Media Slant is Contagious*

Philine Widmer[1], Sergio Galletta[2,3], Elliott Ash[2]

[1] *University of St.Gallen*
[2] *ETH Zürich*
[3] *University of Bergamo*

Abstract

This paper analyzes the influence of partisan content from national cable TV news on local reporting in U.S. newspapers. We provide a new machine-learning-based measure of cable news slant, trained on a corpus of 40K transcribed TV episodes from Fox News Channel (FNC), CNN, and MSNBC (2005-2008). Applying the method to a corpus of 24M local newspaper articles, we find that in response to an exogenous increase in local viewership of FNC relative to CNN/MSNBC, local newspaper articles become more similar to FNC transcripts (and vice versa). Consistent with newspapers responding to changes in reader preferences, we see a shift in the framing of local news coverage rather than just direct borrowing of cable news content. Further, cable news slant polarizes local news content: right-leaning newspapers tend to adopt right-wing FNC language, while left-leaning newspapers tend to become more left-wing. Media slant is contagious.

JEL codes: L82, C53, D72, D23, O33, Z13.

Keywords: Media slant, text as data, local news markets.

*We thank for helpful comments and suggestions Julia Cagé, Mirko Draca, Ruben Durante, Claudio Ferraz, Roland Hodler, Eunji Kim, Michael Knaus, Ro'ee Lee, Josh McCrain, Giovanni Prarolo, Pia Raffler, Jim Snyder, David Yang, Ekaterina Zhuravskaya, and seminar and conference participants at the Harvard Political Economy Seminar, Econometric Society World Congress, Bologna Workshop on Elections, Democracy, and Populism, Bolzano Workshop on Political Economy, Bergamo Advances in Economics Workshop, University of St.Gallen Economics Seminar, and Zurich Text as Data Workshop. Romina Jafarian and Matteo Pinna provided excellent research assistance. This version: February 2022 (First version: December 2020)

Corresponding author: Philine Widmer.

Email addresses: philine.widmer@unisg.ch (Philine Widmer), sergio.galletta@unibg.it (Sergio Galletta) ashe@ethz.ch (Elliott Ash).

1. Introduction

Media regulation in democracies typically aims at providing consumers with a wide choice of (and unrestricted access to) independent news sources. So far, the literature has chiefly addressed whether news sources are independent from the government or other special interest groups (e.g., Besley and Prat, 2006). In comparison, little attention has been dedicated to whether different news sources are independent from each other. That is, little is known about whether the (politically biased) news messaging of a given outlet distorts the output of other media organizations. This question is relevant for media regulators since diverse news sources only translate into diverse reporting if they do not strongly respond to each other (i.e., do not report in unison).

This paper seeks to fill this gap. We study the influence of partisan news messaging by large, national media outlets on smaller, local outlets. Such "contagion" could occur as the preferences of local consumers shift and the small outlets respond through changes in content (Mullainathan and Shleifer, 2005). Specifically, we ask whether the "media slant" of cable TV channels spreads to local newspapers in the United States.

The first step in answering this question is to measure the influence of partisan cable news on local newspaper content. For this purpose, we build a corpus of 24 million article snippets from 600+ U.S. local newspapers in the United States for the years 2005 through 2008. We combine these texts with transcripts of 40 thousand episodes from national cable news networks, specifically Fox News Channel (FNC), CNN, and MSNBC. We use this parallel corpus to construct a novel measure of *cable news slant* – that is, we train a machine learning model to predict, for a given body of text, whether it resembles the language by the relatively conservative network (FNC), rather than language by the relatively liberal networks CNN or MSNBC. We validate the model and associated predictions with human annotations.

After this validation, we apply our model to the corpus of local newspaper articles. For each article, we then have a text-based metric that indexes similarity to language from FNC shows, relative to CNN and MSNBC shows. We aggregate the article similarities at the newspaper-level to get a novel measure of partisan slant of local newspapers. We add rich metadata on newspaper circulation, television channel positioning and ratings, as well as political and demographic covariates.

We then investigate whether relative similarity to language in a cable news network increases in response to higher viewership in a newspaper's market. Cross-sectional estimates of this relationship would likely be confounded, for example by more ideologically conservative counties having both higher Fox News viewership and more conservative local news reporting. To obtain causal estimates, we exploit exogenous variation in cable news exposure across counties coming from variation in the relative channel numbering of the three cable networks (Martin and Yurukoglu, 2017). We provide a number of checks to validate first stage relevance and exogeneity of the instrument. In particular, the instrument (channel position in cable television line-ups) is uncorrelated with other local characteristics that are predictive of viewership or are predictive of the relevant dimensions of local newspaper content.

We find that higher cable news network viewership increases the influence of a network's content on local newspaper articles.[1] Our estimated local average treatment effects survive a number of specification checks, including controls for local demographics, local cable television market characteristics, and text readability metrics (e.g. word length). The results are robust to alternative design choices in sampling, weighting, and instrument construction.

Turning to mechanisms, we first investigate whether the shift in slant is due to coverage of partisan topics or changes in how the same topics are framed. The evidence suggests that framing effects largely drive the shifts. Even when controlling for the topic that an article addresses – such as the economy, education, or crime – we still find that newspapers more exposed to FNC use a more FNC-like slant, and vice versa for CNN/MSNBC.

Next, we check whether local newspapers weave the FNC- or CNN/MSNBC-like slant into their original reporting. We devise a topic-based procedure to distinguish local news from non-local (that is, national or international) news. We find that cable news influences both local and non-local news. Since cable TV shows cover national or international stories, we can thus conclude that the observed diffusion of media slant is not only direct borrowing of content from the cable TV channels. Cable news exposure shifts the original local reporting of the newspapers, consistent with a response to shifts in reader preferences for slanted news.

[1] Our estimates imply that a one-standard-deviation increase in a county's FNC viewership (relative to averaged CNN and MSNBC viewership) would increase the similarity of the local newspaper's content to FNC's content by 0.31 standard deviations. To give some more intuition for the magnitudes, our estimate means that decreasing the relative FNC channel position by 11 positions would shift slant towards FNC by about 3 percent of the difference between FNC and CNN/MSNBC.

