Online Appendix: Local News and National Politics

Contents

Online Appendix

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 viewership 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.[1] The resulting dataset consists of 7.41M 2.5 minute segments of processed transcript text.

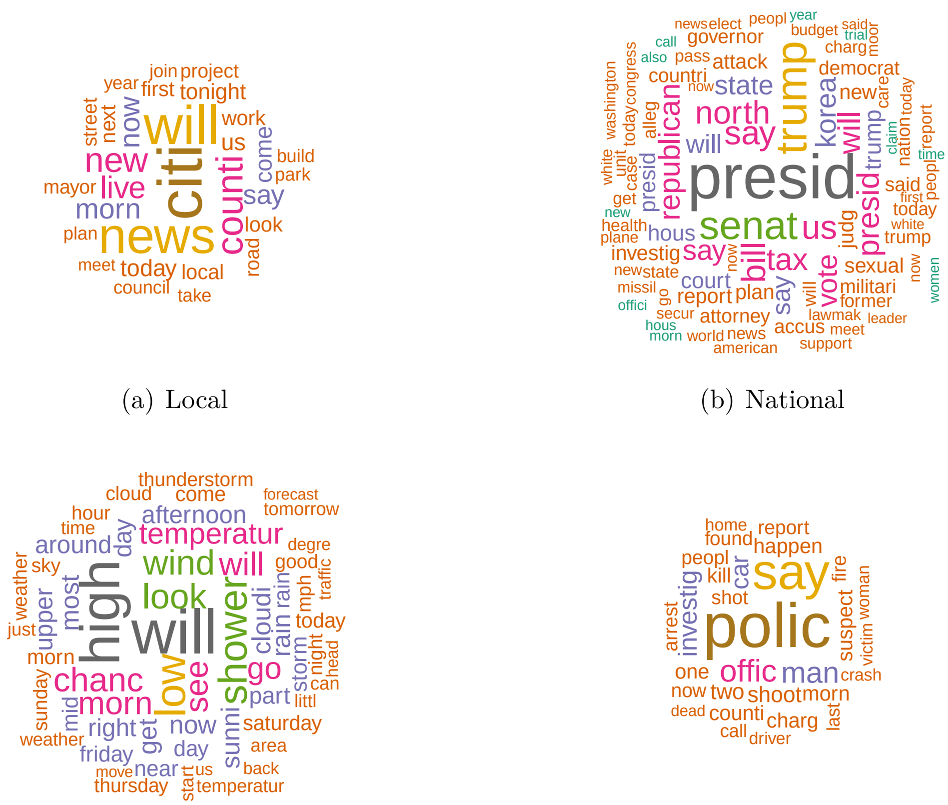
B Topic model details

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

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

"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 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, Bach and Blei (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, Bach and Blei (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 3 and 4. 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.



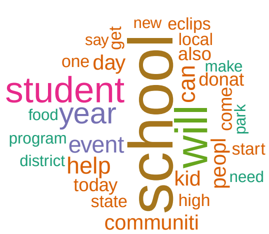
(a) Local

(b) National

(c) Weather

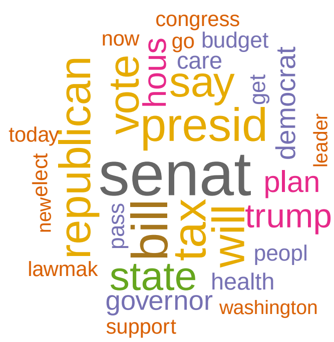
(d) Crime

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.

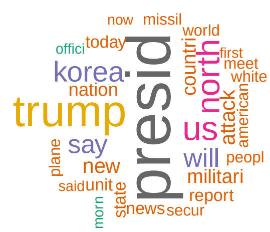


(a) Local Subtopic 1

(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.

