, if so, classified the outlet as either local, regional or national. If the outlet was located outside the United States, workers identified the country within which the outlet was located. We collected classifications for each outlet from two workers. The inter-coder agreement was about 73% (see Supplementary Table 2). If the two workers agreed, the outlet was added to the database with that classification. In cases where the workers disagreed, instead of forcing hard boundaries, we logged both classifications as a boundary category; for example local–regional or regional–national. Supplementary Table 3 reports the share of classifications from the second coder given the classification of the first coder.

As noted elsewhere[46,47], there are many potential ways to define what constitutes a local news outlet, and this decision framework can impact our results. Our definition focuses on the scope of coverage in both geographic and content terms. However, these heuristics can disagree with previous classifications; for example, when we deal with major metro papers, such as *The Boston Globe*, *Houston Chronicle* and *LA Times*. In our models, these papers were classified as being local or regional, but under definitions based on circulation or readership they could be seen as national outlets. Our approach has the advantage that it is based on the actual publishing decisions and intentions of the outlets. This allows us to separate the metro papers listed above from *The New York Times* and *The Washington Post*, both of which ostensibly serve as metro papers but devote substantial attention and resources to covering general political news.

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

The figures and analyses in this paper are based on original data collected by the authors. Raw data, as well as processed minimal datasets necessary for reproducing the analyses and figures, are available via the associated OSF repository for this project (https://osf.io/hwuxf/?view_only=3fa7499661df487689031e11b8ea20b4).

Code availability

Original code is available via the associated OSF repository for this project (https://osf.io/hwuxf/?view_only=3fa7499661df487689031e11b8ea20b4).

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Author contributions

S.F., K.J. and Y.L. designed the study, conducted the analysis and drafted and revised the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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Are Partisans Culturally Polarized?

Background

This project is one of the pilot studies from my dissertation, which considers whether reports of partisans holding widely differing cultural preferences (e.g. this article) were correctly describing the types of differences individuals would experience in their everyday lives. My pilot studies for this project sought out existing data sets or used data collected as parts of other studies. In this case, I analyze survey responses about respondents' cultural preferences (e.g. preferred musical artists or television programs) and their political beliefs (e.g. the most pressing issues facing the country). I find that partisans experience greater levels of polarization when considering political beliefs instead of cultural preferences. In fact, the levels of polarization observed for cultural preferences are nearly zero.

My method of choice for this project, as well as the other projects comprising my dissertation, is network analysis. I use the relationships between respondents and their preferences to ultimately construct a network linking respondents who shared preferences. I then map respondents' demographic features on to their nodes in the network and analyze the relationships between these features and the network structure. My measure of interest is assortativity, a correlation-like measure that describes how likely it is two nodes are similar (or different) on a given measure if they are connected in the network.

This project has not been published in a peer-reviewed journal and what is included here is an early preprint.

Missing Polarization: Comparing Polarization in Political and Cultural Preferences

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Abstract

The popular press has given substantial attention to the notion that Democrats and Republicans hold diverging cultural and lifestyle preferences that manifest in the TV shows they watch, the music they listen to, and the clothes they buy. The academic research in this area is split, though, with some suggesting that such divisions exist and others arguing that they ultimately fail to materialize in real-world behavior. In this study, I use network methods to evaluate whether such partisan cultural polarization exists at the individual-level. I do so by constructing networks of shared cultural preferences and networks of shared political beliefs based on closed-ended survey responses. For each network, I calculate the assortativity (correlation) between linked respondents' partisan identity, ideology, age, gender, race, and education level. I show that the assortativity for the political identity measures is low across the cultural-preference networks compared to the political-belief networks. These results suggest that cultural preferences are not associated with partisan or ideological identities.

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The popular press has devoted substantial attention during and since the 2016 presidential election circulating claims about substantial divisions in the cultural and lifestyle preferences of Democrats and Republicans. These arguments build on the analyses showing aggregate-level associations between partisanship and indicators of culture preferences, such as television viewing habits (Katz, 2016), concert attendance ("Why Obama-Trump swing voters like heavy metal", 2019), and shopping habits (Kapner & Chinni, 2019). The notion that the parties are culturally divided has since become pervasive, with cultural preferences now operating as activators of partisan stereotypes and biases (Deichert, 2018; Hiaeshutter-Rice et al., 2019).

However, academics have not found consistent evidence to support these claims. Early work, like Bishop's seminal analysis of partisan residential sorting (Bishop, 2009), argued that partisans preferred to build and live in communities filled with like-minded others. Building on this concept, DellaPosta, Shi, and Macy conceptualized the parties as Weberian "status groups" and showed that homophily and social influence could produce within-party alignment in regards to cultural preferences (DellaPosta et al., 2015). Contrarily, Mummolo and Nall show that reported preferences for specific community attributes (e.g., more conservative) often do not translate into actual behavior changes when moving (Mummolo & Nall, 2017). Martin and Webster support this finding by showing that partisan biases in residential choice are too small to sustain observed geographic polarization (Martin & Webster, 2020).

It is possible, though, that individual-level psychological and sociological features correlated with partisanship may be associated with cultural and lifestyle preferences. For example, Mutz and Rao demonstrate that liberals are more likely to prefer lattes than conservatives because they are more open to globalization than conservatives (Mutz & Rao, 2018). Similarly, Republicans' greater religiosity levels lead them to give more to charity than Democrats (Margolis & Sances, 2017). As such, it is entirely possible that, while partisanship or ideology is not the primary pathway through which such divides emerge, the parties are effectively divided in their cultural preferences.

