Local News and National Politics

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Abstract

The level of journalistic resources dedicated to coverage of local politics is in a long term decline in the US news media, with readership shifting to national outlets. We investigate whether this trend is demand- or supply-driven, exploiting a recent wave of local television station acquisitions by a conglomerate owner. Using extensive data on local news programming and ratings, we find that the ownership change led to 1) substantial increases in coverage of national politics at the expense of local politics, 2) a significant rightward shift in the ideological slant of coverage and 3) a small decrease in viewership, all relative to the changes at other news programs airing in the same media markets. These results suggest a substantial supply-side role in the trends toward nationalization and polarization of politics news, with negative implications for accountability of local elected officials and mass polarization.

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Local newspapers are in decline in the US, with falling readership and decreasing levels of newsroom personnel (Hayes and Lawless, 2017; Peterson, 2017; Pew Research Center, 2016). Given the importance of news coverage in driving citizen engagement in politics and in allowing citizens to hold their elected officials accountable (Snyder and Strömberg, 2010; Hayes and Lawless, 2015; Shaker, 2014), this trend is worrisome. Economic changes in the production of news and greater national competition in the news market could potentially be imposing negative externalities on the quality of local political information available to citizens and consequently on the performance of local governments.

On the other hand, it is also possible that declines in local coverage are primarily demand- rather than supply-driven. In an age of increasing nationalization of elections (Hopkins, 2018; Abramowitz and Webster, 2016; Jacobson, 2015), dedicated coverage of local politics may no longer be as valuable to citizens as it once was. The more closely do local elected officials' positions align with those of their national party, the more does information about national party leaders suffice for most readers' purposes and the less incremental value is there in coverage of local figures. The long-term decline in local coverage may thus simply reflect adaptation by the news industry as a whole to changes in audience tastes for political information.

Changes in news distribution technologies may be accelerating the influence of such demand-side shifts. The modern news environment, characterized by a proliferation of choices available to news consumers through broadband internet and cable television (Arceneaux and Johnson, 2013; Hindman, 2009), plausibly expands the role of consumer demand in determining news content relative to the late-20th century period of dominance by print newspapers and broadcast TV. Whereas a 1970s news reader unhappy with her city paper's local focus and seeking more national coverage would have had limited and relatively high-cost alternatives, today's news reader can easily access a wide variety of national sources for low or no cost.

This greater opportunity for news consumers to choose their favored sources that modern news media affords has led to a second kind of concern: that proliferation of media choice will lead to increased ideological or partisan polarization of content (Prior, 2007; Lelkes et al., 2017). Evidence from cable news shows that the cable news channels' content has in fact polarized over the past decade and a half (Martin and Yurukoglu, 2017). The emergence of highly partisan misinformation or "fake news" on social media in the 2016 presidential election (Guess et al., 2018; Allcott and Gentzkow, 2017) demonstrates that a more extreme version of the same phenomenon is present in online news as well.

In this paper, we present evidence on the underlying cause of these trends towards the nationalization and polarization of politics coverage, using an extensive data set of local television news broadcasts. Local TV news has large audiences, with ratings on the order of 25 million viewers per night in the aggregate (Pew Research Center, 2017). This aggregate viewership is roughly an order of magnitude larger than the audience of cable news.[1] We analyze the content and viewership of 743 local news stations over the latter two-thirds of 2017, a period which saw the acquisition of a set of local television stations by a large conglomerate owner, the Sinclair Media Group.

We measure news program content using a topic model fit to more than 7.4 million transcript segments from this period. Using a differences-in-differences design that compares the Sinclair-acquired stations to other stations operating in the same markets, we find that the acquisition led to a roughly three percentage point increase in the share of programming devoted to coverage of national politics, a roughly 25% increase relative to the average level in the sample. Furthermore, this increase came largely at the expense of coverage of local politics. We also find that text-based measures of ideological slant (Gentzkow and Shapiro, 2010; Martin and Yurukoglu, 2017) shifted to the right at Sinclair-acquired stations following the acquisition, relative to other stations in the same market.[2] The magnitude of the ideological shift induced following the Sinclair acquisition is equivalent to approximately

[1] And given the documented ability of information from TV sources to spread through viewers' social networks (Druckman et al., 2017), the effective reach is even larger.

[2] Sinclair's conservative slant has received attention in recent popular media (e.g., Levitz, 2017).

one standard deviation of the cross-station ideological distribution.

Using the same differences-in-differences design, we also measure the change in viewership attributable to the change in ownership. Consistent with a supply-driven story, the diff-in-diff estimate of ratings changes at the Sinclair-acquired stations is negative. In ratings terms, the shift towards national politics was costly to these stations: viewers appear to prefer the more local-heavy mix of coverage to the more national-heavy one. Nonetheless, there are very clear economies of scale for a conglomerate owner in covering national as opposed to local politics, thanks to the ability to distribute the same content in multiple markets.[3] Given that the ratings penalty we document is fairly small, it seems likely that these cost efficiencies dominate in Sinclair's calculus.

These results are a flip side of the coin to George and Waldfogel's (2006) finding that the entry of a national competitor (the New York Times) into local newspaper markets led local incumbent papers to focus more on their comparative advantage in local coverage, and Gentzkow et al.'s (2014) finding that greater newspaper competition is associated with greater ideological diversity. Acquisition of existing local outlets by a national conglomerate produces the opposite impact on coverage relative to entry by a new, separately owned national outlet. A conglomerate owner can reduce production costs, perhaps dramatically, by substituting nationally-focused and ideologically unified content produced in a single studio for locally-focused and ideologically diverse content produced by many local journalists. Even if viewers would prefer locally-tailored politics content, the fact that politics coverage is bundled with other kinds of content - crime reporting, weather, sports, and so on - that are less affected by consolidation mutes the demand response.

Taken together, our results contribute to a growing literature showing that supply-side forces in the market for news have real consequences both for the political content of news and on downstream election outcomes (Archer and Clinton, 2017; Durante and Knight, 2012). Media consolidation can produce cost efficiencies in the production of news, but these effi-

[3] Sinclair also received media attention for its policy of distributing nationally produced, "must-run" segments to every station in its portfolio (Gold, 2017).

ciencies are not neutral with respect to the content of news coverage. Consolidation changes the incentives of news providers, shifting coverage towards topics that can be distributed in multiple markets rather than those - such as local politics - that are market-specific. These content changes influence viewers' available information about local elections and elected officials, along with the ideological slant of news to which they are exposed. As existing research (DellaVigna and Kaplan, 2007; Snyder and Strömberg, 2010) has shown, both dimensions of content are consequential for the accountability and preference aggregation functions of elections.

Data and Institutional Background

This paper exploits recent changes in ownership of broadcast television networks as a driver of variation in the content covered by the stations that changed ownership. Specifically, we compare stations acquired by the Sinclair Broadcast Group to other stations within the same Designated Market Area (DMA). Sinclair is of particular interest for two reasons. First, anecdotal evidence suggests the company's political orientation leans strongly to the right, with politics coverage frequently compared to that of the Fox News Channel (Farhi, 2017). This right-leaning coverage is delivered across all Sinclair stations through "must-run" segments which have clearly identifiable partisan messaging. Many recent "must-run" segments feature Boris Epshteyn, a former Trump White House official.[4] Reporting also suggests Sinclair mandates that some of its larger stations produce their own partisan content, which has resulted in the resignation of experienced local news anchors (Farhi, 2014). In addition to the change in ideological slant relative to the pre-existing local coverage, a likely result of these mandated coverage changes is the replacement of some local coverage with coverage of national political issues.

Second, Sinclair is in the midst of acquiring a substantial number of new stations across

[4]For instance, regarding former FBI Director James Comey's testimoney, Epshteyn said, "Contrary to widespread expectations, we actually learned much more about the president's opponents and his critics from Comey's testimony that about any issue involving the president himself." (Gold, 2017)

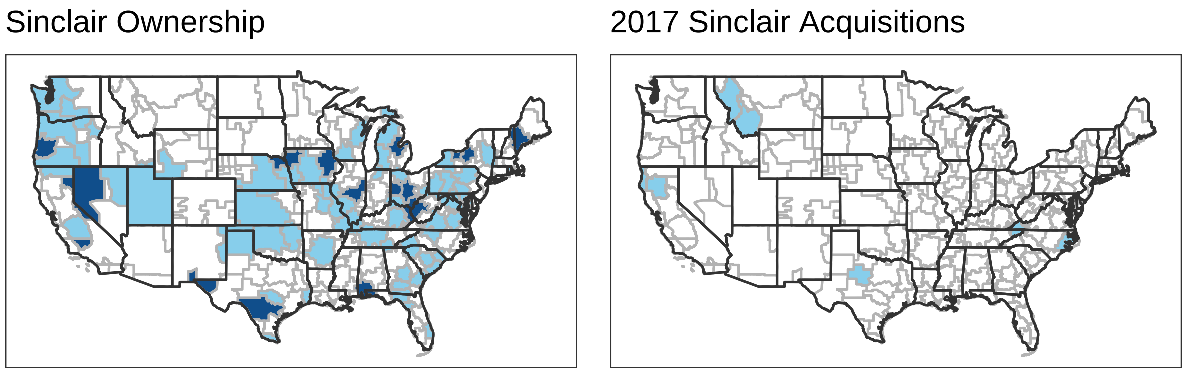


Figure 1: Map of Sinclair Ownership by DMA

The plot on the left shows DMAs pre-2017 in which Sinclair owns 1 (light color) or 2 (dark color) stations. The plot on the right shows DMAs in which Sinclair acquired a station in 2017. The light grey borders outline distinct DMAs.

the country. In the middle of the time period covered by our data (June-December 2017), Sinclair purchased the Bonten Media Group's stations. This purchase, completed on September 1, 2017, added 14 new stations to Sinclair's portfolio in 10 markets, though not all stations broadcast local news - 10 of these stations in 7 markets have their own news broadcast. Sinclair currently owns 193 stations in 89 DMAs (see Figure 1 for geographic coverage). If a planned purchase of Tribune Media is completed, Sinclair's portfolio will grow to 233 stations in over 100 DMAs, meaning a Sinclair-owned station will be viewable in 72% of American households.