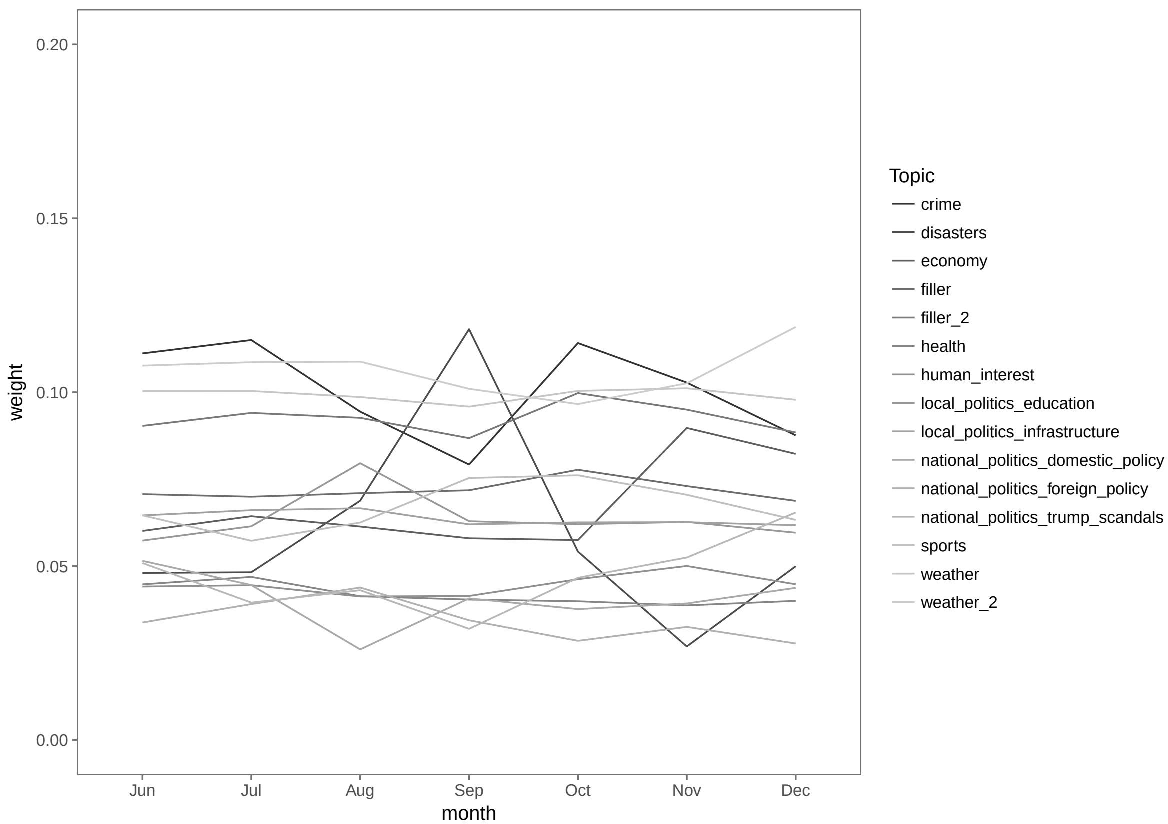


Figure A3: Monthly Topic Weights

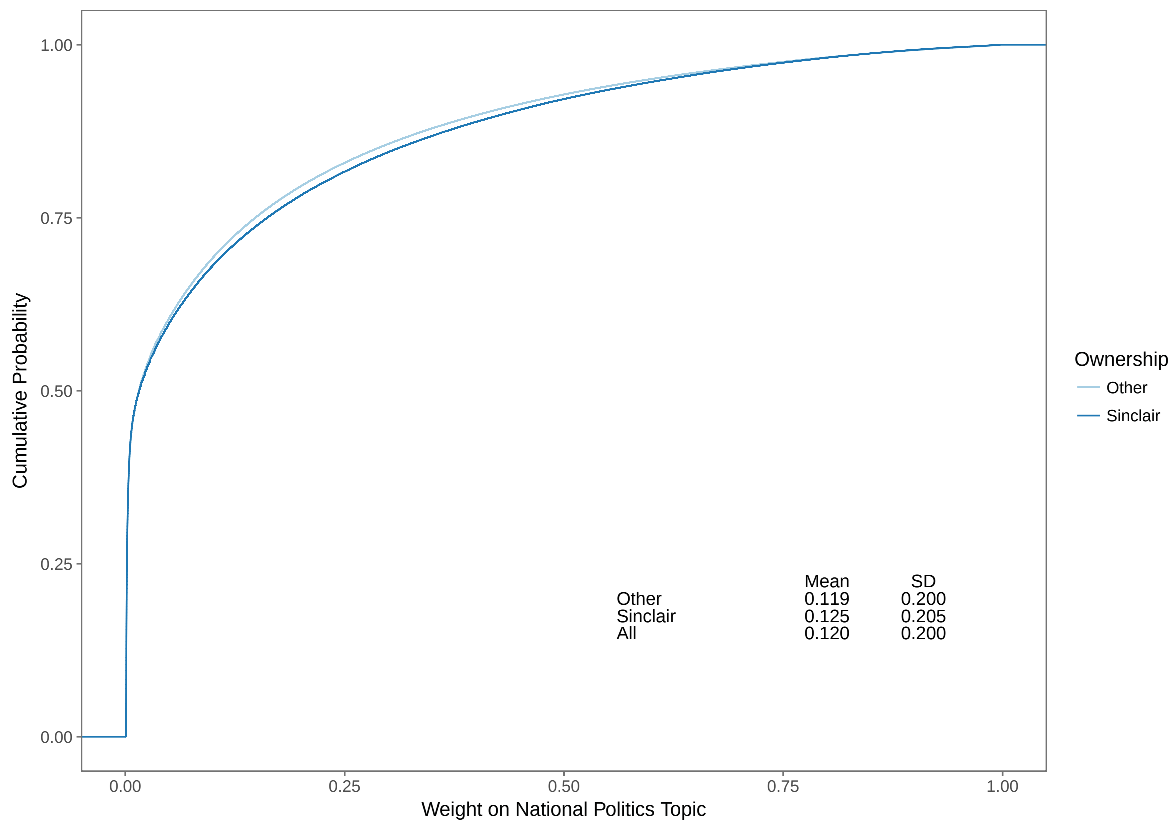


Figure A4: Empirical Cumulative Density Function of National Topic Weights

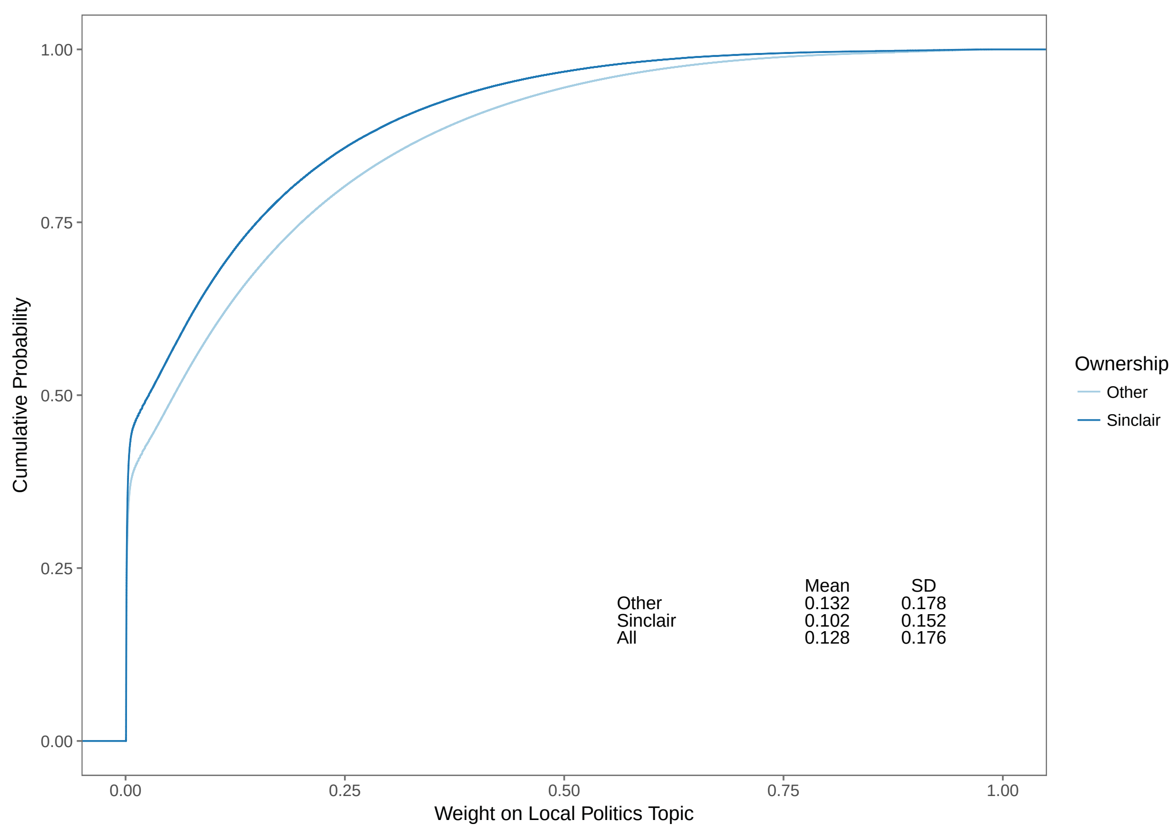


Figure A5: Empirical Cumulative Density Function of Local Topic Weights

The number of topics must be chosen a priori and involves some degree of researcher judgment. 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 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, Bach and Blei 2010). Lower values of this statistic indicate better fit. We took an approach similar to that of Hansen, McMahon and Prat (2018) 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 greater detail 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 first step selects a set of 1000 two-word phrases which are the most highly indicative