Finally, we investigate whether cable news has polarized local news content. We split newspapers into three groups: those who have historically endorsed Democrats, those who have historically endorsed Republicans, and those without or with mixed endorsements. We find that exposure to Fox News (relative to CNN/MSNBC) tends to polarize local reporting: historically Republican newspapers become more conservative (FNC-like), while historically Democrat newspapers become more liberal (CNN/MSNBC-like). Thus, media slant from cable news seems to encourage outlets to re-position themselves on the ideological spectrum in response to a more partisan consumer base. Cable news has remade news landscapes and increased political polarization in local news discourse.

These findings add to the literature in political science and political economy on biased media (e.g., Ashworth and Shotts, 2010; Prat, 2018).[2] This literature provides good evidence that mass media have an impact on election outcomes and readers' policy preferences. For the U.S., Gentzkow et al. (2011) report that the opening of local newspapers boosts voter turnout. Drago et al. (2014) find similar results for Italy. Chiang and Knight (2011) show that a newspaper endorsement for a presidential candidate shifts voting intentions in favor of this candidate. Djourelova (2020) shows, for the case of immigration and border security, that the language used in newspapers can causally shift readers' policy preferences. Beyond the United States, Enikolopov et al. (2011) find that Russian voters with access to an independent television station are more supportive of anti-Putin parties.[3]

Regarding Fox News in particular, DellaVigna and Kaplan (2007) and Martin and Yurukoglu (2017) document that a quasi-experimental increase in exposure leads to higher Republican vote shares (see also Ash et al., 2021). Moreover, it has also been shown that cable news can affect voter knowledge (Hopkins and Ladd, 2014; Schroeder and Stone, 2015), fiscal policy decisions (Galletta and Ash, 2019), as well as behaviors during the COVID-19 pandemic and belief in electoral conspiracy in the 2020 U.S. election (Bursztyn et al., 2021; Ash et al., 2020). None of these previous papers look at the influence of partisan narratives using text analysis, nor do they look at effects on other news outlets.

Our contribution to the debate on mass media persuasion centers around the effects of

[2]For surveys on the empirical and theoretical literature, see Puglisi and Snyder (2015) and Gentzkow et al. (2015), respectively.

[3]Prominent contributions on the persuasive effects of the mass media around the world also include Adena et al. (2015), DellaVigna et al. (2014), or Yanagizawa-Drott (2014). For surveys on the political effects of the mass media, see Prat and Stroemberg (2013) and Stroemberg (2015).

news media outlets on each other. Recent contributions on cross-media influence address the influence of social media on traditional media (Cagé et al., 2020; Hatte et al., 2021). To our knowledge, we are the first to document how content from one media organization can spill over to other media organizations. Hence, our work identifies a potential channel through which partisan media affects political and social outcomes.

Local news outlets are pivotal for citizen engagement and political accountability (e.g., Snyder and Strömberg, 2010). George and Waldfogel (2006) find that the market entry of a national media outlet (in their case, the New York Times) causes local outlets to focus more on local coverage. Martin and McCrain (2019) show that the acquisition of U.S. local TV stations by the national conglomerate owner Sinclair leads to an increased share of national as opposed to local content. Further, Mastrorocco and Ornaghi (2020) document that these acquisitions by Sinclair reduce coverage of local crime and subsequently lower crime clearance rates. We contribute to these debates by analyzing how higher exposure to slanted national cable news changes local news content.

Methodologically, our approach combines natural language processing (NLP), machine learning, and causal inference, extending the use of NLP to understand partisan influences in the media. The current literature on text-as-data approaches to measure partisanship includes Gentzkow and Shapiro (2010), Ash et al. (2017), and Gentzkow et al. (2019), who analyze divisiveness in congressional language. We link text-based methods with an instrumental-variables framework to analyze the diffusion of political messaging across media outlets. The methods could be useful for economists seeking to use text in a causal framework. As detailed below, we address several issues in terms of high dimensionality, lack of interpretability, and omitted variables.

More broadly, our work contributes to the long-lasting debate on the importance of (un)biased media in democratic politics – a topic that has become especially important in the current era of polarization in the U.S. and beyond.

2. Data

This section enumerates our data sources. The data come from cable news channels and from local newspapers. Our resulting panel is from 2005 through 2008, the years for which we can construct cable news viewership by locality. Summary statistics for all variables are reported in Appendix Table A.2.

Figure 1: Example of a local newspaper article snippet

Alameda Times-Star
County outlines ways to lower shelter hostility
8 March 2005

Can Alameda County blunt opposition to current plans to permit emergency homeless shelters at hundreds of residential locations in unincorporated communities? That appeared likely Monday as county planners suggested ways in which shelters - such as in the land-use game Monopoly - would not automatically pass go and neighbors could voice their approval or opposition. [...]

Local newspaper article excerpts. The first ingredient in our analysis is a corpus of local newspaper articles. Our data source is the news aggregation site NewsLibrary, from which we scraped the headlines and first 80 words of all published articles for various local U.S. newspapers for 2005-2008. With a set of scripts, we read through the snippets and extract the newspaper name, the title and the plain text of the article, as well as the date. An example of an article snippet is shown in Figure 1. Our main dataset contains 16 million article snippets of on average 80 words each (starting from the beginning of the article) from 305 unique newspaper titles. In the robustness checks, we use a larger dataset of 24 million articles from 682 titles. Appendix A.1 provides more information.

News show transcripts for FNC, CNN, and MSNBC. Our second corpus is from cable news networks. We gather the news show transcripts for FNC, CNN, and MSNBC from LexisNexis. The corpus includes transcripts from around 40,000 episodes of prime time shows for the three networks for 2005-2008. We have a series of scripts that read through the transcripts to filter out metadata and other non-speech content.

As mentioned, the newspaper article snippets contain approximately the first 80 words of the article. The transcripts tend to be much longer. To make the corpora more comparable, we segment the transcripts into shorter 80-word snippets to match the length of the newspaper article snippets.

Newspaper-level circulation data. Next, we match each local newspaper outlet to one or more counties. We use audited county-level circulation data from the Alliance for Audited Media (AAM), which is available for around 305 unique newspapers (that also appear in the NewsLibrary and the Nielsen ratings data). We thus have 3,781 observation units at the newspaper-county level (see Section 4) for our main analyses. The AAM also provides information on the headquarters location of the newspapers. We will exploit this information to study heterogeneous effects in Section 6.