Clarifying whether such a divide in cultural preferences exists is crucial because of the pervasiveness of partisan cultural stereotypes. These stereotypes that link partisan groups to specific cultural habits and products are used to infer another's partisanship when obvious political signals are not available (Deichert, 2018; Hiaeshutter-Rice et al., 2019). These inferences enable people to activate their own partisan biases (Deichert, 2018), fueling affective polarization in situations that would otherwise be devoid of politics. Losing these apolitical moments is concerning because they provide opportunities for positive cross-party contact and relationships to form that could help partisans recognize similarities in the other side, leading to reductions in political hostility (Levendusky, 2018).

In this study, I take a new approach to assessing the magnitude of the partisan divide in cultural preferences. Drawing on closed-ended survey questions, I construct two sets of networks. The first set represents shared cultural preferences between the survey respondents.

The second set represents shared political concerns between the same set of survey respondents. I then analyze each network's structure and compare the association between that structure and respondents' political identity, ideology, age, gender, race, and education level. I find that the association between network structure and respondents' political identity and ideology is substantively higher in the networks of political concerns than in the networks of shared cultural preferences. In the latter set, the association between individual-level political features and network structure is effectively zero. This result suggests that people do not encounter substantial partisan polarization in their cultural preferences.

Data

This study's data came from multiple waves of a larger study administered on Amazon Mechanical Turk (mTurk) in the Spring and Winter of 2019. Across all waves of the study, over 1,300 workers completed a survey asking about their demographics, cultural preferences, and political opinions. Descriptive statistics about the sample are provided in Appendix B.

The questions about cultural preferences were based on those used by Bourdieu in his study of cultural prestige (Bourdieu, 1984). These questions asked respondents to indicate their three favorite musical artists, television programs, literary genres, and film genres from closed lists, as well as their single favorite style of clothing from a closed list.

The questions about political beliefs and concerns included a similar question asking respondents to indicate their three most pressing political concerns from a closed list. The survey also asked respondents to indicate their specific preference for raising or lowering taxes, involvement in foreign conflicts, and a pathway to citizenship for undocumented immigrants.

All respondents also completed a set of demographic items that asked them to report the year they were born, their highest level of completed education, and how they identify in regards to gender, race and ethnicity, political party, and ideology. These last two items, political identity and ideological identity, were reported on seven-point scales. I collapsed the measure of highest educational achievement into a binary indicator for holding a college degree or not.

For the cultural-preference questions, the political issue concerns questions, and two of the political policy questions, the order of the responses was randomized to avoid order effects.

All questions and response options are included in Appendix A.

Network Methodology

Networks have been employed to study polarization in political beliefs and consumer habits. These networks break from a traditional "social" framework by studying the two-mode networks of people and ob-

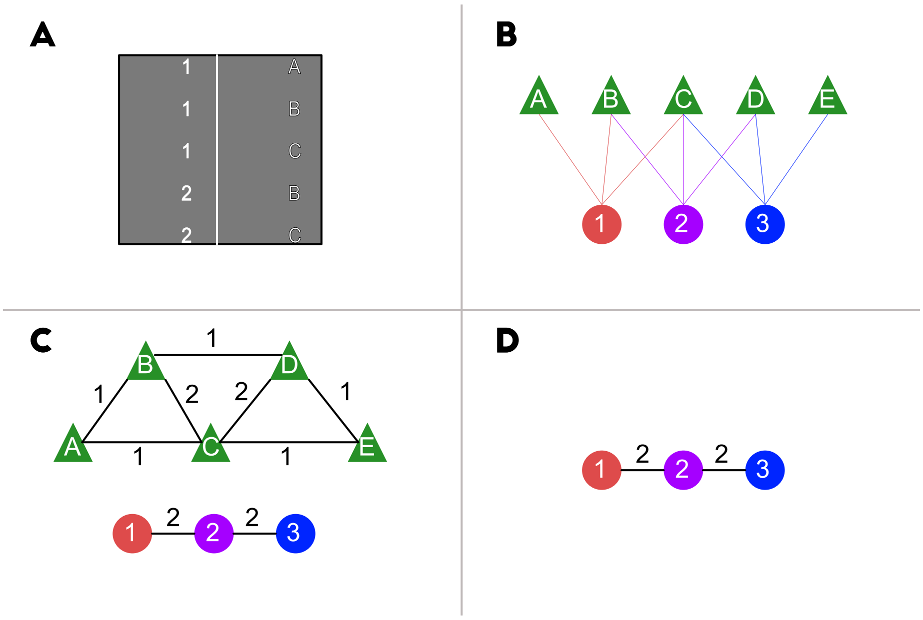

Figure 1: **A.** Data are generated from survey responses. **B.** The survey data are used to create a two-mode network linking respondents to their preferences or beliefs. **C.** The two-mode network is used to create two different one-mode networks. The top network maps the overlap in those who hold any two preferences. The bottom maps the shared preferences between any two respondents. **D.** From the two one-mode networks, I preserve the network of shared preferences between respondents.

jects. These objects may be political beliefs (DellaPosta, 2020) or cultural goods (Hoffman, 2019). In either case, the two-mode networks are converted into single-mode networks for analysis.

Traditionally, these projections have been into networks that map the ties between objects based on them being shared by multiple people. While this does allow for aggregation of features such as the average age or ideology of the people holding a belief or consuming a product, the resulting measures come with their own additional uncertainty.

To avoid this unnecessary uncertainty, I instead take my two-mode networks of people and objects (political concerns and cultural preferences) and convert them into one-mode networks of people. In these new networks, the nodes (people) are connected when they share at least one concern or preference with someone else. The resulting edges then take on a weight equal to the count of shared concerns or preferences, while the nodes are assigned their individual-level demographic features. The network generating process is visualized in Figure 1.