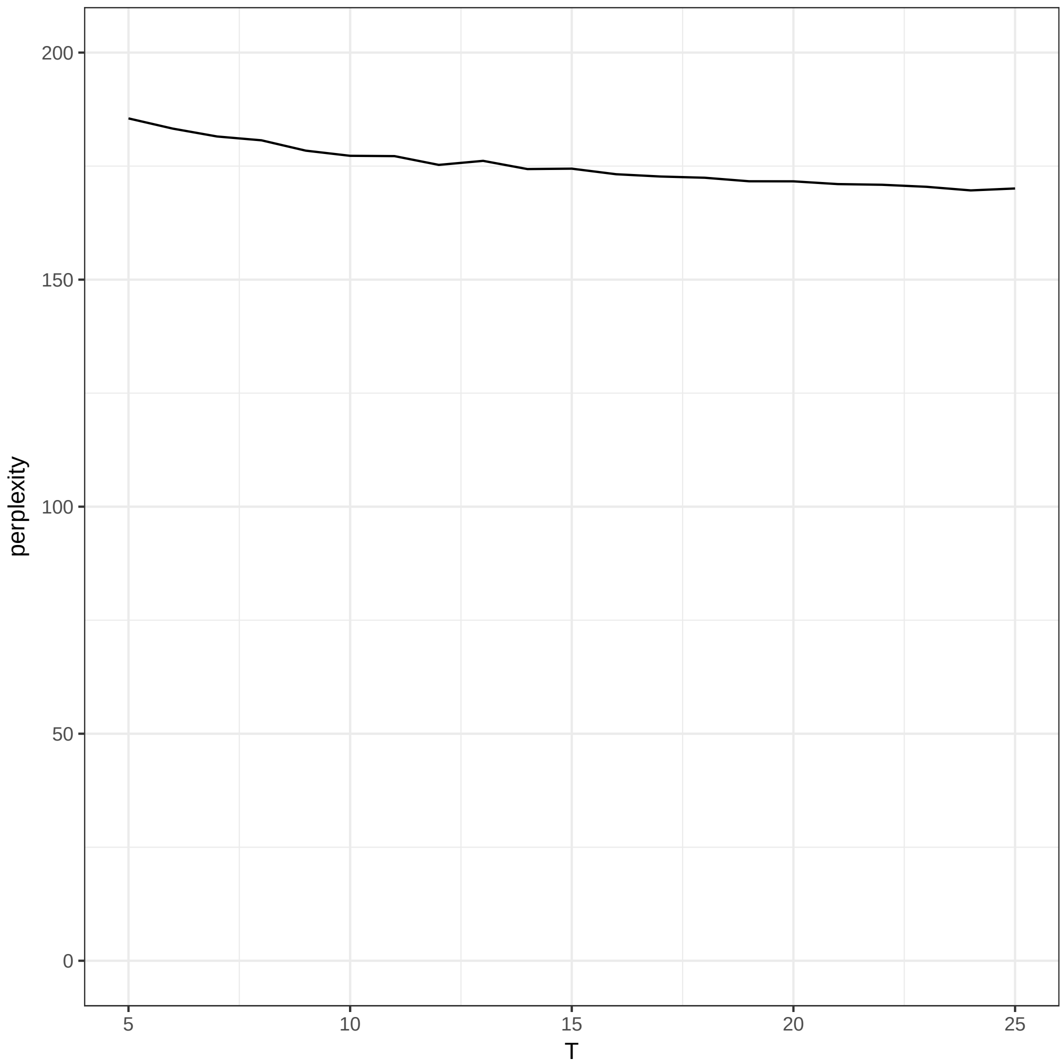


Figure A6: Out-of-sample perplexity estimate, by number of topics in model. Based on a randomly selected 10% hold-out sample from the corpus of segments.

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. Among the set of phrases that appear at least 1000 times in the local news transcripts[2], 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-

[2]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.

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 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

Placebo Tests Table A1 shows the results of a placebo test constructed by running the same local/national content DiD specifications reported in the main text but restricting attention to the months prior to the Sinclair acquisition of Bonten on September 1. We construct a placebo "treatment" variable consisting of the interaction between a dummy for being one of the 2017 Sinclair-acquired stations and a dummy for the month of August. Results show that the estimated DiD coefficients of interest are precise zeros in this specification, confirming the visual evidence in Figures 3(a) and 3(b) that there was no differential trend in the Bonten stations compared to their same market competitors prior to the acquisition.

Table A1: Placebo DiD regressions of politics topic weights.

	Weight on National Politics Topics			Weight on Local Politics Topics		
	(1)	(2)	(3)	(4)	(5)	(6)
Sinclair 2017 Acquisition	0.028^{***}	0.017		-0.010	-0.010	
	(0.010)	(0.011)		(0.033)	(0.008)	
Post August 2017	-0.019^{***}	-0.019^{***}	-0.018^{***}	0.018^{***}	0.018^{***}	0.017^{***}
	(0.006)	(0.006)	(0.006)	(0.002)	(0.003)	(0.003)
Sinclair 2017 x Post August	-0.004	-0.004	-0.006	0.002	0.002	0.003
	(0.010)	(0.010)	(0.010)	(0.006)	(0.006)	(0.006)
Time Slot Dummies:	Y	Y	Y	Y	Y	Y
Day-of-Week Dummies:	Y	Y	Y	Y	Y	Y
Fixed Effects:	None	DMA	DMA x Show	None	DMA	DMA x Show
N	84,224	84,224	84,224	84,224	84,224	84,224
R^2	0.021	0.029	0.043	0.014	0.076	0.092

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

Standard errors (clustered by station) in parentheses. An observation is a segment. In columns 1-3, the dependent variable is the weight on national politics topics; in columns 4-6 the dependent variable is the weight on local politics topics. The sample includes all observations prior to September 1, 2017; the placebo "treatment" is being a Bonten group station in August 2017.

Demographic correlations Table A2 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.

Analysis of national topic components Tables A3 and A4 break apart the composite national politics topic into two of its components. The specifications are exactly the same as those in Table 4 but replace the composite national politics topic weight with, respectively, the "foreign policy" topic weight and the "Trump scandals" topic weight. Both components show significant increases at Sinclair stations in both cross-sectional and DiD specifications.

We interpret this as support for the hypothesis that nationalization of content is driven by consolidation of coverage for cost reasons rather than ideological ones. Both topics share the ability to be disseminated in many markets and thus, if Sinclair's motivation is to generate cost efficiencies by consolidating coverage, both should increase at Sinclair stations relative to local competitors. On the other hand, if Sinclair's motivation is primarily ideological, we would expect coverage of the Mueller investigation, Russian interference in the 2016 election, and so on to decrease at Sinclair stations.

Table A2: 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.

Table A3: Cross-sectional and diff-in-diff regressions of foreign policy topic weight on Sinclair ownership.

	Weight on Foreign Policy Topic				
	(1)	(2)	(3)	(4)	(5)
Sinclair Pre-2017 Station	0.004***	0.005***			
	(0.001)	(0.001)			
Sinclair 2017 Acquisition			0.009	0.010*	
			(0.008)	(0.005)	
Post September 2017			−0.012***	−0.012***	−0.012***
			(0.002)	(0.002)	(0.002)
Sinclair 2017 x Post September			0.008***	0.008***	0.008***
			(0.003)	(0.003)	(0.003)
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	7,182,510	7,090,508	188,806	188,806	188,806
R^2	0.005	0.012	0.004	0.011	0.029

*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 Trump scandals topic weight on Sinclair ownership.

	Weight on Trump Scandals Topic				
	(1)	(2)	(3)	(4)	(5)
Sinclair Pre-2017 Station	0.002*	0.003***			
	(0.001)	(0.001)			
Sinclair 2017 Acquisition			0.005	0.003	
			(0.006)	(0.004)	
Post September 2017			−0.002*	−0.002**	−0.001
			(0.001)	(0.001)	(0.001)
Sinclair 2017 x Post September			0.010***	0.010***	0.009***
			(0.002)	(0.002)	(0.002)
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	7,182,510	7,090,508	188,806	188,806	188,806
R^2	0.004	0.010	0.003	0.007	0.018

*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.