Appendix A.2 describes an alternative method to match newspapers to counties (not relying on the AAM data). This procedure results in 682 observation units, which we use in robustness checks.

Channel positions and viewership. From Nielsen we have yearly data on channel positions and ratings for Fox News Channel, CNN, and MSNBC. These are the same as the data used by Martin and Yurukoglu (2017). First, we have the channel lineup for all the U.S. broadcast operators and the respective zip code areas served. Second, we have viewership information representing the share of individuals tuned in to each channel by zip code. This value is proportional to the average number of minutes spent watching a channel per household. As the original data are at the zip code level, we follow Galletta and Ash (2019) and aggregate both the ratings and the channel positions at the county level. Specifically, we create county-year average channel positions, weighting the observations by population size in the zip code, while we weight ratings by the number of survey individuals in the zip code according to Nielsen. These variables are then collapsed at the county level by computing the mean across the years 2005-2008.

Other demographic covariates. Finally, we have a rich set of demographic covariates from the 2000 census. These variables are measured at the zip code level. To get the aggregate value for the county, we weight them by zip code population. Appendix Table A.2 lists these variables along with summary statistics.

3. Measuring Media Slant

This section describes how we construct the language measures to be used as outcome variables in our regression analysis. We aim at capturing textual similarity between the newspaper article snippets on the one hand and TV show transcripts on the other. Therefore, we implement a supervised machine learning approach to predict if newspaper article language resembles that from a particular TV station (FNC or CNN and

MSNBC).[4]

3.1. Text pre-processing and featurization

First, we preprocess all texts (newspaper articles and TV station transcripts). We convert them to lower case and remove non-meaningful stopwords (like *and* or *or*), all non-letter characters, and extra white-spaces. Second, for each word, we perform stemming (employing the Porter stemming algorithm). Finally, we form bigrams (two-word phrases) from the word stems.

Let M be the set of documents (snippets indexed by m) from the transcripts corpus. We group CNN and MSNBC together (for a simple notation, we refer to the CNN/MSNBC label as CNN). Thus the label we will predict is FNC_m: For each transcript snippet m, $FNC_m = 1$ if it comes from a Fox News transcript and $FNC_m = 0$ otherwise (if it comes from CNN/MSNBC). We produce a balanced sample of documents, with half from Fox and half from CNN/MSNBC.[5]

Let V_k give the vocabulary of bigrams used by a given channel $k \in \{FNC,\ CNN\}$. Let F_k^b be the frequency of bigram b on channel k. We construct V_{FNC} and V_{CNN} and then intersect the two, imposing the condition that any bigram b must appear more than 20 times in *both* corpora. The resulting set of bigrams is denoted as

$$V = \{b \in V_{FNC} \ \&\ b \in V_{CNN} \mid F_{FNC}^b > 20 \ \&\ F_{CNN}^b > 20\}$$

The frequency threshold serves to exclude infrequent bigrams which are highly distinctive for a given channel, but carry little substantive political or topical information. This procedure produces a vocabulary V with 65,000 bigrams.[6]

[4]The approach is related to Gentzkow et al. (2019), who also use a regularized linear model with n-gram inputs. Our different approach reflects a different scientific objective. Gentzkow et al. (2019) are interested in measuring the level of polarization between groups in language. We are interested in forming a predicted probability of the source of a document for scoring influence in a second corpus. Other related methods are Peterson and Spirling (2018) and Osnabrügge et al. (2021).

[5]We have fewer snippets from FNC than from CNN/MSNBC. Thus, we randomly under-sample the snippets from the CNN/MSNBC corpus to match the number of snippets from FNC.

[6]Previous work has shown that supervised learning models using n-grams are rarely sensitive to the specific choices in pre-processing and featurization (e.g., Denny and Spirling, 2018).

3.2. Classifying transcripts by TV source

Now we will train a machine learning classifier to predict whether a transcript snippet m comes from FNC or CNN/MSNBC. We split the corpus into 80% training data and 20% test data. We build the classifier in the training set and evaluate its performance in the test set.

We take two steps to further pre-process the features, both using the training set to ensure a clean evaluation in the test set. First, we do supervised feature selection to reduce the dimensionality of the predictor matrix. Out of the 65,000-bigram dictionary, we select the 2,000 most predictive features based on their χ^2 score for the true label FNC. Second, we scale all predictors in S to variance one (we do not take out the mean, however, as then we would lose sparsity). Let S be the vector of selected and scaled features, indexed by b. Let B_m^b be the frequency of bigram b in transcript m (and B_m the vector of frequencies for transcript m, of length $|S| = 2000$).

Our classification method is a penalized logistic regression (Hastie et al., 2009). We parametrize the probability that a transcript is from Fox News as

$$\widehat{FNC}_m = \Pr[FNC_m = 1|B_m] = \frac{1}{1 + \exp(-\psi' B_m)}$$

where ψ is a 2000-dimensional vector of coefficients on each feature. The L2-penalized logistic regression model chooses ψ to minimize the cost objective

$$J(\psi) = -\frac{1}{M^*}\sum_{m=1}^{M^*}\Big(FNC_m \log(\widehat{FNC}_m) + (1 - FNC_m)\log(1 - \widehat{FNC}_m)\Big) + \lambda|\psi|_2 \quad (1)$$

where M^* gives the number of documents in the training sample.

The rightmost term in Equation (1) is the regularization penalty. We use Ridge regularization, as indicated by the L2 norm $|\cdot|_2$. The Ridge regularization mitigates over-fitting of the training set by shrinking coefficients towards zero.[7] Regularization strength is calibrated by the hyperparameter $\lambda \geq 0$, selected using five-fold cross-validated grid search in the training set. The optimal penalty in our data is $\lambda^* = 2$, although we got almost identical performance with larger or smaller penalties.

We evaluated classifier performance in the test set, obtaining an accuracy of 0.73

[7]We obtained similar test-set accuracy when using an L1 (Lasso) penalty.