In these networks, the network structure, the set of connections between nodes, reflects shared political concerns and cultural preferences. As such, we may ask whether it depends on the demographic features of the nodes. More simply, this network approach allows me to

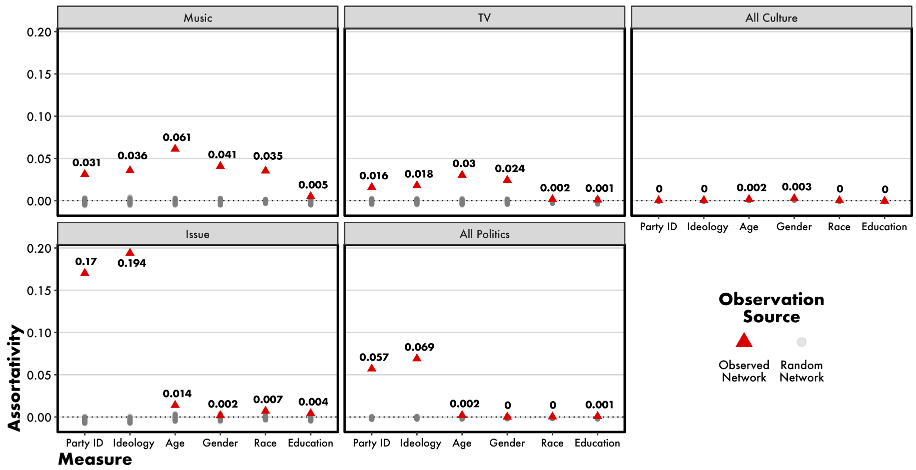

Figure 2: Assortativity by network and measure. Red triangles mark the observed assortativity for each measure in the original networks, while gray circles indicate the assortativity for each measure from a randomly rewired network with the same degree distribution.

ask whether nodes are more likely to share political concerns or cultural preferences with those who are similar to them on a range of demographic features, including political identity, ideology, age, gender, race, and education level. These associations are measured by the network assortativity. Assortativity is a correlation-like statistic ranging between -1 and 1. Higher values indicate that nodes that are more similar on given measure are more likely to share an edge. Lower values indicate that nodes are more likely to be connected to others that are different from them on the given measure. A value close to zero indicates no relationship between the network structure and a given measure.

Results

For the set of networks mapping shared political beliefs and concerns, I constructed two specific networks. I built the first by only using data from the question asking respondents to identify their three most pressing political concerns from a closed list. Pulling from this limited set of data ensured that all ties were based on a single consistent question, which ensured that potentially differing interpretations between concerns and policy beliefs were avoided. In the second network, I included data from the question about pressing issues and three policy opinion questions about taxes, foreign conflict, and a pathway to citizenship for undocumented immigrants.

For the set of networks mapping shared cultural preferences, I built three networks. The first was based only on the data from the question about favorite musical artists. The second was based only on the data from the question about favorite television programs. The third utilized the data generated from all of the cultural preference questions. Again, these distinctions were made to isolate data generated from questions that could have been interpreted differently from the others.

For each network, I calculated the network assortativity based on the partisan identity, ideology, age, gender, race, and education level of each respondent in the networks. Figure 2 presents the statistics for each network based on each category, as well as a distribution of statistics for each network-measure pair that are drawn from random networks with the same degree distribution as the observed network. These observations from the random networks provide essential information about whether the observed values are extreme and go beyond what we would expect from a generating process in which the measures and the preferences were not linked.

We can see in the figure that for the three cultural-preference networks, the assortativity statistic for all five measures is low, although in some cases the statistics from the observed networks are greater than we would expect from the null model. For the music network, assortivity statistics for party identification ($r = 0.031$) and ideology ($r = 0.036$) are comparable to the statistics for age ($r = 0.061$), gender ($r = 0.041$) and race ($r = 0.035$), while the statistic for education is much lower than the other four ($r = 0.005$). In the TV network, the assortativity statistics for party identification ($r = 0.016$) and ideology ($r = 0.018$) are slightly lower than that for age ($r = 0.03$) and gender ($r = 0.024$), but are higher than those for both race ($r = 0.002$) and education ($r = 0.001$). In the network using all of the cultural-preference data, the assortativity statistics for all measures but gender drops close to zero ($r < 0.01$).

By contrast, we can see that in the political-belief networks, the assortativity statistics for party identification and ideology are both much higher than any of those for gender, race, or education. In the network built using only the respondents' three most pressing political concerns, the assortativity statistics for partisan identity ($r = 0.17$) and ideology ($r = 0.19$) reach the two highest marks across all of the observed networks. Notably, these marks, while they indicate only a weak association between the measures and the network structure, are substantively greater than any of the other relationships observed across all of the networks. Additionally, in the issue-concern network, the other four measures produce statistics close to zero, three of which fall in the null model's distribution.

When adding ties based on respondents' political opinions to the issue network, as I do in the full political-beliefs network, the assortativity statistics for partisan identity ($r = 0.057$) and ideology ($r = 0.069$) both drop substantially. However, we see that in this case the other four features all remain effectively zero and within the bands of the observations drawn from random networks. While very weak, the only features that have any association with shared political beliefs are respondents' partisan identity and ideology.

Discussion

In this study, I constructed two sets of networks from survey responses. The first set of networks mapped shared cultural preferences for musical artists, television programs, and a combination of these two, literary genres, film genres, and clothing styles. The second set of networks mapped shared political considerations for specific issue concerns and then a combination of issue concerns and issue positions. For each network, I calculated the assortativity statistic, a measure of the correlation in linked nodes' features, for respondents' party identification, ideology, age, gender, race, and education level. Higher values for these statistics indicate greater levels of homophily, the tendency for like individuals to be connected in the network. By comparing how these statistics vary across networks, I can assess whether some preferences are more associated with political identities than others.