Broadcast Transcripts and Ratings Data

To measure the effect of a change in ownership on the content of local news broadcasts, we collect data on 743 stations in every DMA throughout the country. Our analyses employ

Table 1: Station Summary Statistics

	Overall			Sinclair Only		
	Total	Mean	S.D.	Total	Mean	S.D.
Unique Stations	743	-	-	99	-	-
Total DMAs	210	-	-	72	-	-
Distinct Shows	6,710	9.7	15.7	665	7.9	4.3
Timeblocks	5,771	7.8	2.3	601	7.2	2.7

Timeblocks refers to 30 minute periods. Shows are differentiated by the title of the program broadcast during a 30 minute timeblock.

transcript and ratings data which come from the data vendor TVEyes and cover June-December 2017. We collect the viewership data and full transcripts from every weekday news broadcast in each station throughout this time period.[5] The resulting dataset has 7.41 million 2.5 minute segments which we then process and run against an LDA topic model, producing 15 distinct topics.[6] Finally, we collected a variety of demographic data from the US census aggregated to the DMA level and matched to each station based on the DMA that contains the station. Summary statistics are displayed in Table 1 below.

Figure A3 in the Appendix displays aggregate trends in the fifteen topics uncovered by the topic model over the time period of the data. Local and national politics have both remained relatively stable, with the latter seeing a slight decrease on average. The largest change in relative coverage of a topic is due to the strong hurricane season that affected the United States around September 2017; the "disasters" topic, which contains words like "hurricane," "Irma," and "Harvey," saw a spike around this time and then declined as hurricane season ended.

Our analysis focuses on the topics clearly associated with coverage of politics. Figure A1 in Appendix B shows word clouds of the most indicative words for each of these topics, as well as the "weather" and "crime" topics for comparison purposes. There are five total topics

[5] Our process for identifying local news broadcasts and filtering out national network news and other non-news programming is described in detail in Appendix A.

[6] The process used to fit the topic model and choose the number of topics is described in detail in Appendix B. We use 2.5 minute segments because that is how they are separated in the raw TVEyes data.

which we identify as politics-related: three national politics topics (one which focuses on domestic policy, one focused on foreign policy, and one we label "Trump scandals") and two local politics topics (one focused on schools and education and the other on local government, particularly local infrastructure projects). We group the three national and two local topics together for purposes of the analysis.

Figure 2(b) depicts the trends in the composite local and national politics topics, disaggregated by station ownership. This figure shows clear parallel trends in how Sinclair and non-Sinclair stations split their coverage in national versus local politics, with Sinclair-owned stations consistently spending more time on average on national politics at the expense of local politics. Figure 3 displays the trends in local and national politics and slant, disaggregated by ownership, only among the stations in DMAs in which Sinclair acquired a station. These provide further evidence for parallel trends in coverage up to the acquisition of a station by Sinclair, when they begin to diverge.

For segments that discuss the national politics topics, we construct a text-based measure of left-right slant based on the method used in Martin and Yurukoglu (2017), which is itself an extension of the method of Gentzkow and Shapiro (2010). The approach is described in detail in Appendix C, but the basic idea is to compare language use in news outlets to language use by members of congress in the Congressional Record (CR). The method produces an estimated ideology for every segment that is a function of its frequency of use of phrases that are indicative of partisanship in the CR. Because these phrases are fairly uncommon on local news and the resulting estimates can be noisy, we 1) limit to segments that have at least 50% estimated weight on the national politics topics from the topic model, and 2) aggregate to the level of station-day.

Figure 4 shows the density of the resulting slant estimates across stations. There is some dispersion across stations in the measure, with standard deviation equal to about .02.[7]

[7] The slant measure is on the DW-NOMINATE scale, which ranges from -1 to 1. Like Martin and Yurukoglu's (2017) analysis of cable news transcripts, we find the distribution across media outlets to be compressed relative to the underlying distribution of DW-NOMINATE scores. This is a result of the fact that partisan-indicative phrases make up only a small portion of total phrase usage in the transcripts. Martin

Sinclair's portfolio of stations is, unsurprisingly given the anecdotal reports, shifted to the right relative to non-Sinclair stations; the mean difference is about .012.

We also examine viewership (ratings) before and after the acquisition in Sinclair-acquired and non-Sinclair-acquired stations. Ratings come from Nielsen Media Research and are estimates based on Nielsen's panel of households.[8] Figure 2(a) demonstrates that Sinclair and non-Sinclair stations have parallel trends in viewership, with Sinclair stations having on average somewhat lower viewership numbers.[9]

Finally, Table 2 shows the results from regressions of DMA-level demographic characteristics on Sinclair ownership (both pre- and post-2017). The general pattern is that Sinclair's portfolio of stations skews towards smaller, more racially homogeneous localities with lower average incomes.[10] Interestingly, Sinclair's stations are not located in markets with higher Republican vote share in the 2016 election. In the Appendix, we show the correlations of the DMAs in which Sinclair acquires stations with a variety of other demographic variables.

Table 2: Regressions of DMA characteristics on Sinclair ownership, pre-2017 stations.

	R Vote %	Pop (MM)	White %	% College	% Income >= 100K	% Age >= 60
	(1)	(2)	(3)	(4)	(5)	(6)
Sinclair Pre-2017 Station	−0.006	−0.612**	0.028**	−0.004	−0.010*	0.002
	(0.013)	(0.283)	(0.012)	(0.010)	(0.006)	(0.004)
Sinclair 2017 Acquisition	0.035	−1.404***	0.053	−0.040	−0.053***	0.018**
	(0.059)	(0.282)	(0.041)	(0.026)	(0.009)	(0.009)
Constant	0.535***	1.704***	0.788***	0.354***	0.195***	0.210***
	(0.009)	(0.276)	(0.009)	(0.007)	(0.005)	(0.002)
N	694	700	700	700	700	700
R^2	0.002	0.008	0.008	0.003	0.015	0.005

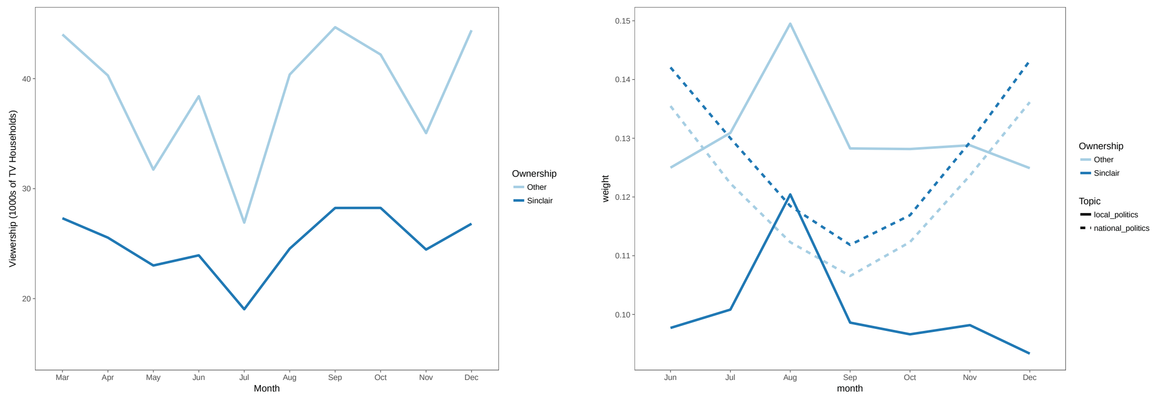
$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

and Yurukoglu (2017) estimate a scale factor for viewer perception of the channels' slant that is significantly greater than one, indicating that viewers perceive differences in slant across outlets to be larger than that indicated by the raw slant score differences.

[8]Larger markets use automated collection of viewership data using Nielsen's "Local People Meter" technology; the smallest markets still use manual diary-based collection.

[9]This difference is mostly accounted for by the fact that many of Sinclair's existing stations are in smaller markets, as can be seen in Figure 1.

[10]This pattern will change substantially if the Tribune purchase is approved.



(a) Viewership (b) Topic Weights

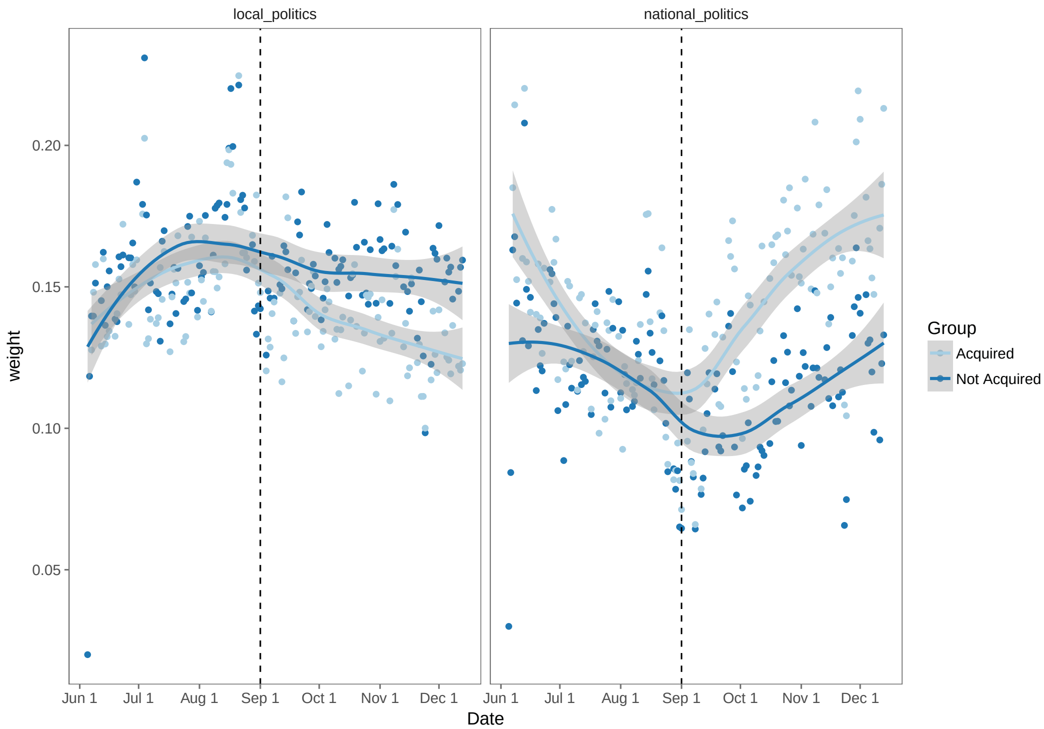
Figure 2: Trends in local news ratings (left panel) and topic weights (right panel) around the time of Sinclair's acquitision of Bonten in September 2017. Lines are monthly averages among all Sinclair-owned stations (darker lines) and all non-Sinclair-owned stations (lighter lines).