Table 1: Test-Set Prediction Performance for Identifying Cable News Source

	Predicted CNN	**Predicted FNC**
Actual CNN	38.3% (235K)	11.7% (72K)
Actual FNC	15.0% (92K)	35.0% (215K)

Notes: Confusion matrix for test-set predictions. Top left gives true positives for the CNN/MSNBC class; bottom right gives true positives for the FNC class; top right gives false negatives for CNN/MSNBC; bottom left gives false negatives for FNC.

(with a standard deviation of 0.02 across five folds). This performance is much better than guessing (which would produce an accuracy of 0.5 in the balanced sample) and comparable with other works in this literature.[8] The confusion matrix in Table 1 demonstrates the good performance in terms of precision and recall across the two categories. The on-diagonal cells have most of the mass and are quite balanced.[9]

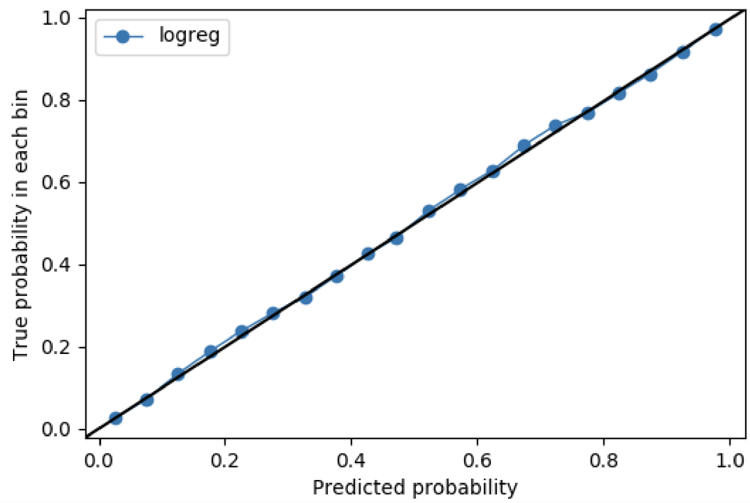
Figure 2 reports the calibration plot for our predictions. The figure shows – for the test set – the binned means (rates) of coming from the Fox News transcripts, conditional on the predicted probability from our model. The 45 degree line indicates how the line would look if the model replicated the distribution in the data – for example, for the set of observations with about 30% predicted probability, we see that about 30% of them are truly from Fox News transcripts. Similarly, this holds for all twenty bins (of 5% increments). As can be seen in the figure, the fit is remarkably good. The conditional predicted rates are almost perfectly on top of the 45 degree line.

Another criterion for evaluating the model is how well it compares with human judgment. To make such a comparison, we asked a team of human annotators (U.S. college students) to guess whether 80-word TV transcript snippets come from FNC or CNN/MSNBC. The annotators are between 73% and 78% accurate in their guesses, and they agree on the annotation about 59% of the time. Thus, our machine learning model is quite similar in performance to human annotations. The 80-word snippets do contain significant information about the source network, and our text-based model captures it. See Appendix B.2 for more details on the human validation.

[8] For example, the prediction accuracy for partisan affiliation in U.K. parliament obtained by Peterson and Spirling (2018): They obtain an accuracy of between 0.6 and 0.8, depending on the time period in the data. Kleinberg et al. (2017) obtain an AUC of 0.71 in predicting recidivism from criminal defendant characteristics.

[9] Our finding on systematic differences in FNC and CNN reporting aligns well with previous case study-based evidence. Harmon and Muenchen (2009) show that FNC and CNN cover a range of politically salient topics differently, such as the Iraq war in the early 2000s.

Figure 2: Model Predicted Probabilities Accurately Reproduce Test-Set Distribution



Notes: Calibration plot for our predictions. The figure shows – for the test set – the binned means (rates) of coming from the Fox News transcripts, conditional on the predicted probability from our model. The 45 degree line indicates how the line would look if the model replicated the distribution in the data perfectly – for example, for the set of observations with a 30% predicted probability, exactly 30% of them are truly from Fox News transcripts. Similarly, this holds for all twenty bins (of 5% increments). As can be seen in the figure, the fit is remarkably good. The conditional predicted rates are almost perfectly on top of the 45 degree line.

To understand better how the model is making these predictions, we examine the bigram features that are most important for its classification choices. An advantage of logistic regression in this respect is its interpretability: The estimated coefficients of the trained model, $\hat{\psi}_b$, provide a ranking across the 2,000 predictive bigrams in terms of their relative contribution to the predictions. Because the predictors are standardized to the same variance, the coefficients are comparable and roughly interpretable as the relative marginal effect of the associated bigram on the predicted probability that a document is from Fox News.

Table 2 shows examples of bigrams with positive (predictive for FNC transcripts) or negative (predictive for CNN/MSNBC) values of $\hat{\psi}_b$.[10] Prominent figures like Sean Hannity (predictive of FNC) or Anderson Cooper (predictive of CNN/MSNBC) appear among the bigrams. Fox bigrams allude to intuitively conservative priorities such as the troops, crime, terrorism, and (implied) extremism of political counterparts ("far left"). CNN/MSNBC bigrams have a more liberal flavor, with mentions of health-policy related tokens and emphasis on international perspectives. Interestingly, both sets of features

[10] Appendix Table B.1 includes a longer list.

Table 2: Distinctive phrases associated with Fox News and CNN/MSNBC

FNC	**CNN/MSNBC**
al qaida	eastern pacif
homicid detect	chief medic
war stori	report baghdad
captur terrorist	person world
sean hanniti	anderson cooper
far left	polit analyst

Notes: Examples of bigrams with positive (predictive for FNC transcripts) or negative (predictive for CNN/MSNBC) coefficient values in the penalized logistic regression (of a label equaling one for FNC snippets, and zero for CNN/MSNBC snippets on the bigrams used in a snippet).

mention to similar topics or events (e.g., war). This already suggests that the differences in cable news rhetoric are, at least in part, due to framing of topics, rather than just topic choices (we investigate this question in Section 6.1).