I find that the political networks, particularly the network based on shared issue concerns, show higher levels of political homophily and much lower levels of age-, gender-, race-, or education-based homophily than the cultural-preference networks. In these cultural-preference networks, all of the features besides education-level show very weak associations with shared preferences.

These patterns undermine claims made in the popular press and scholarly research that partisans are deeply divided in their cultural and lifestyle preferences. I show that partisans are not any more likely to share their cultural preferences with fellow in-party respondents than out-party respondents. Furthermore, my results indicate that the very weak associations observed between cultural preferences and political identities are not substantively different from those observed in regards to age, gender, and race. The lack of differentiation suggests that this very weak association is not likely to stand out in everyday experiences.

By contrast, the observed associations between political identities and shared political beliefs are likely to stand out, especially regarding issue concerns. While the observed relationships are still weak, they are substantially stronger than those observed for any other demographic feature. This difference in the magnitudes makes these relationships more likely patterns to be casually observed in everyday life.

However, this study comes with an important set of limitations. First, the networks I built and studied were constructed based on closed-ended survey questions. It is possible that these closed-ended questions did not properly represent the set of musical artists, television programs, political issue concerns, or policy preferences that matter to most Americans. For the cultural-preference questions, list items were chosen based on current popular artists and television programs. Other cultural-preference topics were broader, with lists composed of genre descriptors. Without examples, these descriptors may not have been well understood by respondents. While based on existing question designs used in large surveys, the political-belief questions could also have been hard to understand and interpret for respondents, leading to confusion when answering. Additionally, the issue-concern question did not provide respondents with the ability to indicate their preferred policy, if any, in response to the issue; Democrats and Republicans could easily have said the same issues were concerns because of prominent political debates at the time, but held drastically different opinions about how best to address the issues. While it is unclear how addressing other concerns about the questions used would affect the observed results, in this case it is likely that improving the issue concern question to include information about how to respond to those issues or which party would be better suited to addressing the issue would produce even higher levels of partisan homophily in the issue network, making the observed relationships likely lower-bounds for this empirical network.

Furthermore, generating the data used to build these networks through direct survey questions leaves open the possibility that respondents would bias their responses either through satisficing or motivated responding. In the case of satisficing, respondents may have selected the first items in the randomly ordered lists presented to them or only selected a few very popular artists because they were quickly identifiable without giving proper consideration to their preferences. It is unclear in which direction this type of behavior would bias the resulting network statistics. In the case of motivated responding, respondents may have felt the need to align their answers to these questions with their stated identities earlier in the survey. For example, Republican respondents may have felt the need not to indicate a preference for musical artists that supported Hillary Clinton in the 2016 election, like Beyoncé, even though they actually enjoy their music. Depending on which identities respondents felt motivated to align their responses with, some observed relationships may have appeared greater than they actually are.

Altogether, these limitations likely balance out for the cultural-preference networks and negatively bias the observed relationships between political issue concerns and partisan identity and ideology. Of course, these results should be replicated under other conditions, ideally using trace data or other records of actual behavior paired with surveys. This approach would resolve many of the concerns and limitations involved with relying on closed-ended survey responses.

Even so, this study presents essential first evidence contradicting the view of partisan cultural polarization. By using networks to map shared preferences and individual-level demographic features, we can see that Democrats and Republicans do not hold diverging cultural preferences across various domains, while such divisions do appear, as expected, in regards to political considerations.

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Appendix A - Survey Questions

1. What year were you born?

2. Which of the following best describes your gender?
   - Man
   - Woman
   - Nonbinary
   - Other (please specify)

3. Which of the following best describes your own background in racial and ethnic terms?
   - African American
   - White
   - Hispanic or Latino
   - Asian
   - Native American or American Indian
   - Middle Eastern
   - Other (please specify)

4. Which of the following best describes the highest level of education you have completed?
   - Some high school, but no degree
   - High school degree
   - Some college, but no degree
   - Associate's or Bachelor's degree
   - Some graduate school, but no degree
   - Gradutae degree (e.g. MA, PhD, MD, or JD)
   - Other (please specify)

5. Which of the following best describes your party affiliation?
   - Strong Democrat
   - Democrat
   - Independent, but I lean Democrat
   - Independent
   - Independent, but I lean Republican
   - Republican
   - Strong Republican

6. Which of the following best describes your ideology?
   - Very liberal
   - Liberal
   - Moderate, but I lean liberal
   - Moderate
   - Moderate, but I lean conservative
   - Conservative
   - Very conservative

7. Which are your three favorites among the following musicians?
   - Childish Gambino
   - Kacey Musgraves
   - Dua Lipa

- Lady Gaga
- Willie Nelson
- Ariana Grande
- Silk City
- Justice
- Steve Gadd Band
- Chris Cornell
- High on Fire
- Greta Van Fleet
- Beck
- H.E.R.
- Leon Bridges
- Beyoncé
- JAY-Z
- Kendrick Lamar
- Drake
- Cardi B
- Keith Urban
- John Daversa
- Cécile McLorin Salvant
- The Wayne Shorter Quartet
- Brandi Carlille
- Ludwig Göransson
- John Williams
- None of the above

8. Which style of clothes do you prefer the most?
   - Classically cut and good value for your money
   - Sober and correct
   - Daring and out of the ordinary
   - Comfortable
   - Chic and stylish
   - Other

9. Which are your three favorites among the following types of books?
   - Thrillers
   - Poetry
   - Love stories
   - Political
   - Travel / exploration
   - Philosophical
   - Historic novels
   - Classical authors
   - Scientific
   - Modern authors
   - Fiction
   - None of the above