Estimating the Influence of Station Ownership

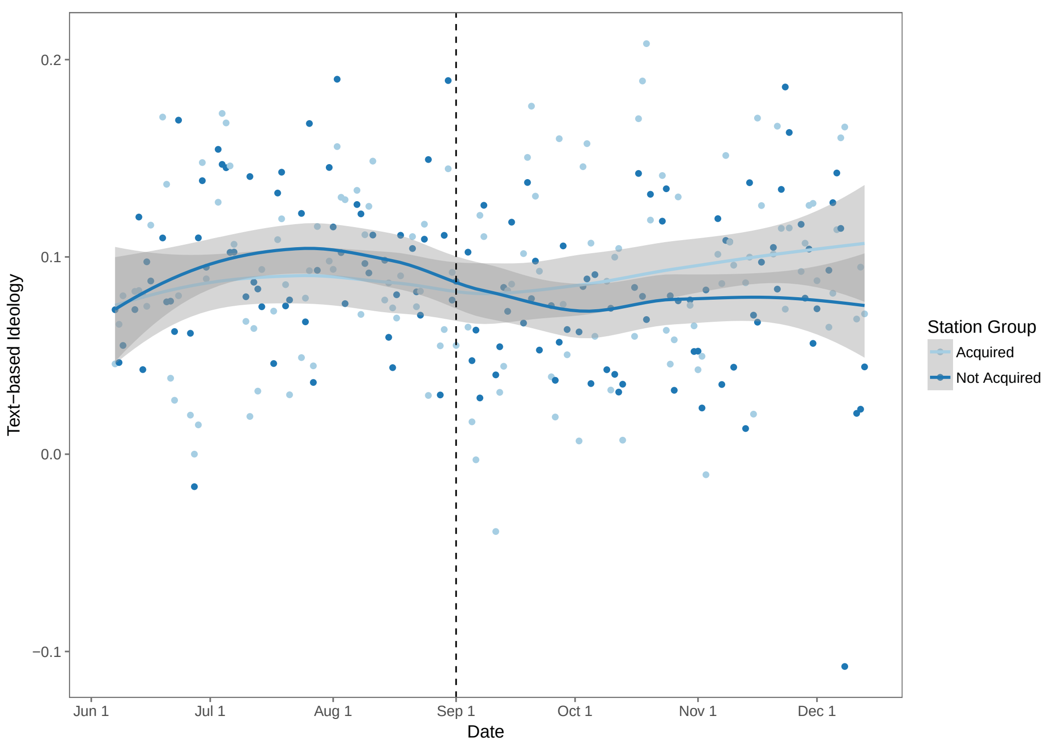
To estimate the influence of station ownership on content and viewership we run both cross-sectional and difference-in-differences regressions employing a station's pre-2017 ownership status by Sinclair as the independent variable in the former and 2017 Sinclair acquisition as the treatment in the latter. In Tables 3 through 6 we present five model specifications for each dependent variable. The level of observation for each model is an individual 2.5 minute transcript segment; we cluster standard errors by station to match the level at which the treatment variable (Sinclair ownership) varies. All models include time slot[11] and day-of-week dummy variables, so we estimate the effect of Sinclair ownership in all models within individual show times and days. Local news content and ratings vary systematically by time of day and day of week; for example, traffic reports are much more prevalent in early-morning time slots than in the evening news slot. The inclusion of a complete set of dummy variables for time and day ensures that our estimates of the treatment effect are not biased by a differing mix of air times or days at Sinclair- versus non-Sinclair-owned stations.

The first and second models in each table are cross-sectional regressions run on the entire

[11] A time slot here is the 30 minute block in which the segment aired, e.g. 5:30AM, 6:00AM, etc.



(a) Local and National Pre-trends



(b) Slant Pre-trends

Figure 3: Trends in local and national politics coverage and ideological slant in markets affected by a new Sinclair acquisition (i.e., only including stations in a DMA where Sinclair acquired a station in 2017). Lines are a locally weighted regression smoother. Darker lines / dots indicate stations acquired by Sinclair; lighter lines / dots indicate other stations in the same markets that were not acquired. The date of acquisition is noted by the vertical dashed line.

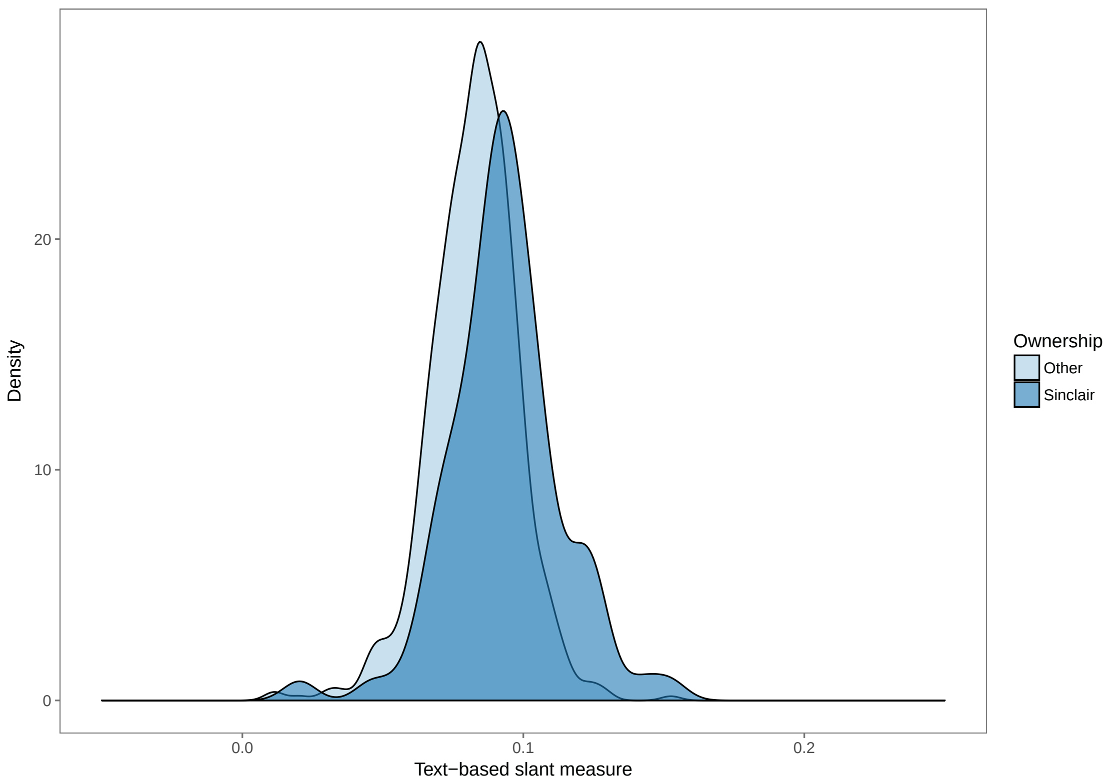


Figure 4: The density of estimated text-based slant, aggregated to the station level. The lighter-shaded density is non-Sinclair stations; the darker-shaded density is Sinclair-owned stations.

dataset. The first column is a pooled regression including only the time/day dummies, while the second column introduces DMA-level fixed effects. The DMA fixed effects hold constant all time invariant market characteristics - observables like age, income and education levels, as well as unobservables like tastes for news content. Hence, their inclusion eliminates differences in content between Sinclair and non-Sinclair owned stations attributable to differences in characteristics of viewers in markets in which Sinclair operates compared to characteristics of viewers in markets in which it does not operate. Hence, the DMA fixed effects partially eliminate demand-driven sources of variation in news content.

However, DMA fixed effects do not rule out the possibility that Sinclair operates or acquires those stations within a given market that already attract a relatively more conservative, or more national-news focused audience. In models 3-5 in each table we implement a difference-in-differences (DiD) design on a subset of the data limited to those DMAs in which Sinclair acquired a station in September 2017 (see Table 1 for descriptive statistics on stations acquired by Sinclair, and Figure 1 for a map of the location of these markets). In these models, we include an interaction of an indicator for being acquired by Sinclair in 2017 with a dummy variable indicating whether the observation is after September 2017, as well as main effects for both dummies. In other words, we now analyze the change in content for individual stations before and after the acquisition by Sinclair relative to other stations and programs operating in the same media market. The coefficient on the interaction term is the differential effect of Sinclair ownership on the change in a station's content from pre- to post-September 2017.

The DiD approach eliminates confounding by fixed unobservables specific to the stations acquired by Sinclair, as well as common seasonal trends in news coverage from the pre-acquisition (summer) to post-acquisition (fall) periods.[12] The first of the DiD specifications includes no additional fixed effects beyond the time slot and day-of-week dummy variables.

[12]As previously noted, and as depicted in Figure 2(b), there is strong evidence for the parallel trends assumption holding in this setting: stations display the same trends in topic coverage except for change in station ownership.

In the second, we include DMA fixed effects, estimating the effect of Sinclair ownership within DMA. In the final specification (with the exception of Table 5, for reasons previously discussed), we include DMA by show fixed effects, estimating the effect of ownership within a given show within a DMA. The inclusion of the DMA by show fixed effect holds audience attributes constant at an even more fine-grained level than DMA fixed effects alone. It rules out possible confounding by, for instance, the set of anchors or reporters on Sinclair-owned or -acquired stations being more appealing to certain types of viewers, e.g. those with greater taste for national politics news. If we find an effect in the DiD here, it cannot be simply because Sinclair-acquired stations were already set up to appeal to a relatively nationally-focused or relatively conservative segment of the local news audience.