In a related test, Table A5 shows the effect of Sinclair ownership, again using the same set of specifications as in Tables 3 and 4, on coverage of crime as measured by the crime topic weight. Given the importance of crime to post-civil rights era conservative politics in the US (Weaver 2007) and the importance of media coverage in shaping public perceptions of crime, an ideological or partisan motivation should push Sinclair to increase coverage of crime stories. On the other hand, crime stories are generally local and, with the exception of the occasional sensational crime that makes national news, difficult to distribute to multiple markets. Again, the ideological and cost-efficiency motives push in opposing directions. Results show that in the cross-section, Sinclair stations appear to cover crime slightly *less* than other stations in the same market. Diff-in-diff results are indistinguishable from zero.

Table A5: Cross-sectional and diff-in-diff regressions of crime topic weight on Sinclair ownership.

	Weight on Crime Topic				
	(1)	(2)	(3)	(4)	(5)
Sinclair Pre-2017 Station	−0.003	−0.007**			
	(0.003)	(0.003)			
Sinclair 2017 Acquisition			−0.0003	0.005	
			(0.018)	(0.005)	
Post September 2017			−0.007**	−0.006**	−0.005**
			(0.003)	(0.002)	(0.002)
Sinclair 2017 x Post September			0.005	0.004	0.003
			(0.005)	(0.004)	(0.004)
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	7,182,510	7,090,508	188,806	188,806	188,806
R^2	0.007	0.028	0.005	0.025	0.036

*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.

Viewership regressions in ratings points Finally, Table A6 shows results analogous to to those in Table 6, but measuring viewership in terms of ratings points (the percentage of total TV households in the market who watch) rather than the absolute number of viewing households. Although our main specifications use market fixed effects to absorb differences in market sizes, it is possible that the effects of Sinclair ownership are multiplicative rather than additive, in which case the ratings specification would be the appropriate one. We find very similar results here to the base specification, with significant negative effects of Sinclair ownership in the DMA-fixed-effect specification and generally negative but statistically indistinguishable from zero effects in the DiD specification. The magnitude of the estimated effect of Sinclair ownership in column (2), the DMA-fixed-effect specification, implies a ratings penalty of just over one percentage point.

Table A6: Cross-sectional and diff-in-diff regressions of news program ratings on Sinclair ownership.

	Ratings (Percentage Points)				
	(1)	(2)	(3)	(4)	(5)
Sinclair Pre-2017 Station	-0.741^{***}	-1.055^{***}			
	(0.277)	(0.342)			
Sinclair 2017 Acquisition			1.345	1.065	
			(1.803)	(1.651)	
Post September 2017			0.623^{**}	0.625^{**}	
			(0.300)	(0.303)	
Sinclair 2017 x Post September			-0.301	-0.342	0.187
			(0.350)	(0.354)	(0.209)
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	522,985	522,985	4,364	4,364	4,364
R^2	0.207	0.458	0.247	0.315	0.524

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

Ratings are constructed as Nielsen total viewership (in households) by DMA-level total TV households and then multiplying by 100. 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.

E Cable News Scaling

Our primary measure of ideological slant in television content measures the similarity of word usage in news transcripts to that by members of Congress in floor speeches recorded in the Congressional Record. The measure relies on the idea that similarities in speech patterns reveal underlying similarities in ideology. However, speech on television differs from speech in Congress for a variety of reasons, and there are many words that are frequent on TV but rarely or never appear in Congressional speeches and vice versa. One consequence of this fact is that the distribution of predicted ideological scores among TV stations is very compressed relative to the distribution in Congress.

As an alternative approach, we also scaled local TV news segments relative to the cable news outlets MSNBC and the Fox News Channel (FNC). Although the cable news channels do not have voting records in Congress to produce roll-call ideology scores, they do have widely understood partisan sympathies, reflected in audiences that skew towards, respectively, Democratic or Republican partisans.

To accomplish this scaling, we estimate two predictive regressions in a sample of 6606 transcripts of cable news shows (on FNC, CNN or MSNBC) that aired during our analysis period of May-December 2017. The right hand side variables in these regressions are the frequencies of the same vocabulary of words used in the estimation of our topic model. The left hand side is a binary indicator for the transcript having been aired on FNC (in regression 1) or MSNBC (in regression 2). Because this is a situation with sparse predictors and $p >> n$, we estimate this predictive model using an L1-penalized (lasso) regression.[3]

We then apply the models to our local news transcripts to produce predicted scores from each regression. These can be interpreted as, respectively, the probability that a given local news segment came from FNC or MSNBC. We then compute the difference between the two scores to produce a single-dimensional score, with positive values indicating greater similarity to FNC and negative scores indicating greater similarity to MSNBC.

Figure A7 shows that the classifiers perform well in sample. FNC transcripts are reliably identified as originating from FNC, and similarly for MSNBC transcripts. CNN transcripts appear to look somewhat more like MSNBC transcripts than FNC transcripts. The difference column shows that on our combined scale, FNC itself scores at 0.773 on average, and MSNBC at -0.765. These values are useful for interpreting predicted values generated out-of-sample (on the local news transcripts).

Table A8 shows a set of specifications analogous to those presented in the tables in the main text, but where we use this FNC-MSNBC score as the dependent variable. Analo-

[3]We use the `glmnet` package in `R`, choosing tuning parameters using 10-fold cross-validation.