10. Which are your three favorite types of films?
    - Adventure
    - War

- Musicals
- Westerns
- Comedies
- Thrillers
- Dramas
- Historical
- Documentary
- Superhero
- Fantasy
- Action
- Romances
- Sci-Fi
- None of the above

11. Which three of the following television shows do you like the best?
    - The Umbrella Academy (Netflix)
    - Game of Thrones (HBO)
    - True Detective (HBO)
    - The Walking Dead (AMC)
    - Doom Patrol (DC Universe)
    - Whiskey Cavalier (ABC)
    - Dirty John (Bravo / Netflix)
    - Grey's Anatomy (ABC)
    - Sex Education (Netflix)
    - Shameless (Showtime)
    - Russian Doll (Netflix)
    - The Orville (Fox Broadcasting Company)
    - Brooklyn 99 (NBC)
    - Vikings (History)
    - Black Mirror (Channel 4 / Netflix)
    - The Punisher (Netflix)
    - The Big Bang Theory (CBS)
    - Supernatural (CW)
    - Suits (USA)
    - Star Trek Discovery (CBS)
    - None of the above

12. Which of the following do you think are the three most important problems the United States is facing today?
    - Dissatisfaction with government / poor leadership
    - Immigration / illegal aliens
    - Race relations / racism
    - Unifying the country / divisions in country
    - Healthcare
    - Environmental concerns / pollution / global warming
    - The media
    - Guns / gun control
    - Education
    - Crime / Violence / Justice System
    - Welfare
    - Ethics / Moral / Religious / Family Decline

- Lack of respect for each other
- The economy, in general
- Unemployment
- Distribution of wealth / inequality / poverty
- Federal budget deficit / federal debt / government spending
- Taxes
- Corporate corruption
- Foreign policy, in general
- National security / defense
- Foreign trade, in general
- International issues
- Terrorism / war

13. Which of the following options comes closest to your view on what we should be doing about federal income taxes?
    - Taxes should be cut
    - Taxes should be kept pretty much as they are
    - Taxes should be raised if necessary in order to maintain current federal programs and services
    - Taxes should be raised in order to expand federal programs and services
    - None of the above

14. Do you mainly consider yourself ...
    - A “hawk” who believes military force should be used frequently to promote US policy
    - A “dove” who believes the US should rarely or never use military force
    - None of the above

15. Please indicate whether you favor or oppose the following proposal addressing immigration: provide a path to citizenship for some undocumented immigrants who agree to return to their home country for a period of time and pay substantial fines.
    - Strongly favor
    - Somewhat favor
    - Somewhat oppose
    - Strongly oppose
    - None of the above

Appendix B - Sample Details

The survey sample studied here was collected in three waves of a larger study in Spring and Winter 2019 via Amazon Mechanical Turk.

The mean birth year among respondents was 1982, while the median was 1985. The interquartile range ran from 1976 to 1991.

The sample was relatively balanced in regards to gender. 681 respondents identified as men, 645 as women, 6 as nonbinary, and 1 as Other.

This relative balance was not repeated in regards to race. 939 of the respondents identified as white, 159 as African American, 100 as Asian, 96 as Latino, 28 as Other, 9 as Native American or American Indian, and 2 as Middle Eastern.

Similarly, educational attainment was not well balanced. 910 respondents reported achieving a college degree, while 423 did not.

Political identity was also slightly imbalanced. 158 respondents reported identifying as a Strong Democrat, 334 as Democrats, 167 as Independents that leaned Democrat, 235 as Independents, 126 as Independents that lean Republican, 231 as Republican, and 82 as Strong Republicans.

Ideological identity followed the same pattern. 180 reported being very liberal, 311 as liberal, as moderate, but leaning liberal, 254 as moderate, 131 as moderate leaning conservative, 201 as conservative, and 78 as very conservative.

PARTISAN ANGER ONLINE

BACKGROUND

This analysis is taken from a larger book chapter that is currently undergoing revisions. The book chapter presents an overview of the relationships between emotions, digital media, and affective polarization. There have been many projects examining these features in a variety of contexts related to the effects of partisan digital media on emotions or emotions on partisan digital media consumption. However, few studies have analyzed emotions while using digital media in relation to partisanship and affective polarization. To provide an example for our readers, my coauthor and I applied a framework for conceptualizing of anger in online political discourse to Reddit comments in r/Democrats and r/Republican, two hubs of partisan discourse on the site, from January, 2012 to October, 2019. We found that the group whose party did not hold the White House had much higher shares of their comments referencing the other-party than referencing their own party, an indicator of political anger. This descriptive analysis was buoyed by our finding that posts about the out-party became much more angry and negative in sentiment than those about the in-party for both groups as time went on.

The analysis presented in this excerpt is largely description of trends over time. My coauthor and I do provide a more detailed specification of these patterns via a regression analysis, but our primary concern was about identifying general patterns over time. To this end, I focused on calculating our metric of interest and generating helpful visuals to communicate the patterns over time. Deciding to keep the analysis this simple was helpful because the project required collecting Reddit data from publicly available repositories on Google Big Query and applying text analysis methods in R.

This project has not been published and is currently undergoing the editorial review process.

The following is excerpted from a work-in-progress draft for a chapter in an edited volume.

Anger in Digital Communities

We know that exposure to partisan media and incivil media can lead one to adopt incivility in their own political discourse, but the evidence for this phenomenon mostly comes from lab experiments. There is little description of such incivility beyond a small set of studies on incivility in the comments on news sites (Muddiman and Stroud, 2017; Coe, Kenski, and Rains, 2014). These studies focus on the use of specific features of incivility, such as curse words, name-calling, or instances of lying or spreading misinformation. These features capture violations of classic norms of civil discourse, but do not capture political anger in particular.