3.3. Text similarity between newspapers and TV stations

Having validated that our model captures useful information, we can now take it to the newspaper snippets to score their relative similarity to each cable news network. Let N be the set of newspaper article snippets (indexed by n) and A_n^s the frequency of predictive bigram s in snippet n. A_n is the vector of frequencies (of length S) for article n. Our prediction of FNC, $\widehat{FNC}$, for snippet n is hence:

$$\widehat{FNC}_n = \Pr[FNC = 1|A_n] = \frac{1}{1 + \exp(-\hat{\psi}' A_n)}$$

which gives a predicted probability (between zero and one) for how likely each newspaper snippet was generated by Fox News.

Note that, as newspaper article snippets do not come with any label, we cannot evaluate accuracy in predicting newspaper article language. However, we provide some interpretive validation in Appendix C, where we list the news article snippets with the highest and lowest $\widehat{FNC}_n$. We find that the topical and rhetorical content of the article snippet reflects intuitions about the ideological commitments of the networks. In Appendix Table B.2, we see that FNC-related articles include defenses of U.S. military involvement in Africa, crime, Bush's opposition to troop withdrawals, and a Supreme Court case about the Second Amendment (right to bear arms). Articles that are closest to CNN/MSNBC (Appendix Table B.3) are about campus groups supporting gay rights, the AIDS crisis in Africa, President Bush's responsibility for the financial crisis, and HIV in the gay community.

We now have $\widehat{FNC}_n$ as a similarity measure between TV channel language and the language in newspaper article n. To link the article-level data to the other datasets at the newspaper level i or the county level j, we aggregate by taking the mean values of the contained news articles. Hence, we define Slant_{ijs} as our newspaper-level slant measure, equal to the average probability of snippets by newspaper i (in county j in state s) to be FNC-like.

For the main analysis, we combine our text similarity measures with data on cable news viewership. In our main dataset, there are 305 newspapers circulating in 12.4 counties on average (the median is six counties), resulting in the aforementioned 3,781 observations. Appendix Figure B.1 shows the distribution of linguistic similarity with FNC for the 305 unique newspapers in our main dataset (i.e., Slant_{ijs}).

3.4. Topic model

When studying the mechanisms of slant contagion in Section 6, we require topic labels for the transcripts and news articles. To learn topics directly from our parallel corpus, we use the Latent Dirichlet Allocation (LDA) topic modeling approach of Blei et al. (2003). LDA is the standard approach for topic modeling in social-science applications (e.g., Hansen et al., 2018; Bybee et al., 2020). It represents documents as combinations of a finite number of latent topics, while the topics are characterized by a distribution over words.

We build two different topic models: one based on the TV transcripts and one based on the newspaper article snippets. For both models, we specify 128 topics and train LDA on a random sample of 1 million documents (TV transcript snippets or newspaper article snippets, respectively).[11] The topics are labeled manually based on the associated words (see Appendices B.5 and B.6).

We then use the trained models to assign topic(s) to all transcripts and all newspaper articles. The TV-transcripts-based topic model is used for the analysis of framing in

[11] We use the online variational Bayes (VB) implementation by Hoffman et al. (2010). To select the number of topics, we started with 32 topics and doubled the number of topics until they became largely interpretable to humans. 128 topics ended up working well for both corpora.

Section 6.1. The newspaper-articles-based topic model is used to label articles as either local or non-local, as discussed further in Section 6.2.

4. Econometric Framework

Our main hypothesis is that higher viewership of a cable channel in a county will cause the local newspapers to feature content similar to that channel's. This section outlines our method to test for this causal relationship.

4.1. Instrumental variables specification

The empirical strategy uses an instrumental variable regression. The main outcome variable is Slant_{ijs}, the textual similarity to Fox News for newspaper i circulating in county j in state s (see Section 3.3 above). Slant_{ijs} is a relative measure. It is interpretable as the average predicted probability that the articles of a newspaper came from FNC, rather than CNN or MSNBC. Correspondingly, we are interested in the causal effect on this outcome of *relative* local viewership of FNC compared to CNN/MSNBC. Hence, we specify our main treatment variable, Viewership_{js}, as the county-level Fox News viewership relative to the averaged county-level CNN and MSNBC viewership: FNC Viewership - 0.5×(MSNBC viewership+CNN viewership).[12]

We specify the relationship between slant and viewership using a linear model:

$$\text{Slant}_{ijs} = \alpha_s + \theta \text{Viewership}_{js} + X_{ijs}\beta + \epsilon_{ijs} \tag{2}$$

where θ is the causal parameter of interest. Besides the outcome and treatment, the regression includes state fixed effects (α_s), a vector of county and newspaper controls (X_{ijs}), and an error term (ϵ_{ijs}). The set of covariates X_{ijs} varies across specifications, but can include demographic controls (see Appendix Table A.2), channel controls (population share with access to each of the three TV channels), and generic newspaper language controls (vocabulary size, avg. word length, avg. sentence length, avg. article length).

Estimating Equation (2) using OLS is likely to produce biased estimates of θ. There are many political and economic factors that may correlate with both Fox News viewer-

[12] This specification for the treatment is different from Martin and Yurukoglu (2017) and reflects our different outcome and research question. Still, we will report the more standard specification of just (non-relative) FNC viewership in robustness checks.

ship and the use of Fox-like language by local newspapers – in particular, any pre-existing ideological preferences of the county. The potential correlation between Viewership_{js} and ϵ_{ijs} due to these confounders would add bias to OLS coefficients. To address this problem, we take an instrumental-variables approach.

Inspired by Martin and Yurukoglu (2017), we use cable network channel positioning to construct an instrument Position_{js} that affects Viewership_{js} but is otherwise unrelated to any factors affecting Slant_{ijs}. As first shown by Martin and Yurukoglu and since used in a number of papers (e.g., Galletta and Ash, 2019), there is arbitrary variation in cable channel positioning across U.S. localities. This channel positioning leads to exogenous shifts in viewership because television watchers spend more time on networks with lower channel positions. Thus, we instrument viewership using channel position. Because our treatment is a relative measure of FNC viewership compared to CNN/MSNBC viewership, we specify the instrument Position_{js} as the county-level FNC channel position relative to the averaged channel position of MSNBC and CNN: FNC Position - 0.5×(MSNBC Position+CNN Position).[13] The first stage estimating equation is

$$\text{Viewership}_{js} = \alpha_s + \delta \text{Position}_{js} + X_{ijs}\beta + \eta_{ijs} \tag{3}$$

where the other terms are as above.