Channel	Mean MSNBC Similarity	Mean FNC Similarity	Difference
CNN	0.088	0.060	-0.027
FNC	0.077	0.849	0.773
MSNBC	0.825	0.061	-0.765

Table A7: In-sample scores of cable transcripts. Numbers are the average score of all transcripts from the indicated channel in MSNBC similarity score (column 1) and FNC similarity score (column 2), and the difference between the two (column 3). The range of the two scores is 0-1.

gously to the main results, we use the model to predict a score for all transcripts identified by our topic model as having at least 50% weight on the national politics topics. The treatment variable of interest is, again, Sinclair ownership, either in cross-sectional specifications (columns 1-2) or DiD (columns 3-5). We find very similar results to those presented in Table 5; Sinclair ownership predicts higher scores on this measure, indicating that Sinclair stations' content is more similar to that of FNC, and less similar to that of MSNBC, than other stations operating in the same market (in the cross-sectional regressions) or to the same station prior to the Sinclair acquisition (in the DiD).

Table A8: Cross-sectional and diff-in-diff regressions of cable news similarity on Sinclair ownership.

	Cable News Similarity Score				
	(1)	(2)	(3)	(4)	(5)
Sinclair Pre-2017 Station	0.107***	0.118***			
	(0.031)	(0.030)			
Sinclair 2017 Acquisition			−0.329*	−0.309*	
			(0.175)	(0.167)	
Post September 2017			0.288***	0.289***	0.256***
			(0.055)	(0.054)	(0.062)
Sinclair 2017 x Post September			0.214	0.213*	0.259**
			(0.130)	(0.129)	(0.130)
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	521,253	515,437	16,729	16,729	16,729
R^2	0.015	0.021	0.029	0.029	0.043

*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. The dependent variable is the cable news similarity score (see text for details). Positive values indicate greater similarity to Fox News Channel content, negative values indicate greater similarity to MSNBC content.

To give some context for the levels of the cable similarity score, Figure A7 shows, anal-

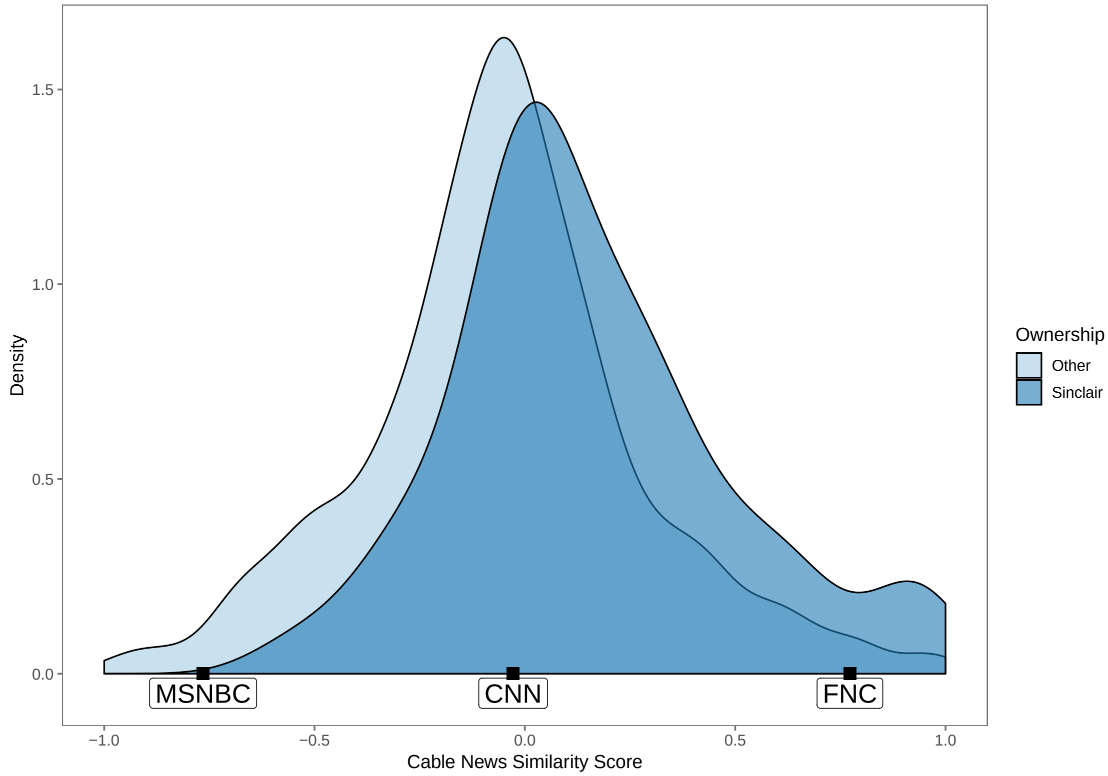


Figure A7: The density of estimated text-based cable similarity scores, aggregated to the station level. The lighter-shaded density is non-Sinclair stations; the darker-shaded density is Sinclair-owned stations. The labeled points on the x-axis correspond to the average locations of transcripts from MSNBC, CNN, and FNC shows, respectively.

ogously to Figure 4, the distribution of slant scores in the sample of local TV stations. To produce this figure, we aggregate to the level of stations and plot kernel density estimates separately for Sinclair-owned and non-Sinclair-owned stations. As expected given the regression results, Sinclair stations are shifted in the FNC direction compared to non-Sinclair stations. The magnitude of the difference in means is about three-fourths of a standard deviation in the distribution of stations.