To this end, Webster (2020) argues that contemporary politics in the United States is defined by such a strong mutual antipathy between the parties that partisans are incentivized to create and direct anger towards members of the opposite party. To this end, political candidates are rewarded when they insult and attack their opponents. Based on this premise and the conclusion that the overwhelming majority of references to one's political opponent are intended to generate anger (Rhodes and Vayo, 2018), Webster shows that both Hillary Clinton and Donald Trump devoted a substantial number of their tweets during the 2016 campaign to generating anger towards the other. Using the same set of assumptions, Webster also demonstrates that the same patterns occur across partisan media outlets, with Fox News and MSNBC both frequently direct their audience's attention to issues involving the opposite party, with the likely hope of making them angry at the opposition.

Is the same true for members of the mass public discussing politics online? Webster's analysis falls short of answering the question. Yet, it is plausible, given the observed patterns in lab settings of incivility moving from media discourse to consumers' discourse, that non-elite members of each party will adopt similar practices of directing attention towards members of the out-party in the hopes of generating anger and validating their position in their group. To assess whether this is a credible theory and to begin to fill this gap in the literature, we provide a descriptive analysis of the messages sent in Democrat and Republican Reddit communities from January, 2012 through October, 2019.

Reddit offers a unique opportunity to generate descriptive accounts of the mass public's political discourse by enabling partisans to create their own topically distinct discussion communities. For this analysis, we collected all of the comments posted in the subreddits r/Republican and r/Democrats from January, 2012 through October, 2019. We then isolated the comments containing references to the out-party and in-party for each group. To identify references to Democrats, we selected posts containing the keywords "D/democrat/s", "L/liberal/s", "O/obama", "C/clinton", "P/pelosi", and "the L/left". To identify reference to Republicans, we selected posts containing the keywords "R/republican/s", "C/conservative/s", "T/trump", "McConnell/mcconnell", "R/ryan", and "the R/right".

Following Webster's analysis of partisan media outlets, the key metric of our analysis is the ratio of the number of references to the out-party to the number of references to the in-party made by each subreddit each month, as this gives us a better sense of the balance in discussing the in- and out-parties. As such, we calculated this ratio for every month in our time window. A higher value in this metric indicates that the group had more references to the out-party than the in-party.

We see in Figure 1 that prior to 2016, members of r/Republican talked about Democrats 15% more than they talked about republicans (x = 1.15). The members of r/Democrats, though, discussed Republicans about 25% less than they talked about Democrats (x = 0.80).

This asymmetry reverses, though, following Donald Trump's entrance into the Republican primary in June, 2015. At this point, the members of r/Republican begin to discuss Republicans much more than they do Democrats (x = 0.70). The members of r/Democrats also began to discuss their own party more during the primary season, from about March, 2015 (when Hillary Clinton announced her candidacy) through May, 2016 (x = 0.655). May, 2016 marked the point at which Trump became the presumptive nominee for the Republican Party. Since this point in time, the members of r/Democrats have begun discussing Republicans much more than they do Democrats (x = 1.22), with the ratio of out-group references to in-group references increasing rapidly up to the 2016 election and then more gradually, but still steadily, since. By comparison, the members of r/Republican have shown no substantial change during this time in their preference to discuss their fellow Republicans (x = 0.45).

[Figure 1About Here]

These results present us with the interesting conclusions that anger, measured as we have done so following Webster (2020), changes over time, likely in response to changing political conditions offline. While Barack Obama was the central political figure in the United States, Republicans exhibited more anger than Democrats in their intra-group discussion. However, the emergence of Donald Trump as a viable candidate for the presidency marks the point when Democrats began to display higher levels of anger and Republicans lower levels of anger. This descriptive account suggests that non-elite partisans may adopt the same anger-based political discourse of elites and the media when their political fortunes decline.

But do non-elites talking about the other side translate into negative emotions, especially anger? To answer this question, we conducted a dictionary-based sentiment analysis of the comments we had collected. Using the NRC Word-Emotion Association Lexicon (Mohammad & Turney, 2013), we calculated two metrics: the percentage of a post comprised of angry words and the overall sentiment of the post, calculated by taking the difference in the share of positive and negative words. This linguistic dictionary, which classifies a large list of words as being indicative of certain emotions, was built by asking coders to report whether a given word is associated with a specific valence, positive or negative, and emotions, such as anger, fear, or joy. Each word was reviewed by five different coders. In just over 90% of cases, at least four out of five coders agreed on a word's coding. If references to out-party members are angrier, we should see that comments referencing out-party members use more angry words than comments referencing in-party members. Additionally, if our assumptions about how references to the in- and out-party are reflective of certain emotional states, we should also expect to see that comments about the out-party are more negative than comments about the in-party.

We see in Figure 2 that, over time, both groups of partisan commenters have become more angry (top row) and more negative (bottom row) in their discussions of the out-party compared to their discussion of the in-party. It appears that both trends also begin to appear during the 2016 presidential campaign, with more rapid changes since the election itself in November, 2016.

[Figure 2 About Here]

A regression analysis confirms these intuitive conclusions from the figure. Models show that comments about the out-party have always been angrier than those about the in-party and that this difference has been growing with time. We arrived at these results by fitting standard linear regression models estimating a post's level of anger and its sentiment based on the subject of the post (was it about the in-party or the out-party), whether the post came after the 2016 election, and a count of how many days till or since the 2016 election. To assess whether these associations varied with time, we also included interactions between the continuous measure of time and the indicator of being post-2016-election, the subreddit and subject group, and the three-way interaction between subreddit, subject group, and the continuous measure of time to or from the 2016 election.