Content choices Across all specifications we find strong evidence in both statistical and substantive terms that Sinclair ownership affects the content of the stations they operate. In Table 3, we find in the cross-section that coverage at stations owned by Sinclair prior to 2017 places, on average, just under 4 percentage points less weight on local politics than at non-Sinclair stations in the same DMA. Given that the average local politics weight in the sample is about 12.6 percentage points, this is a substantively large reduction. In the DiD specifications, we find that when a station is acquired by Sinclair its weight on local politics coverage drops by around 1.5 percentage points, relative to the change in other stations operating in the set of DMAs in which Sinclair acquired a station. The coefficients on the topic weights can be thought of as the proportion of time spent on a specific topic, so a reduction of 4 percentage points in this context can be interpreted as 4 percent less coverage of local politics.[13]

In Table 4 we find the reverse effects for the national politics topic. Cross-sectionally, Sinclair stations allocate about 1 percentage point more weight to national politics on average.

[13] Appendix B includes descriptive statistics of both the national and local topic weights disaggregated by station ownership. For Sinclair stations, the mean and standard deviation for national topic weights is 0.123 and 0.203, respectively, and 0.119 and 0.199 for non-Sinclair stations. For local topic weights the same statistics are 0.099 and 0.151 for Sinclair and 0.129 and 0.178 for other stations.

Table 3: Cross-sectional and diff-in-diff regressions of local politics topics weight on Sinclair ownership.

	Weight on Local Politics Topics				
	(1)	(2)	(3)	(4)	(5)
Sinclair Pre-2017 Station	-0.029^{***}	-0.037^{***}			
	(0.004)	(0.004)			
Sinclair 2017 Acquisition			-0.008	-0.010	
			(0.031)	(0.009)	
Post September 2017			-0.006	-0.007	-0.006
			(0.004)	(0.004)	(0.004)
Sinclair 2017 x Post September			-0.014^{**}	-0.013^{*}	-0.014^{**}
			(0.006)	(0.007)	(0.007)
Time Slot Dummies:	Y	Y	Y	Y	Y
Day-of-Week Dummies:	Y	Y	Y	Y	Y
Fixed Effects:	None	DMA	None	DMA	DMA x Show
N	7,182,509	7,090,507	188,806	188,806	188,806
R^2	0.009	0.062	0.015	0.067	0.083

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

Standard errors (clustered by station) in parentheses. An observation is a segment. Columns 1-2 use the full sample of markets and stations. Columns 3-5 restrict to markets in which Sinclair acquired at least one station in 2017.

Table 4: Cross-sectional and diff-in-diff regressions of national politics topics weight on Sinclair ownership.

	Weight on National Politics Topics				
	(1)	(2)	(3)	(4)	(5)
Sinclair Pre-2017 Station	0.009^{***}	0.011^{***}			
	(0.003)	(0.003)			
Sinclair 2017 Acquisition			0.028^{***}	0.017	
			(0.010)	(0.012)	
Post September 2017			-0.013^{***}	-0.014^{***}	-0.012^{***}
			(0.002)	(0.002)	(0.003)
Sinclair 2017 x Post September			0.030^{***}	0.031^{***}	0.029^{***}
			(0.005)	(0.005)	(0.006)
Time Slot Dummies:	Y	Y	Y	Y	Y
Day-of-Week Dummies:	Y	Y	Y	Y	Y
Fixed Effects:	None	DMA	None	DMA	DMA x Show
N	7,182,509	7,090,507	188,806	188,806	188,806
R^2	0.006	0.016	0.020	0.027	0.040

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

Standard errors (clustered by station) in parentheses. An observation is a segment. Columns 1-2 use the full sample of markets and stations. Columns 3-5 restrict to markets in which Sinclair acquired at least one station in 2017.

Table 5: Cross-sectional and diff-in-diff regressions of estimated text-based slant on Sinclair ownership.

	Estimated Slant (DW-NOMINATE scale)			
	(1)	(2)	(3)	(4)
Sinclair Pre-2017 Station	0.008***	0.010***		
	(0.002)	(0.001)		
Sinclair 2017 Acquisition			−0.009	−0.012**
			(0.007)	(0.006)
Post September 2017			−0.021***	−0.021***
			(0.006)	(0.006)
Sinclair 2017 x Post September			0.023**	0.023**
			(0.009)	(0.010)
Time Slot Dummies:	Y	Y	Y	Y
Day-of-Week Dummies:	Y	Y	Y	Y
Fixed Effects:	None	DMA	None	DMA
N	6,756,741	6,673,159	175,435	175,435
R^2	0.006	0.019	0.012	0.014

*p < .1; **p < .05; ***p < .01
Standard errors (clustered by station) in parentheses. An observation is a segment. Columns 1-2 use the full sample of markets and stations. Columns 3-4 restrict to markets in which Sinclair acquired at least one station in 2017.

However, after being acquired by Sinclair, stations see a substantial shift in coverage towards national politics of about 3 percentage points – a 25% increase relative to the average level in the sample.

Appendix E shows that this analysis is not an artifact of the specific topic model we use to measure content characteristics. The results showing reduced coverage of local politics at Sinclair stations also hold if we measure coverage of local politics by counting mentions of the names of locally-elected officials who hold office in the market in which the station operates.

In Table 5, we analyze the ideological slant of coverage, as measured by our text-based slant estimate described in Appendix C. For purposes of this analysis, we focus on segments with 50% or more weight on the national politics topics. We restrict to national-politics-focused segments because the training set used to fit our model of ideology on phrase frequency comes from the Congressional Record (CR), and hence focuses on national rather than local issues. Including other non-national-politics segments tends to compress the distribution of slant estimates because doing so adds numerous phrases with no ideological valence in the CR.

Columns 1-2 of this table show that according to this measure, Sinclair stations on average are more right-leaning compared to the rest of the sample (column 1) and other stations in the same market (column 2). The DiD results in columns 3-4 show that, first, Sinclair's 2017 acquisitions were actually somewhat left-leaning prior to the acquisition (row 2). Second, after the acquisition, coverage shifted to the right at these acquired stations, relative to other stations in the same set of markets (row 4). The size of the effect is an increase of 0.023 in the projected DW-NOMINATE score of the national politics coverage on these stations. In terms of the distribution of DW-NOMINATE scores in Congress, this is a small increase, but as Figure 4 shows, the distribution of projected scores for local news coverage is much more compressed than the distribution in Congress.[14] The magnitude of the DiD estimate here corresponds to an increase of roughly one standard deviation of the distribution of slant scores for local news programs.

The difference-in-difference results demonstrate that evidently, the content difference we see in the cross-section is not purely a function of differences in audience characteristics - stations newly acquired by Sinclair in 2017 shifted their coverage after the acquisition, making their coverage look more like that at existing Sinclair-owned stations in other markets. The large relative magnitudes of the shifts in content we measure imply that the supply-side role in the determination of news content is substantial.

Viewer response Table 6 estimates the reaction of viewers to the change in ownership. Here, the dependent variable is the number of households (in thousands) viewing the news show, as measured by the Nielsen company. The unit of observation here is a show-day, as this is the level at which Nielsen estimates viewership. We present analogous specifications as in the content regressions above.

In Table 6 we see from the first two columns that stations owned by Sinclair prior to 2017 had news shows with relatively low viewership. This is partially explained by the fact that the

[14] This is due both to the fact that the model fit in the Congressional record is far from perfect, and to the fact that ideology-indicative phrases are relatively rare in local news coverage. Both features compress the distribution of projected ideology scores on local news.

Sinclair portfolio tilts towards smaller markets (see Table 2) but the difference persists even within market. The overall average difference is a drop of about 13K households, which aligns with the differences in means seen in Figure 2(a). Restricting to within-market variation, Sinclair stations draw viewership of about 7K less than other competitors operating in the same market.

The DiD results in columns 3-5 of Table 6 show that there is a small, but not statistically significant, drop in viewership at the 2017 Sinclair-owned stations after the change in ownership, relative to other stations in the same market. The magnitude of the drop is around 600 households, or about 2.5% of the median news show viewership in the sample. The 95% confidence interval is narrow enough to rule out an increase of more than about 700 households. On average, then, the response of viewers to the change in content driven by the Sinclair acquisition is close to zero, with a small decline more likely than a small increase. These are short-term changes, however, and over time the gap may grow closer to the average within-market ratings difference at existing Sinclair stations.

Sinclair's influence on content choices at its newly-acquired stations was, on the whole, costly in ratings terms. The fact that Sinclair nonetheless implemented the changes in content we document suggests that cost efficiencies on the production side (for example, airing the same nationally-focused and right-leaning segments on all stations in the portfolio) dominated the potential loss of advertising revenues from the ratings decline.

Discussion

Our findings show that ownership matters for the content of local news. Following the acquisition of Bonten Media Group by Sinclair, the former Bonten stations' content shifted towards coverage of national politics at the expense of local politics, relative to other stations in the same media market. Acquired stations' content also moved to the right on the ideological dimension, again relative to other stations in the same media markets. This

Table 6: Cross-sectional and diff-in-diff regressions of news program viewership on Sinclair ownership.

	Viewership (000s)				
	(1)	(2)	(3)	(4)	(5)
Sinclair Pre-2017 Station	-13.210^{***}	-7.410^{***}			
	(2.856)	(2.412)			
Sinclair 2017 Acquisition			2.855	1.938	
			(6.517)	(2.863)	
Post September 2017			0.895	0.986	0.968
			(0.714)	(0.765)	(0.706)
Sinclair 2017 x Post September			-0.129	-0.606	-0.679
			(0.785)	(0.829)	(0.755)
Time Slot Dummies:	Y	Y	Y	Y	Y
Day-of-Week Dummies:	Y	Y	Y	Y	Y
Fixed Effects:	None	DMA	None	DMA	DMA x Show
N	525,636	522,985	4,364	4,364	4,364
R^2	0.133	0.500	0.183	0.509	0.666

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$
Standard errors (clustered by station) in parentheses. An observation is a program. Columns 1-2 use the full sample of markets and stations. Columns 3-5 restrict to markets in which Sinclair acquired at least one station in 2017.

change brought the acquired stations closer in line with the pattern of coverage at existing Sinclair-owned stations, at the cost of a small decline in viewership relative to the stations' same-market competitors.