The first stage (3), combined with Equation (2), can be estimated with two-stage least squares (2SLS) to procure causal estimates for the local average treatment effect θ. To facilitate the interpretation of the coefficients, we standardize the instrument, endogenous regressor, and outcome by dividing the original values by the standard deviations. Standard errors are two-way-clustered by newspaper and county.[14]

Our estimates use weighted regressions. Most newspapers serve more than one county, yet the circulation across counties is unevenly distributed. To account for how much each newspaper is influenced by the channel position in its associated counties, newspaper-county observations are weighted by a newspaper's circulation in that county.[15]

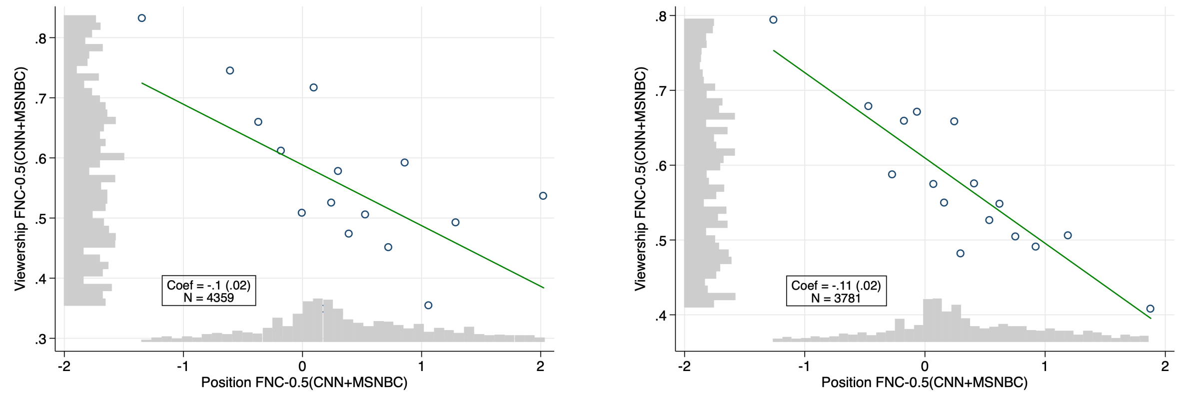
[13] As mentioned above, we will also report the more standard specification of just (non-relative) FNC channel position in robustness checks.

[14] We show that our results are also significant when standard errors are clustered by state.

[15] We demonstrate robustness to other weighting schemes, including a variant of the approach in Martin and Yurukoglu (2017) which weights by the number of households in a locality surveyed by Nielsen.

Figure 3: First Stage: Cable Channel Position and Cable News Viewership

(a) No controls (b) With controls



Notes: Binned scatterplots (16 bins) of standardized viewership of FNC-0.5(CNN+MSNBC) against standardized position of FNC-0.5(CNN+MSNBC). Cross-section with newspaper-county-level observations weighted by newspaper circulation in each county. On the left, state fixed effects are included. On the right, state fixed effects, as well as demographic controls (see Appendix Table A.2), channel controls (population share with access to each of the three TV channels), and generic newspaper language controls (vocabulary size, avg. word length, avg. sentence length, avg. article length) are included. In grey (next to the axes), we show the distributions of the underlying variables.

4.2. Instrument validity

2SLS requires relevance in the first stage. Figure 3 visualizes the first-stage relation between the FNC channel position (relative to the averaged position of CNN and MSNBC) and FNC viewership (also relative to CNN/MSNBC).[16] The relationship is significantly negative and similar without controls (panel a) and with the addition of controls (panel b). A one-standard-deviation decrease in the relative channel position (11 positions in the lineup) increases relative viewership by about 10% of a standard deviation (0.041 rating points). A one-tenth of a rating point equals roughly 45 minutes per month of (additional) viewership per household. Hence, our first-stage coefficient means that decreasing the channel position of FNC by 11 (while holding the positions of CNN and MSNBC constant) would increase the viewership of FNC and decrease the viewership of CNN/MSNBC such that the FNC-to-CNN/MSNBC viewership difference goes up by 22 minutes per month. In the tables below, we report Kleinbergen-Paap cluster-robust first-stage F-statistics and they are consistently above 30, indicating a well-powered first stage.

Beyond relevance, 2SLS imposes three requirements for consistent estimates. The

[16] See Appendix Table C.1 for coefficients and standard errors in tabular format.

first two, exclusion and monotonicity, are not problematic in our context. Exclusion requires that the channel position affects local news reporting only through its effect on cable news viewership. We believe this is a reasonable assumption in our context. The monotonicity assumption is that the channel position influences news viewership in the same direction for all counties. It is reasonable to assume that increasing the channel position would not systematically increase viewership.

The third assumption, exogeneity, is that Position_{js} is uncorrelated with ϵ_{ijs}. More concretely, we need that the channel position is not endogenously selected with county-specific preferences for conservative or liberal news reporting. The main identification problem is that channel positions could be allocated strategically in response to local factors correlated with conservative news messaging.

Martin and Yurukoglu (2017) provide a detailed discussion and a set of checks supporting the exogeneity assumption. Based on qualitative research, they highlight that channel positions have an important arbitrary, historical component, with significant inertia and path dependence. Quantitatively, the instrument is not correlated with Republican vote shares before the introduction of Fox News Channel. Galletta and Ash (2019) report a number of additional checks at the county level showing the instrument to be unrelated to demographic characteristics that predict policy preferences or news channel viewership.

We apply the same identification checks to the counties in our sample (newspaper-county-level data). As in Galletta and Ash (2019), we use linear regressions with demographic characteristics and state fixed effects as covariates to predict viewership and newspaper content. Specifically, we obtain predictions related to the endogenous regressor (viewership) and to the outcome (the probability of newspaper content to be Fox-like). These predictions summarize the variation in viewership and news content that is due to pre-existing cultural, economic, and political characteristics of these counties.