F Supervised Classifier

Our main results employ an unsupervised method to locate topic clusters in the transcript data. We then interpret the topic model output and identify several of these topics as national-politics or local-politics related. To ensure that we are not missing important aspects of local coverage that might not show up in the topic model, we also used a supervised classifier based on a training sample of 10,000 segments that were manually classified as pertaining to local politics or national politics by human coders.[4] We blocked on ownership (Sinclair / non-Sinclair) in the generation of this random sample to ensure that the fraction of Sinclair segments included in the training set matched that in the overall data. Of this sample, 8.5% of segments were classified by our coders as discussing local politics, and 13.4% as discussing national politics. The remainder were classified as non-political.

We used this human-coded data to train a classifier to predict local politics versus national politics content, again using the same input data of word frequencies employed to fit the topic model. We fit these classifiers using an L1-penalized (lasso) regression,[5] and used them to produce predicted values (interpretable as the probability that a segment discusses national politics or local politics, respectively) for every segment in the full sample of 7.4 million.

Tables A9 and A10 show how these human classifications - and the supervised classifier we built from them - compare to the output of the topic model. Each table shows regression coefficients and standard errors from regressions of either the human coding (in the Training data) or the classifier prediction (in the Test data) on topic weights for the same segment. We show coefficients on the corresponding topic weight - the composite national politics topic for national politics classification, and the composite local politics topic for local politics classification - as well as the weather and crime topic weights for comparison purposes.

Results of the comparison exercise in Table A9 show that our national politics topic weight correlates strongly (with regression coefficient close to unity) with the coders' assessment of

[4]Each transcript in the training sample of 10,000 was classified twice, by two of four coders. Inter-coder agreement was 88%. Coders were instructed to classify as national- (local-) politics related any segment discussing federal (state/local) officials or federal (state/local) elections.

[5]Tuning parameters for the lasso were chosen by 10-fold cross-validation.

national politics content in the training sample. Out-of-sample predictions from the classifier introduce some additional noise and hence the regression coefficient declines somewhat, but still remains strongly positive and close to 1. Correlations with unrelated topics such as weather and crime are, as one would hope, negative or close to zero.

Dataset	National	Weather	Crime
Training	1.139	-0.191	-0.0347
	(0.01524)	(0.02036)	(0.02467)
Test	0.865	-0.163	-0.0184
	(0.00021)	(0.00035)	(0.00042)

Table A9: Regression coefficients of national politics supervised classifier prediction on topic weights. Each entry is the coefficient in a regression of the human classification (in the Training data) or supervised learning prediction (in the Test data) on the topic weight of the same segment. In column 1 the independent variable is the national politics topic weight, in column 2 it is the weather topic weight, and in column 3 the crime topic weight. Standard errors are in parentheses.

Table A10 shows that our local politics topic weight also correlates positively with the coders' assessment of local politics content. However, the correlation is substantially weaker - in the training and in the test data - than that for the national politics topic. We interpret this as reflecting the greater difficulty of predicting local politics coverage compared to national politics coverage from word frequency representations. For example, the crime topic has small but significant positive correlation with our coders' classification of local politics content, reflecting some degree of ambiguity in distinguishing between coverage of crime per se and coverage of local elected officials involved in the criminal justice system such as sheriffs, district attorneys or judges. We expect our various measures of local politics content to have correspondingly higher levels of noise, and hence less precision in regression estimates, compared to our national politics content measures.

The influence of any measurement error in our topic model on the regression results using topic model output depends entirely on the correlation of the measurement error with Sinclair ownership. If measurement error in the our topic weights is larger for Sinclair stations than for non-Sinclair stations (e.g., the local politics topic weight is less correlated with true local

Dataset	Local	Weather	Crime
Training	0.362	-0.1251	0.0731
	(0.02163)	(0.0170)	(0.02054)
Test	0.214	-0.0948	0.0451
	(0.00024)	(0.0002)	(0.00025)

Table A10: Regression coefficients of supervised classifier prediction on topic weights. Each entry is the coefficient in a regression of the human classification (in the Training data) or supervised learning prediction (in the Test data) on the topic weight of the same segment. In column 1 the independent variable is the local politics topic weight, in column 2 it is the weather topic weight, and in column 3 the crime topic weight. Standard errors are in parentheses.

politics content for Sinclair stations than it is for non-Sinclair stations), we would be biased towards finding a negative Sinclair effect on the corresponding coverage area (e.g., towards finding a negative Sinclair effect on coverage of local politics). The opposite correlation - lower measurement error for Sinclair stations - would produce the opposite bias, and no correlation implies no bias in the regression estimates.

Table A11 attempts to assess the correlation of measurement error in the topic weights with Sinclair ownership, by regressing our coders' classifications of local or national politics content in the training set on topic weights for the same segments, interacted with a dummy for Sinclair ownership. The results show that for local politics, measurement error in the topic weight is *smaller* for Sinclair stations: the correlation between the local politics topic weight and our coders' assessment of local politics content is larger for Sinclair stations than non-Sinclair stations. Additionally, the fact that the Sinclair main effect is small and negative implies that, conditional on a particular level of the local politics topic weight, Sinclair segments are not more likely to cover local politics according to our coders. Both facts imply that our local politics regressions are likely over-estimates of the true Sinclair effect, which is in reality *more* negative than what we find using the topic model. The regressions using local politics topic weights are thus conservative. For national politics, there appears to be no correlation in measurement error, implying that the regression estimates using national politics topic weights are unbiased.

Table A11: Correlation of manual classifications with topic weights, for Sinclair and non-Sinclair stations.