Both dimensions of content are important for political outcomes. Given the decline of local print media, local TV news is one of the few remaining sources of locally-focused journalism. The substantial post-acquisition drop in local coverage at Sinclair-acquired stations can be expected to reduce viewers' knowledge of the activities of local officials. Although the recency of the Bonten acquisition limits the set of downstream political outcomes which we can study, existing evidence (Snyder and Strömberg, 2010; Hayes and Lawless, 2015) suggests a strong prior that the local coverage drop will translate into reductions in both accountability for local officials and citizen engagement in local and state-level politics. These results are a counterpoint to Hopkins (2018), who finds "no evidence of a shift away from state and local content (pp. 199)" in a sample of seventy stations from 2005-2009. While there may not be a secular long-term trend away from local and state content in TV news, we show that consolidation can generate meaningful changes in the levels of local content even in the very short term. Insofar as the current trend in local TV is towards greater concentration (Matsa, 2014), it is likely that this local-to-national shift will continue.

The rightward shift in content at Sinclair-acquired stations can also be expected to have real consequences for election outcomes and mass polarization. Media outlets' persuasive power is mitigated by the sensitivity of their audience to content changes - if all left- (right-)leaning viewers fled following a leftward (rightward) shift in content, then "persuasion rates" (DellaVigna and Kaplan, 2007) would be small and subsequent electoral influence minimized. In the local news case, the demand response to the content shift that we measure is fairly small. The estimated average viewership decline in our sample is about 700 households, compared to the median program-level viewership in the sample of about 25,000 households. The vast majority of viewers watching before the acquisition date continued to watch afterwards, despite the substantial changes in political content. For these non-switching viewers, the ideological valence of their news diet lurched rightwards following the acquisition.

Our results have strong implications for the regulatory oversight of mergers in the TV industry. Such oversight has traditionally focused on measures of concentration defined at the local market level, such as the FCC's prohibition on a single entity owning both a full-power TV station and a daily newspaper in the same market and caps on DMA-level TV market share that can be owned by a single entity.[15] Prat (2017) has previously argued that this traditional approach is good at measuring a media owner's pricing power but very bad at measuring its *political* power; to measure the latter, Prat shows, one needs a measure of ownership concentration defined at the individual rather than the market level.

Our analysis points to a distinct but similarly consequential problem with the use of such market level concentration statistics to assess mergers in the TV industry. Prat observed that two configurations of reader- or viewer-ship could produce identical concentration statistics but very different implications for media influence and polarization: contrast, for example, a hypothetical world where all consumers devote equal time to each of three media outlets, to one where one-third of consumers read only the first outlet, one-third only the second, and

[15] `https://www.fcc.gov/consumers/guides/fccs-review-broadcast-ownership-rules`

one-third only the third.

Our analysis shows that an analogous property is true when moving in the opposite direction of aggregation: the news content that would be provided by a TV industry consisting of a handful of national conglomerates would look very different than that provided by one comprising numerous single-market operators, even holding measures of market-level concentration fixed. The cost efficiencies of consolidating news production appear to be large enough to make up for net losses in viewership it induces. Even though consumers on average appear to prefer the more local-focused (pre-Sinclair) mix of coverage to the more national-focused (post-Sinclair) mix, Sinclair management still opted to reduce local heterogeneity in coverage across its stations by substituting centrally-produced, nationally focused segments for locally-produced content.

Given the importance of local news provision for the accountability of local elected officials, regulators should not neglect this effect of ownership consolidation on local news content. Current trends towards national consolidation in TV ownership have worrying implications for the performance of local governments and for mass polarization.

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A Data construction details

We collected text transcripts of weekday morning, evening and night local news programs for a set of 743 broadcast stations tracked by the data vendor TVEyes. Because there is some cross-station variation in both the number of news programs produced and the air times of these programs, we identified potential news time blocks by searching for a set of key words indicative of news coverage, and selected times with a sufficient number of hits. We manually removed blocks corresponding to national programs (such as the *Late Show with Stephen Colbert*, *Today*, or sporting events) by searching for national network program titles. We then downloaded all transcripts in the identified station-specific time blocks for the period July 1 - December 14, 2017. We dropped any segments from non-news programs (identified by screening for programs with unusually high ratings relative to the typical local-news level and inspecting the resulting program titles).

Using TVEyes-provided time stamps, we split each half-hour block into 2.5 minute chunks, generating a total of 12 transcript chunks per half-hour. The raw transcripts from each chunk were preprocessed by removing common "stop words" and reducing words to their stems using the Porter stemming algorithm, as implemented in the `tm` package in the `R` language.[16] The resulting dataset consists of 7.41M 2.5 minute segments of processed transcript text.

B Topic model details

From the preprocessed transcripts, we constructed the "bag of words" representation of each chunk. This is just the number of occurrences of each word in each chunk; e.g., the sentence "From each according to his ability; to each according to his need" would be represented as "to:3 each:2 according:2 his:2 from:1 ability:1 need:1." Because the frequency distribution features a large mass of very infrequent words - 59% of words occur only once in the entire

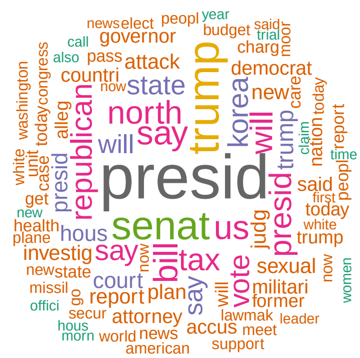
[16] `https://cran.r-project.org/web/packages/tm/index.html`

collection of transcripts - we apply a minimum frequency criterion to limit the set of words input to the topic model: we include only words that appear on at least 750 distinct episodes. This condition drops both words that are uncommon overall (such as “piglet”, which occurs 1154 times in 700 program-episodes) and words that are common but limited to a few programs or stations (such as “mankiewicz,” a reporter’s name, which occurs 2484 times across only 66 program-episodes).

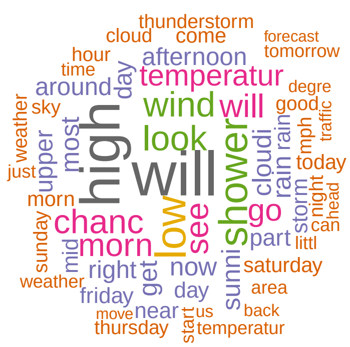
A total of 21,437 words survived this check. The frequency counts for words in this set in all 7.41M “documents” - 2.5-minute chunks of transcript text - were then input to a LDA topic model which was fit using the online algorithm of Hoffman et al. (2010). We estimated a model with 15 topics, using a minibatch size of 4096 documents, 2 passes over the corpus and tuning parameter values recommended by Hoffman et al. (2010). We assigned each topic a descriptive label based on the words involved; the top 25 words for four common topics are shown in word-cloud form in Figure A1. The average weight, across all channels and programs, on each topic over time are plotted in Figure A3. The $T = 15$ model produced three distinct national politics topics: one focusing on domestic policy, one on foreign policy, and the other on various scandals and ongoing investigations related to president Trump. There are two local politics topics: one which focuses on schools, and the other which appears to primarily cover infrastructure and transportation projects. We combine the two local into a composite local politics weight, and the three national politics topics into a composite national politics weight, for purposes of estimating the regressions of content on ownership in Tables 4 and 3. Figure A1 shows the most-indicative words for the composite local and national topics; figure A2 shows the most-indicative words for each of the five component topics. Figures A4 and A5 show the empirical CDF of the weights on national and local topics, respectively, and summary statistics disaggregated by Sinclair ownership status.

The number of topics must be chosen a priori and involves some degree of researcher judgement. We tested numbers of topics (T) in the range from 5-25, and used our evaluations of the output from each to choose what we felt was the best-fitting model at T=15. Choices

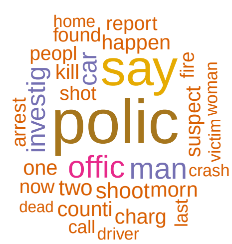
(a) Local



(b) National

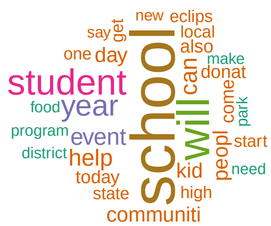


(c) Weather



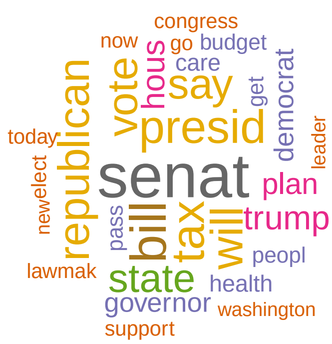
(d) Crime

Figure A1: Word clouds for four topics, displaying the top 25 words most associated with each topic. The national and local politics topics consist of subtopics, outlined in the next figure. The size of the word is proportional to the posterior probability on that word conditional on the topic.

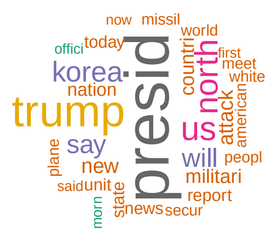


(a) Local Subtopic 1

(b) Local Subtopic 2



(c) National Subtopic 1



(d) National Subtopic 2

(e) National Subtopic 3

Figure A2: Word clouds for the subtopics within national and local politics, displaying the top 25 words most associated with each topic. The size of the word is proportional to the posterior probability on that word conditional on the topic. The first two figures are local topics and the remaining three are national topics.