We then regress these predictions on different definitions of our instrument Position_{js}. Table 3 shows the results of this identification check. Columns 1 and 2 document that there is no significant relationship between the absolute position of Fox News and the predicted values for viewership or newspaper content. Columns 3 and 4 show that there is no significant relationship between relative FNC channel position and the respective

Table 3: Identification checks: Instrument Uncorrelated with Relevant Covariates

	Reduced form			
	Viewership FNC* (absolute) (1)	Slant_{ijs}* (2)	Viewership FNC* (rel. to CNN/MSNBC) (3)	Slant_{ijs}* (4)
FNC position (absolute)	-0.022	0.017		
	(0.043)	(0.013		
FNC position (rel. to CNN/MSNBC)			0.006	-0.006
			(0.025)	(0.006)
N observations	3781	3781	3781	3781
State FE	X	X	X	X

Notes: Estimates are based on OLS with newspaper-county-level observations weighted by newspaper circulation in the respective county. Asterisks (*) indicate linear predictions: The dependent variable is the predicted viewership of FNC in column (1), the predicted newspaper language similarity with FNC in columns (2) and (4), and the predicted viewership of FNC relative to averaged MSNBC and CNN viewership in (3). The predictions are derived from regressions that include the full set of demographic controls and state fixed effects. Standard errors are multiway-clustered at the county and at the newspaper level (in parenthesis): * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

predicted values.[17]

Overall, these results support the view that channel positions are not selected or adapted to county characteristics that are otherwise important for our endogenous regressor or outcome. The placebo nulls provide additional support for instrument validity and more generally for our empirical strategy.

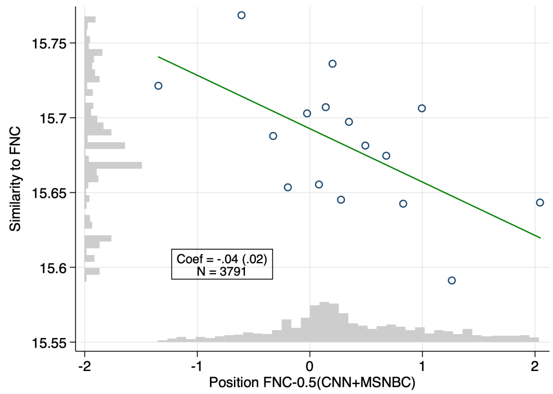
5. Results

This section first presents the main results, which include reduced form and two-stage-least-squares estimates. Second, it reports robustness checks.

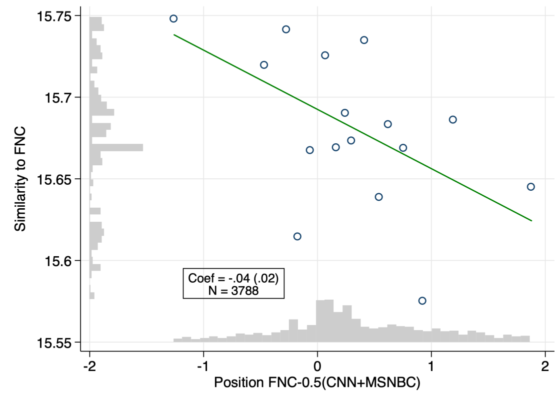
[17] As an additional placebo we estimate our main specifications but using as the predicted text similarity to cable news using local newspaper articles from 1995 and 1996 (pre-FNC/MSNBC). The placebo check estimates, reported in Appendix Table C.2, show no significant effects. Reassuringly, there was not a pre-existing Fox-like language dimension in locations that later had a lower Fox channel position. Note that the placebo regressions are based on fewer observations than the main results because some newspaper titles are not yet available in NewsLibrary in 1995 and 1996, or their circulation data is not yet available from the AAM. Our main results remain qualitatively similar and are significant at the $p<0.01$ level if we only use the observations entering the placebo regression.

Figure 4: Reduced form: Cable News Channel Position and Local Newspaper Content Similarity

(a) No controls



(b) With controls



Notes: Binned scatterplots (16 bins) of standardized textual similarity with Fox News against standardized position of FNC-0.5(CNN+MSNBC). Cross-section with newspaper-county-level observations weighted by newspaper circulation in each county. On the left, state fixed effects are included. On the right, state fixed effects, as well as demographic controls (see Appendix Table A.2), channel controls (population share with access to each of the three TV channels), and generic newspaper language controls (vocabulary size, avg. word length, avg. sentence length, avg. article length) are included. In grey (next to the axes), we show the distributions of the underlying variables.

5.1. Main results

Figure 4 visualizes the reduced form relationship between the FNC channel position (relative to the averaged MSNBC and CNN position) and local newspaper content similarity to FNC. In the left part of the Figure (panel a), the outcome and the instrument are residualized on state fixed effects. On the right-hand side (panel b), we additionally include demographic controls, channel controls (share of households with access to each of the three channels), and generic newspaper language features (vocabulary size, average word length, average sentence length, and average article length).[18] There is a clear downward relationship, suggesting that easier access to FNC is associated with more FNC-like language in the local county newspapers.[19]

Table 4 shows two-stage-least-squares estimates of the effect of higher FNC viewership on newspaper language similarity with FNC (the average probability that a snippet from a newspaper is predicted to be from FNC based on the bigrams it contains). The right-hand side variable of interest is instrumented FNC viewership relative to averaged CNN and MSNBC viewership. All columns include state fixed effects and demographic

[18] As discussed further in Section 6.1 below, we find that the instrument does not have a direct effect on these language features (see Appendix Table C.13).

[19] See Appendix Table C.4 for the reduced-form results in tabular format.

Table 4: Cable News Effects on Newspaper Content (2SLS)

Dep. variable: Slant_{ijs}=$\Pr(FNC\|\text{Text}_{ijs})$	(1)	(2)	(3)
FNC Viewership (rel. to CNN/MSNBC)	0.314***	0.311***	0.318**
	(0.114)	(0.113)	(0.126)
K-P First-Stage F-stat	36.553	36.298	34.147
N observations	3781	3781	3781
State FE	X	X	X
Demographic controls	X	X	X
Channel controls		X	X
Newspaper language controls			X

Notes: 2SLS estimates. Cross-section with newspaper-county-level observations weighted by newspaper circulation in each county. The dependent variable is newspaper language similarity with FNC (the average probability that a snippet from a newspaper is predicted to be from FNC), Slant_{ijs}. The right-hand side variable of interest is instrumented FNC viewership relative to averaged CNN and MSNBC viewership: *Viewership (FNC - 0.5(MSNBC - CNN))*. All columns include state fixed effects and demographic controls as listed in Appendix Table A.2. Column 2 also includes channel controls (population shares with access to each of the three TV channels). Column 3 controls for generic newspaper language features (vocabulary size, avg. word length, avg. sentence length, avg. article length). Standard errors are multiway-clustered at the county and at the newspaper level (in parenthesis): * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

controls. Column 2 also includes controls for the share of households with potential access to each of the three TV channels. Column 3 additionally controls for generic newspaper language features.