	Coded Local Politics	Coded National Politics
	(1)	(2)
Sinclair	−0.010	0.001
	(0.007)	(0.006)
Local Topic Weight	0.351***	
	(0.012)	
Sinclair x Local Topic Weight	0.180***	
	(0.041)	
National Topic Weight		1.124***
		(0.009)
Sinclair x National Topic Weight		0.013
		(0.025)
Constant	0.043***	−0.008***
	(0.003)	(0.002)
N	18,796	18,796
R^2	0.051	0.468

*p < .1; **p < .05; ***p < .01
Standard errors in parentheses. An observation is a segment. The sample consists of a stratified random sample of 10,000 segments which were human coded as covering local politics, national politics, or other. The dependent variables are indicators for coders' classifications as local politics related (column 1) or national politics related (column 2).

For comparison purposes, Tables A12 and A13 show the results of specifications analogous to those in the main article but replacing the weights from the topic model with predicted values from these lasso regressions. Consistent with the results of the comparison exercise, we find very similar results across the board from our national politics supervised classifier to those in the main specifications involving unsupervised topic weights. The local politics supervised classifier generates similar (negative) regression estimates of the Sinclair effect in the cross sectional regressions but, in the much smaller diff-in-diff sample, we cannot reject the null of zero Sinclair effect.

Finally, Tables A14 and A15 show the same specifications estimated only on the training data: the subset of human-coded transcript segments. Statistical power is low here, particularly in the diff-in-diff specifications where the sample is reduced to a few hundred segments. Nonetheless we generally find results consistent with those in the main tables.

Table A12: Cross-sectional and diff-in-diff regressions of national politics classification on Sinclair ownership.

	Predicted Probability of National Politics Coverage				
	(1)	(2)	(3)	(4)	(5)
Sinclair Pre-2017 Station	0.009***	0.011***			
	(0.003)	(0.003)			
Sinclair 2017 Acquisition			0.023**	0.018*	
			(0.010)	(0.010)	
Post September 2017			−0.006***	−0.006***	−0.005**
			(0.002)	(0.002)	(0.002)
Sinclair 2017 x Post September			0.027***	0.027***	0.025***
			(0.003)	(0.003)	(0.003)
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	7,182,510	7,090,508	188,806	188,806	188,806
R^2	0.005	0.012	0.016	0.021	0.032

*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. The dependent variable is the predicted probability of the segment covering national politics, generated by a lasso model fit to a human-coded sample of 10,000 segment transcripts.

Table A13: Cross-sectional and diff-in-diff regressions of local politics classification on Sinclair ownership.

	Predicted Probability of Local Politics Coverage				
	(1)	(2)	(3)	(4)	(5)
Sinclair Pre-2017 Station	−0.003**	−0.006***			
	(0.001)	(0.001)			
Sinclair 2017 Acquisition			0.014***	0.009*	
			(0.005)	(0.005)	
Post September 2017			−0.001	−0.001	−0.001
			(0.004)	(0.004)	(0.004)
Sinclair 2017 x Post September			0.002	0.003	0.002
			(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	7,182,510	7,090,508	188,806	188,806	188,806
R^2	0.005	0.015	0.008	0.011	0.015

*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. The dependent variable is the predicted probability of the segment covering local politics, generated by a lasso model fit to a human-coded sample of 10,000 segment transcripts.

Table A14: Cross-sectional and diff-in-diff regressions of human coders' national politics content classification on Sinclair ownership.

	Human-Coded National Politics Coverage				
	(1)	(2)	(3)	(4)	(5)
Sinclair Pre-2017 Station	0.006	0.019*			
	(0.011)	(0.011)			
Sinclair 2017 Acquisition			0.158	0.154*	
			(0.096)	(0.091)	
Post September 2017			0.014	0.003	−0.014
			(0.036)	(0.040)	(0.053)
Sinclair 2017 x Post September			−0.118	−0.118	−0.159
			(0.084)	(0.093)	(0.158)
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	9,687	9,564	274	274	274
R^2	0.011	0.037	0.107	0.143	0.335

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$
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. The dependent variable is human coders' binary assessment of the segment's national politics content. This is 1 for segments for which both coders agreed that the segment discusses national politics, and 0 otherwise.

Table A15: Cross-sectional and diff-in-diff regressions of human coders' local politics content classification on Sinclair ownership.

	Human-Coded Local Politics Coverage				
	(1)	(2)	(3)	(4)	(5)
Sinclair Pre-2017 Station	−0.0003	−0.006			
	(0.006)	(0.007)			
Sinclair 2017 Acquisition			0.059	0.050	
			(0.047)	(0.052)	
Post September 2017			0.040	0.040	0.023
			(0.043)	(0.044)	(0.059)
Sinclair 2017 x Post September			−0.033	−0.031	−0.049
			(0.073)	(0.077)	(0.120)
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	9,687	9,564	274	274	274
R^2	0.007	0.033	0.059	0.063	0.228

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$
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. The dependent variable is human coders' binary assessment of the segment's local politics content. This is 1 for segments for which both coders agreed that the segment discusses local politics, and 0 otherwise.

G 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.[6] Leadership Directories collects the names of locally-elected officials from cities 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.[7] 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.[8] 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

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

[7] 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.

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

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.

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,[9] all names mentioned more than 50 times seemed to be accurately matched.[10] 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 officials by name 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

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

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

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 A16 shows results with local officials mentions as the dependent variable, Table A17 shows results with elected state officials, Table A18 combines state and local mentions, Table A19 also combines state and local mentions but collapses to the show-month level to reduce the number of observations with zero mentions, and Table A20 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. 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 A16: 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 A17: 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 A18: 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 A19: 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 A20: 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.

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