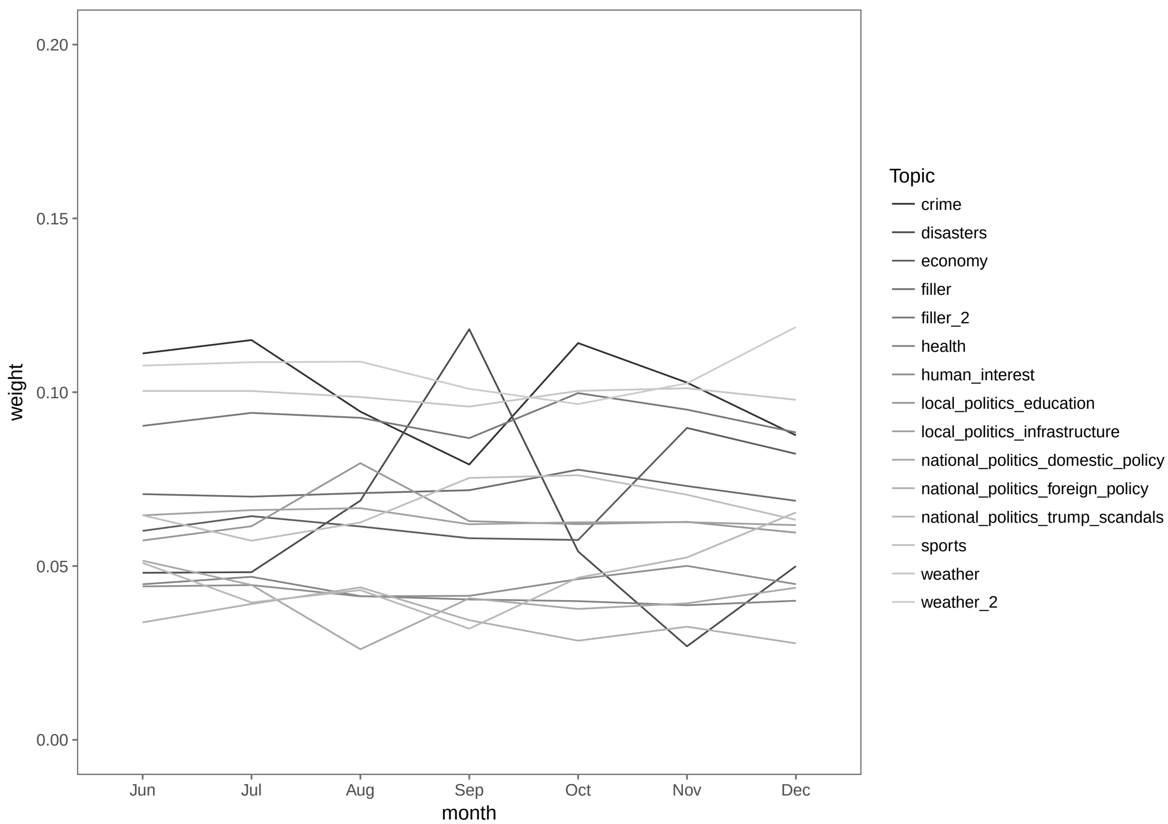


Figure A3: Monthly Topic Weights

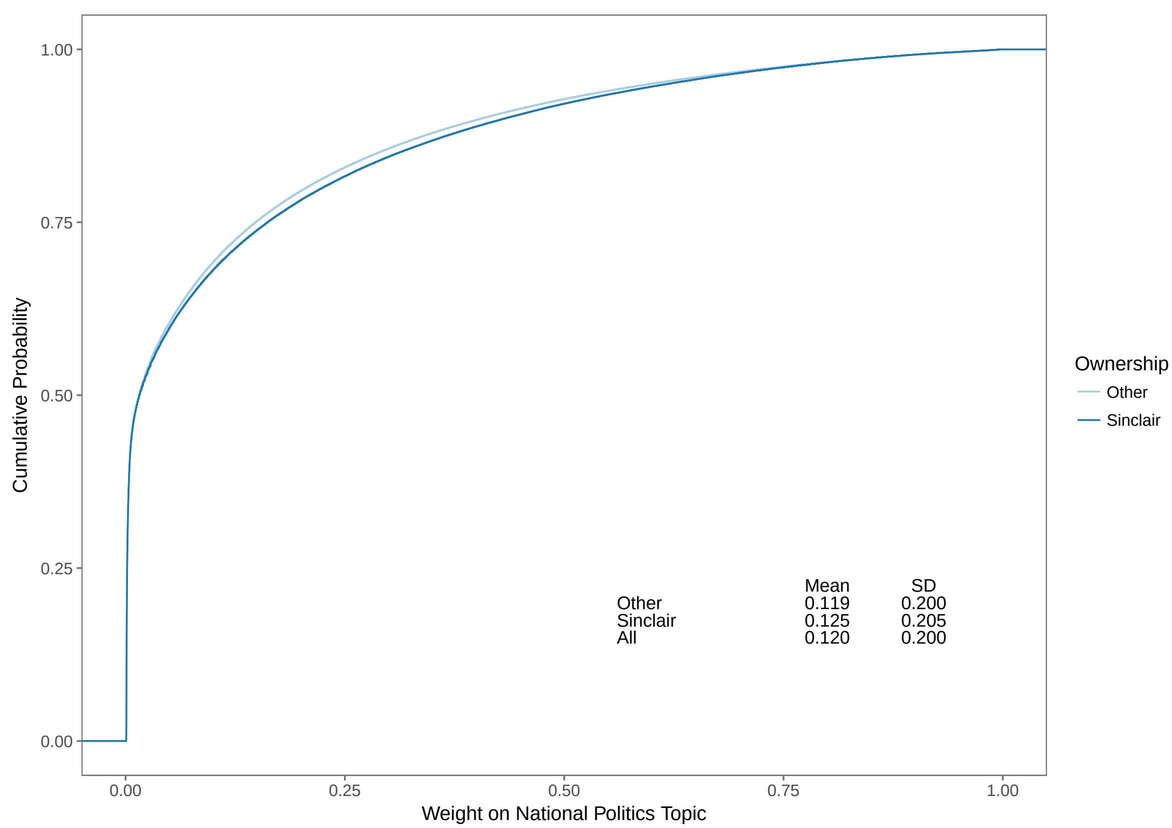


Figure A4: Empirical Cumulative Density Function of National Topic Weights

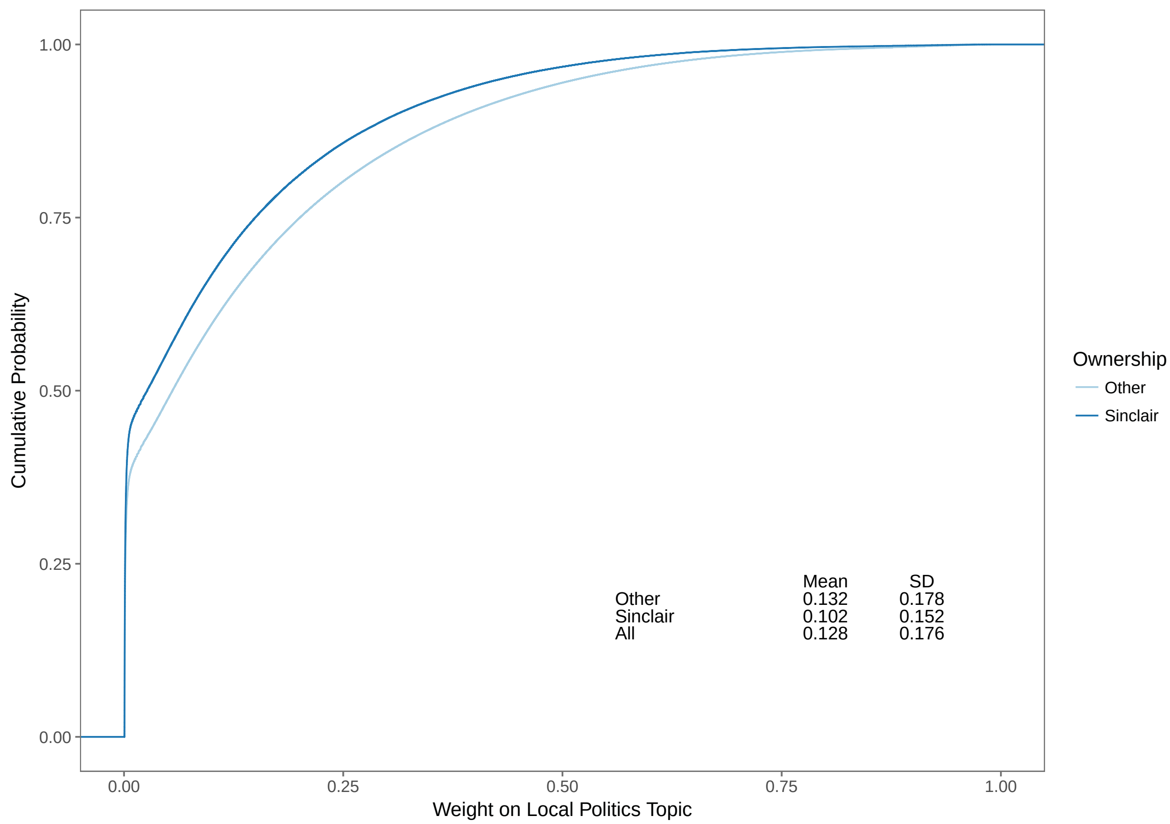


Figure A5: Empirical Cumulative Density Function of Local Topic Weights of T below 9 tended to group all politics discussion (both local and national) together, while choices of T above 15 quickly began to generate duplicative topics (for example, two or three distinct weather topics).

In addition to manual inspection, we also performed a quantitative analysis of model fit by computing the perplexity, a likelihood-like statistic that is commonly used to assess the performance of topic models (Hoffman et al., 2010). Lower values of this statistic indicate better fit. We took an approach similar to that of Hansen et al. (2017) in assessing perplexity as a function of model dimension. The method involves randomly selecting a hold-out sample of 10% of the corpus, fitting the model on the remaining 90% of documents, and then computing perplexity on the remaining 10% for each value of T in the range from 5 to 25. Perplexity values thus provide a measure of the out-of-sample fit of the model for each value of T.