These models showed that holding all else constant, including the time period and the subreddit, posts about the out-party were angrier and more negative than posts about the in-party. Similarly, holding all else constant, posts in r/Republican were angrier and more negative than those in r/Democrats. Even so, time moderates these relationships. For example, the differences in anger and sentiment between posts about the out-party and the in-party have grown over time. The same is true of the difference in anger between posts on r/Republican and r/Democrats, while that is not the case in regard to their overall sentiment. Crucially, though, our models show that across both subreddits and posts referencing both parties, anger and negative sentiment have increased at a greater rate following the 2016 election than before it.

These results lead us to conclude that non-elite partisans replicate the same emotional patterns as partisan elites and the partisan media when discussing politics online. Posts and comments referencing the other side are angrier and more negative than those referencing their political allies. This replication is concerning because it suggests that opportunities for cross-cutting civil discourse (e.g. Mutz, 2006) are not as vast as early visions for the Internet idealized. At the same time, given that the political self-expression is reinforcing in regard to partisan cognition and political attitudes (Cho et. al., 2018), we must now be concerned that these online discussions may be reinforcing the links between the out-party and anger and negativity. The more deeply entrenched these links become, the more readily partisans will abandon long-standing norms around political civility and democracy, such as respecting the outcomes of elections and opposing violence towards the opposition (Kalmoe and Mason, 2019).

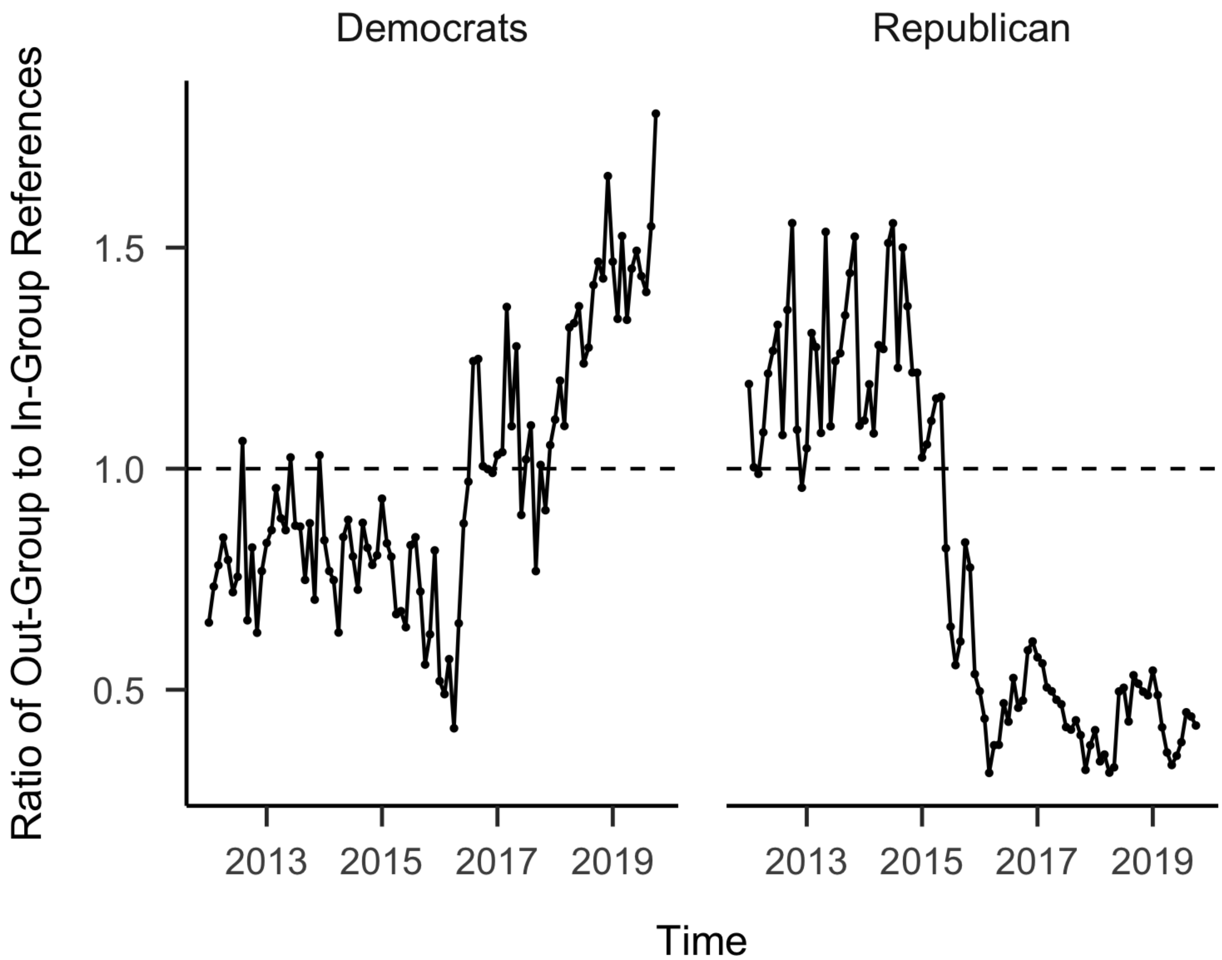

Figure 1:. Ratio of out-group to in-group references in comments over time for r/Democrats and r/Republican.