Figure A6 shows that most gains in perplexity are achieved by $T = 15$. There are marginal gains to be had by increasing the number of topics beyond this point, but these come at the cost of added complexity. By $T = 20$, the slope of the curve is essentially flat.

C Slant measure details

Our measure of text-based slant follows the method described in Martin and Yurukoglu (2017). The method uses the usage patterns of members of Congress in floor speeches to infer the ideological content of a set of two-word phrases. These per-phrase weights can then be used to project an ideological location (on the DW-NOMINATE first-dimension scale) for news programs based on their usage of each phrase.

The method has several steps, which are described in detail in Martin and Yurukoglu (2017). The first step selects a set of 1000 two-word phrases which are the most highly indicative of partisanship among speakers appearing in the 2017 Congressional Record, by computing the partisanship Chi-square statistic of Gentzkow and Shapiro (2010) for each phrase.

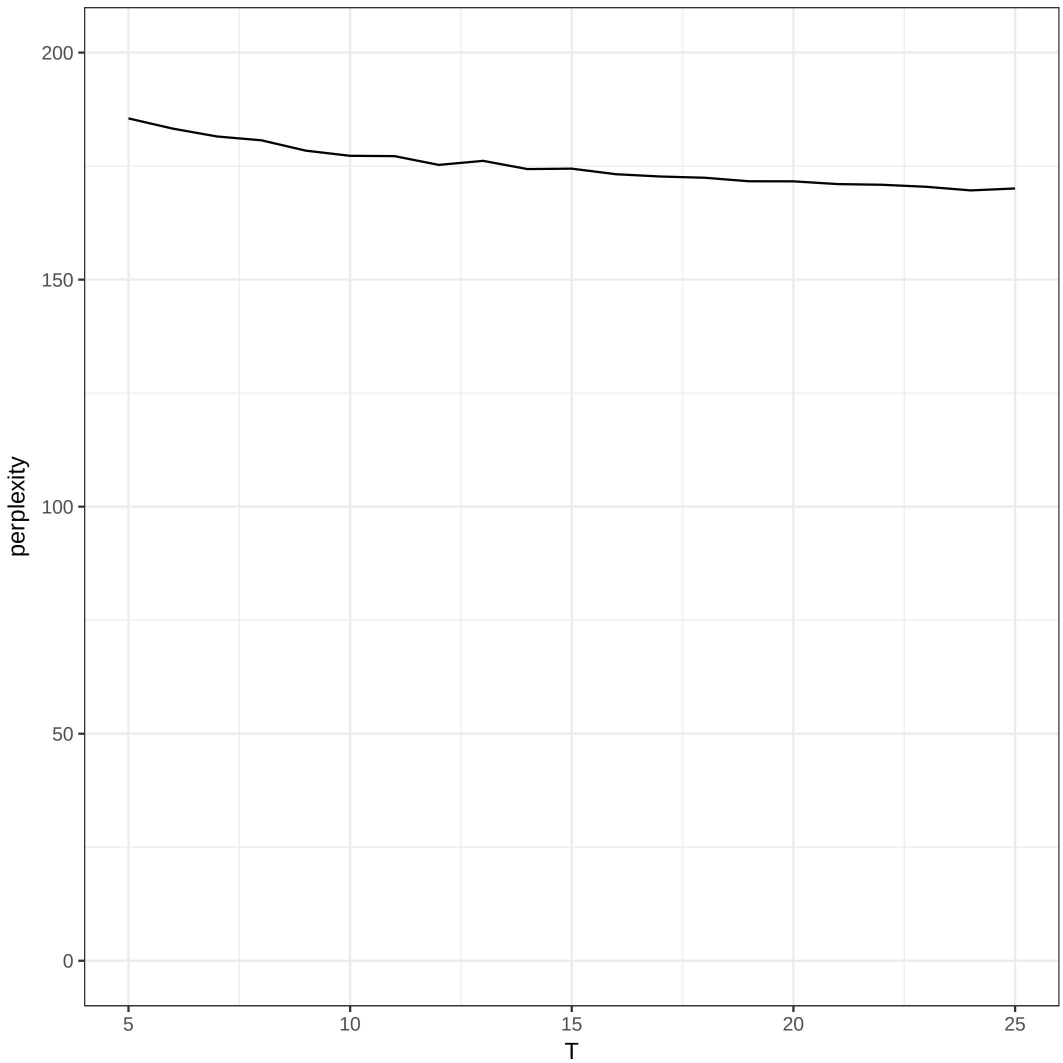


Figure A6: Out-of-sample perplexity estimate, by number of topics in model. Based on a randomly selected 10% hold-out sample from the corpus of segments.

Among the set of phrases that appear at least 1000 times in the local news transcripts[17], we select the 1000 with the highest value of the Chi-squared criterion in the 2017 Congressional Record. Second, we use an elastic-net regression to predict members of Congress' first-dimension DW-NOMINATE score from their standardized usage frequency of each of these 1000 phrases in speech in the Congressional Record. Finally, we use the fitted model to project DW-NOMINATE scores for each local news segment on the basis of its usage of

[17]We impose this minimum frequency criterion to exclude the (many) procedural phrases in the Congressional Record which appear highly partisan due to their relatively more common use by the majority party, but which rarely or never appear on TV.

the same 1000 phrases.

To improve the model fit and exclude some of the non-political content present in local news transcripts, we restrict the segments included in the phrase-selection and projection steps to include only those which the topic model identifies as having at least 50% weight on the composite national politics topic. This step reduces the amount of noise in the estimates from attempting to estimate the ideological slant of segments focusing on, say, highlights from the previous night's major league baseball games. These segments almost never use the phrases identified as highly partisan in the Congressional Record. Even with this restriction, the phrases are still rare enough that the slant measure is quite variable at the segment level. To reduce variance, we aggregate the slant estimates and conduct all of our analyses of slant at the station-day- rather than segment-level.

D Additional regression tables

Table A1 shows the correlations among a variety of DMA-level attributes and their relationship with news coverage and viewership. The DMA-level characteristics come from census-tract level data aggregated up to DMAs. This table shows a handful of interesting relationships; for example, independent stations (those not affiliated with one of the four main broadcast networks) cover much less political news. Additionally, stations in more educated areas cover less local politics and lower income areas cover more local politics and less national.

E Local Politician Mentions

To determine the names of the local politicians to search for in the transcript text, we extracted the universe of local- and state-level officials from the online Leadership Directories database.[18] Leadership Directories collects the names of locally-elected officials from cities

[18] `https://www.leadershipconnect.io/`

Table A1: Regression of viewership on DMA demographics and national politics coverage.

	Weight on National Politics Topic	Weight on Local Politics Topic	Viewership (000s)
sinclair	0.008^{***}	-0.035^{***}	-2.839^{**}
	(0.003)	(0.004)	(1.369)
affiliationIND	-0.077^{***}	-0.068^{***}	
	(0.006)	(0.009)	
age10_19_pct	-0.103	1.019	-676.775^{**}
	(0.606)	(0.886)	(300.938)
age20_29_pct	0.132	-0.046	-514.231^{***}
	(0.271)	(0.444)	(171.594)
age30_39_pct	-0.465	0.727	-694.167^{**}
	(0.700)	(1.002)	(327.097)
age40_49_pct	0.259	-0.764	47.508
	(0.311)	(0.621)	(171.488)
age50_59_pct	0.618	-0.198	-431.474^{*}
	(0.464)	(0.637)	(239.814)
age60_69_pct	-0.651	1.361^{*}	-495.675^{**}
	(0.400)	(0.783)	(214.468)
age70_79_pct	1.018^{*}	-0.600	-453.128^{**}
	(0.559)	(0.747)	(202.906)
age80_pct	-1.002^{**}	0.118	-246.355
	(0.472)	(0.908)	(242.148)
edu_hs_grad_pct	-0.096	0.162	73.328
	(0.077)	(0.139)	(49.248)
edu_some_college_pct	0.065	-0.260^{*}	-58.074
	(0.075)	(0.141)	(36.592)
edu_college_grad_pct	0.025	-0.489^{***}	66.547
	(0.098)	(0.156)	(41.200)
edu_grad_deg_pct	0.232	0.497^{*}	-86.195
	(0.197)	(0.300)	(79.214)
inc_10k_20k_pct	-0.209	1.533^{**}	-355.283^{**}
	(0.328)	(0.598)	(156.483)
inc_20k_30k_pct	-0.027	-0.947	-235.663
	(0.373)	(0.614)	(172.622)
inc_30k_40k_pct	-0.722	1.151	23.480
	(0.444)	(0.731)	(173.884)
inc_40k_50k_pct	0.149	0.700	-449.146^{**}
	(0.458)	(0.860)	(178.391)
inc_50k_60k_pct	-1.126^{**}	0.168	309.832^{*}
	(0.440)	(0.708)	(183.327)
inc_60k_75k_pct	0.250	0.388	-274.028^{*}
	(0.438)	(0.649)	(165.577)
inc_75k_100k_pct	0.132	0.745	-573.701^{***}
	(0.354)	(0.634)	(216.018)
inc_100k_125k_pct	0.367	0.940	-186.691
	(0.508)	(0.900)	(206.566)
inc_125k_150k_pct	-1.447^{*}	0.717	39.790
	(0.875)	(1.236)	(332.200)
inc_150k_200k_pct	-0.181	-0.804	206.651
	(0.578)	(0.972)	(227.489)
inc_200k_pct	-0.076	0.803^{*}	-472.974^{***}
	(0.330)	(0.479)	(143.661)
race_white_pct	-0.050	-0.095	11.507
	(0.038)	(0.077)	(20.624)
race_black_pct	-0.067^{*}	-0.050	21.449
	(0.039)	(0.070)	(18.772)
race_asian_pct	0.014	-0.049	-34.756
	(0.075)	(0.139)	(40.532)
I(total_pop/1e+06)	-0.001^{**}	-0.004^{***}	6.060^{***}
	(0.001)	(0.002)	(1.210)
dem_vote_pct	0.021	0.025	-2.472
	(0.020)	(0.036)	(8.406)
Time Slot Dummies:	Y	Y	Y
Day-of-Week Dummies:	Y	Y	Y
Fixed Effects:	None	None	None
N	7,216,421	7,216,421	700,060
R^2	0.226	0.007	0.470

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$
Standard errors (clustered by DMA) in parentheses. An observation is a segment in columns 1 and 2 and a program in column 3.

or municipalities with more than 30,000 people and all elected state officials. There were a total of 13,074 unique local officials and 8,048 state officials.

We then matched the local officials data to DMAs based on the name of the municipality and/or the name of the county in which they were elected. There were 11 DMAs that did not have cities with a population greater than 30,000. For these we searched for the largest city within each DMA and found the name of the mayor or city leader and added this to the data. For state officials, we matched these names to the DMA data by which state the DMA is in to avoid complications with overlapping state-level districts and DMAs.[19] In other words, a state representative, senator or governor (or any other official) from North Carolina is matched to all DMAs within North Carolina.

Next, we extracted names from the scraped transcript data using the Stanford Name Entity Recognizer software.[20] This resulted in a dataset where each unique name had its own observation tied to the transcript in which it was mentioned. We then kept only full names mentioned (i.e., first and last). For the local officials, we determined name mentions by joining the local officials' full names to the transcript name mentions dataset by full name and DMA. We did the same process for state officials but joined by full name and state. This process ensured that we did not generate false positives across DMA (or state) lines. This process resulted in a dataset where each 2.5 minute transcript segment has a 1 if it mentions a local official and 0 if it does not. As a further robustness check for locally-elected officials, since they were mentioned so rarely overall, we also created a dummy variable for mentions of the words "mayor", "councilperson", "councilman", "councilwoman", "state senator", "state representative", "governor", "council member", and "alderman".

We then created a count of national politician mentions as an additional robustness check for the national politics topic. To do this we looked for the names of Donald Trump, Paul Ryan, Mitch McConnell, Chuck Schumer and Nancy Pelosi.

[19]For instance, state house and senate districts frequently do not follow county lines or DMA lines, making the process of matching individual state officials to individual DMAs challenging.

[20]https://nlp.stanford.edu/software/CRF-NER.html

For the elected officials name matching, we checked the validity of the name matching by looking at all names that were mentioned more than 50 times and spot-checking the transcripts in which they were mentioned. With only one exception,[21] all names mentioned more than 50 times seemed to be accurately matched.[22] A problem related to false positive matches for our analysis would be if a local politician shared a name with, for instance, a national politician (e.g., Paul Ryan). After manually examining the matches, this did not seem to be a prevalent issue. This process could not rule out all false positives, but we are confident that any false positives that do exist should bias us against finding results through adding noise to the data.

Mentions of local official names in news transcripts are rare. The mean levels in the data are an average of 0.0011 mentions of local officials per 2.5-minute segment and 0.0028 mentions of state-level officials per 2.5-minute segment. The vast majority of segments do not mention any state or local official by name. When we aggregate to the level of show-month, the averages rise to 0.045 and 0.11 respectively. That is, the average local news show mentions a state or local official by name about once every 6 months.

The results from regressions using the name mentions as outcome variables are included below. These results follow the same structure as the main results in the paper, with the first two employing cross-sectional regressions and the last three difference-in-differences regressions. Table A2 shows results with local officials mentions as the dependent variable, Table A3 shows results with elected state officials, Table A4 combines state and local mentions, Table A5 also combines state and local mentions but collapses to the show-month level to reduce the number of observations with zero mentions, and Table A6 shows results where the dependent variable is a mention of a local official job title.

These results support the findings of the topic model regressions in the paper. Though the coefficient on the DiD estimate is imprecisely estimated in these regressions, likely a product of the relative rarity of name mentions, is consistently in the correct direction.

[21] The exception was a police chief that had the same name as a mayor from a city within the DMA.

[22] The most mentioned names were typically mayors of big cities, governors, or state congressional leaders.

However, the coefficient in the cross-sectional regressions including those with DMA fixed effects is statistically significant, in the correct direction, and of substantive interest in all of these robustness checks. These results give credibility to the findings employing the topic model probabilities as dependent variables.

Table A2: Cross-sectional and diff-in-diff regressions of mentions of local officials on Sinclair ownership.

	Mentions of Local Elected Officials				
	(1)	(2)	(3)	(4)	(5)
Sinclair Pre-2017 Station	-0.0003^{*}	-0.001^{***}			
	(0.0002)	(0.0001)			
Sinclair 2017 Acquisition			0.0004	0.0004	
			(0.0003)	(0.0004)	
Post September 2017			0.0003	0.0003	0.0003
			(0.0004)	(0.0004)	(0.0004)
Sinclair 2017 x Post September			−0.0005	−0.0005	−0.0004
			(0.0004)	(0.0004)	(0.0004)
Time Slot Dummies:	Y	Y	Y	Y	Y
Day-of-Week Dummies:	Y	Y	Y	Y	Y
Fixed Effects:	None	DMA	None	DMA	DMA x Show
N	7,343,787	7,251,579	196,775	196,775	196,775
R^2	0.0001	0.002	0.0004	0.001	0.002

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$
Standard errors (clustered by station) in parentheses. An observation is a segment. Columns 1-2 use the full sample of markets and stations. Columns 3-5 restrict to markets in which Sinclair acquired at least one station in 2017.

Table A3: Cross-sectional and diff-in-diff regressions of mentions of state officials on Sinclair ownership.

	Mentions of State Elected Officials				
	(1)	(2)	(3)	(4)	(5)
Sinclair Pre-2017 Station	-0.001^{***}	-0.001^{***}			
	(0.0003)	(0.0002)			
Sinclair 2017 Acquisition			−0.0001	0.0004	
			(0.001)	(0.001)	
Post September 2017			0.00000	0.00001	0.0002
			(0.001)	(0.001)	(0.001)
Sinclair 2017 x Post September			−0.0002	−0.0002	−0.001
			(0.001)	(0.001)	(0.001)
Time Slot Dummies:	Y	Y	Y	Y	Y
Day-of-Week Dummies:	Y	Y	Y	Y	Y
Fixed Effects:	None	DMA	None	DMA	DMA x Show
N	7,343,787	7,251,579	196,775	196,775	196,775
R^2	0.0002	0.003	0.001	0.001	0.002

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$
Standard errors (clustered by station) in parentheses. An observation is a segment. Columns 1-2 use the full sample of markets and stations. Columns 3-5 restrict to markets in which Sinclair acquired at least one station in 2017.

Table A4: Cross-sectional and diff-in-diff regressions of mentions of local or state officials on Sinclair ownership.

	Mentions of Local or State Elected Officials				
	(1)	(2)	(3)	(4)	(5)
Sinclair Pre-2017 Station	-0.001^{***}	-0.002^{***}			
	(0.0004)	(0.0003)			
Sinclair 2017 Acquisition			0.0003	0.001	
			(0.001)	(0.001)	
Post September 2017			0.0003	0.0003	0.0005
			(0.001)	(0.001)	(0.001)
Sinclair 2017 x Post September			-0.001	-0.001	-0.001
			(0.001)	(0.001)	(0.001)
Time Slot Dummies:	Y	Y	Y	Y	Y
Day-of-Week Dummies:	Y	Y	Y	Y	Y
Fixed Effects:	None	DMA	None	DMA	DMA x Show
N	7,343,787	7,251,579	196,775	196,775	196,775
R^2	0.0002	0.002	0.001	0.001	0.002

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$
Standard errors (clustered by station) in parentheses. An observation is a segment. Columns 1-2 use the full sample of markets and stations. Columns 3-5 restrict to markets in which Sinclair acquired at least one station in 2017.

Table A5: Cross-sectional and diff-in-diff regressions of mentions of local or state officials on Sinclair ownership, aggregated to show-month level.

	Mentions of Local or State Elected Officials				
	(1)	(2)	(3)	(4)	(5)
Sinclair Pre-2017 Station	-0.054^{***}	-0.066^{***}			
	(0.014)	(0.013)			
Sinclair 2017 Acquisition			0.0003	0.001	
			(0.001)	(0.001)	
Post September 2017			0.0003	0.0003	0.0005
			(0.001)	(0.001)	(0.001)
Sinclair 2017 x Post September			-0.001	-0.001	-0.001
			(0.001)	(0.001)	(0.001)
Time Slot Dummies:	Y	Y	Y	Y	Y
Day-of-Week Dummies:	Y	Y	Y	Y	Y
Fixed Effects:	None	DMA	None	DMA	DMA x Show
N	186,539	184,281	196,775	196,775	196,775
R^2	0.011	0.070	0.001	0.001	0.002

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$
Standard errors (clustered by station) in parentheses. An observation is a show-month. Columns 1-2 use the full sample of markets and stations. Columns 3-5 restrict to markets in which Sinclair acquired at least one station in 2017.

Table A6: Cross-sectional and diff-in-diff regressions of mentions of local or state official titles on Sinclair ownership.

	Segment uses Local or State Official Title				
	(1)	(2)	(3)	(4)	(5)
Sinclair Pre-2017 Station	-0.018^{***}	-0.015^{***}			
	(0.004)	(0.002)			
Sinclair 2017 Acquisition			0.017	0.022^{*}	
			(0.016)	(0.012)	
Post September 2017			-0.001	-0.0001	0.001
			(0.008)	(0.008)	(0.008)
Sinclair 2017 x Post September			0.009	0.008	0.009
			(0.015)	(0.015)	(0.015)
Time Slot Dummies:	Y	Y	Y	Y	Y
Day-of-Week Dummies:	Y	Y	Y	Y	Y
Fixed Effects:	None	DMA	None	DMA	DMA x Show
N	7,344,285	7,252,073	196,779	196,779	196,779
R^2	0.002	0.007	0.002	0.004	0.006

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

Standard errors (clustered by station) in parentheses. The dependent variable is an indicator for the segment containing one of the phrases mayor, councilperson, councilman, councilwoman, state senator, state representative, council member, or alderman. An observation is a segment. Columns 1-2 use the full sample of markets and stations. Columns 3-5 restrict to markets in which Sinclair acquired at least one station in 2017.