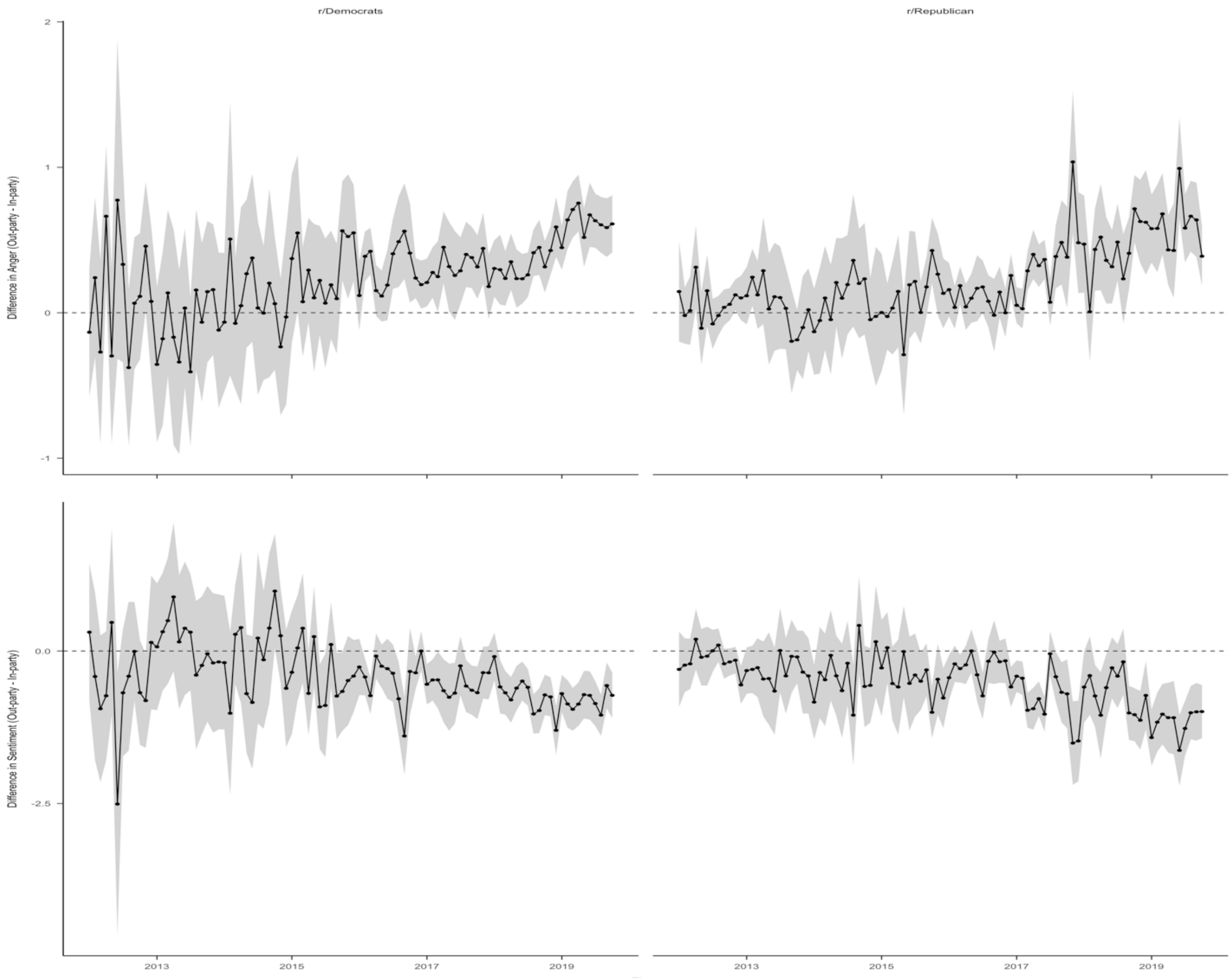

Figure 2: Trends in the difference in average anger (top row) and sentiment (bottom row) between posts about the out- and in-party collected from r/Democrats and r/Republicans from January, 2012 through October, 2019. Shaded area denotes the 95% confidence interval for the difference between the two averages each month.

Table 1: *Models regressing comment anger and sentiment scores on subreddit, subject, and time to/from the 2016 election.*

	Anger				Sentiment			
Predictor	b	CI	t	p	b	CI	t	p
Intercept	1.66	[1.61, 1.71]	67.09	0.00	0.96	[1.61, 1.11]	12.87	0.00
Subreddit (r/Republican)	-0.07	[-0.12, -0.02]	-2.67	0.01	0.17	[-0.12, 0.25]	3.99	0.00
Days To/From 2016 Election	-0.14	[-0.2, -0.07]	-4.08	0.00	0.25	[-0.2, 0.39]	3.50	0.00
Subject (Out-Party)	0.28	[0.22, 0.34]	8.86	0.00	-0.46	[0.22, -0.34]	-7.78	0.00
Post-2016-Election	-0.13	[-0.21, -0.05]	-3.08	0.00	0.04	[-0.21, 0.23]	0.43	0.67
Subject (Out-Party) : Post-2016-Election	0.03	[-0.07, 0.14]	0.62	0.53	-0.08	[-0.07, 0.12]	-0.79	0.43
Subreddit (r/Republican) : Subject (Out-Party)	-0.03	[-0.09, 0.02]	-1.29	0.20	-0.09	[-0.09, 0.01]	-1.86	0.06
Subject (Out-Party) : Days To/From 2016 Election	0.15	[0.08, 0.22]	4.17	0.00	-0.21	[0.08, -0.09]	-3.37	0.00
Subreddit (r/Republican) : Days To/From 2016 Election	0.07	[0.02, 0.12]	2.82	0.00	0.06	[0.02, 0.14]	1.51	0.13
Days To/From 2016 Election : Post-2016-Election	0.19	[0.11, 0.28]	4.57	0.00	-0.54	[0.11, -0.38]	-6.57	0.00
Subreddit (r/Republican) : Subject (Out-Party) : Days To/From 2016 Election	0.00	[-0.05, 0.05]	-0.18	0.86	-0.02	[-0.05, 0.07]	-0.46	0.64