In all three columns, the estimated treatment effects are positive and statistically significant. The magnitudes across columns are highly similar, they range from 0.31 in columns 1 and 2 to 0.32 in column 3. This means that the channel and language controls do not change the estimates relative to the baseline in column 1 where only state fixed effects and demographic controls are included. All variables are standardized, so the interpretation is as follows: if Fox News viewership (relative to averaged CNN and MSNBC viewership) increases by one standard deviation in county j where newspaper i circulates, the similarity of i's content with FNC increases by 0.31 standard deviations.[20] Alternatively, a one-standard-deviation decrease in the relative FNC channel position (11 relative positions) would increase slant by 0.03 standard deviations.

To interpret the magnitudes, note that the average difference of slant between an

[20] As already mentioned, OLS estimates of the relationship between FNC viewership and FNC-related language in local newspapers do not have a causal interpretation. These are reported in Appendix C.3. Overall, we find that OLS coefficients have a positive sign, as with the 2SLS coefficients, though they are smaller in magnitude and only significant for absolute FNC viewership.

FNC transcript snippet and a CNN/MSNBC transcript snippet *in standardized units* is 0.99 (the raw difference, in predicted probabilities, is 0.21). Given the estimated 2SLS coefficient (0.31), we can say that a one-standard-deviation decrease in the relative FNC channel position (11 positions) will shift slant towards FNC by about 3 percent of the difference between FNC and CNN/MSNBC. Regardless, we emphasize that 2SLS estimates identify a local average treatment effect (LATE), so they are externally valid only for the set of newspaper-county observations that are responsive to the channel-position instrument.

5.2. Robustness checks

This section provides various checks to assess the robustness of the main results. First, we show robustness of the results to alternative samples. Appendix Table C.5 replicates the baseline estimates but only considering newspaper-county observations where the county coincides with where the immediate owner of the newspaper is based.[21] The effect size is more than doubled relative to the entire sample and still statistically significant despite a smaller sample.[22]

Second, we show robustness to alternative weighting specifications. In Appendix Table C.8, we show that the results are robust to weighting by circulation from the pre-FNC/MSNBC era (1995), meaning that our main results are not driven by potential changes in circulation due to cable news exposure.[23] Next, we weight observations by *relative* circulation shares by county, multiplied by the number of surveyed individuals for each county by Nielsen (Appendix Table C.9). In using the number of surveyed individuals, we follow Martin and Yurukoglu (2017).[24] The results are again positive and statistically significant.

Third, we replicate the main results using different specifications for the instrument (Appendix Table C.11). Instead of FNC viewership relative to CNN and MSNBC view-

[21] We assign the city where the owner of the local newspaper is based to a U.S. county, using data from the Alliance for Audited Media (see Section 2). We focus on *immediate* owners – that is, we do not consider the location of the parent company for newspapers that are owned by a conglomerate.

[22] On the other hand, as shown in Appendix Table C.6, the effect is smaller and no longer significant when excluding headquarters counties.

[23] We do not use the pre-FNC/MSNBC county-level circulation data in our main analysis because it is available for fewer outlets, resulting in half the sample size. Our baseline specification (contemporary circulation weights) is robust to using the subsample of observations where 1995 circulation is available.

[24] Similarly, we also weight observations by relative circulation shares by county, multiplied by county population (Appendix Table C.10).

ership combined, we look at FNC viewership relative to CNN and MSNBC separately (columns 1/2 and columns 3/4, respectively), or FNC viewership on its own (columns 5 and 6). The estimates are positive and overall consistent with our main results, yet not statistically significant in the FNC-vs-CNN specification.

Fourth, we replicate our main results, but relying on a different matching of newspapers to counties. We assign each newspaper to a main county based on its name and other metadata, producing a larger sample but with less detailed information on circulation (see Appendix Section A.2 for details on this approach). The results are fully robust (Appendix C.6).

Finally, Appendix C.10 reports two additional checks. Our main results are still statistically significant when clustering by state rather than by county and newspaper (Appendix Table C.12). The results are consistently statistically significant when dropping each newspaper individually (Appendix Figure C.2).

6. Heterogeneous Effects and Mechanisms

This section provides some additional supporting results to better understand the mechanisms for the contagious slant effect. First, we distinguish topics from framing. Second, we check whether there is an effect for local news or just for national news. Third, we show some evidence that FNC has had a polarizing effect on local newspapers.

6.1. Slant effects are mostly driven by framing rather than topics

A first mechanism question is what features of newspaper language are changing in response to cable news. The politicized nature of the bigrams predictive of FNC versus MSNBC/CNN (see Section 3.2) suggests that the diffusing slant consists of ideological or political content, but one alternative we would like to check is whether more stylistic (that is, apolitical) features of the newspaper language change in response to higher FNC exposure. In Appendix Table C.13, we show there is no effect of FNC exposure on generic style features (vocabulary size, average word length, average sentence length, and average article length).

Within the space of political content, we explore whether the changes in the newspaper language are driven by changes in the topics or in the framing. It could be that cable news changes the news agenda, so that local newspapers cover the same types of stories (e.g., writing more about the military, rather than about poverty). Or instead, it could be that the broad stories are constant, but framed differently (e.g., writing more supportively of the military, or more dismissively of poverty). To check for the relevance of topics, we re-run our penalized logistic regression (see Section 3.2), but now with the topic shares instead of the bigrams as features, to predict whether a TV transcript snippet is from FNC or CNN/MSNBC (for details on the topic model, see Section 3.4). Using this feature set, we obtain a test set accuracy of just 55%, much lower than the 73% with bigram features. That is, our classifier cannot distinguish the cable networks using broad topics. This finding is an initial indication that our measure of slant is primarily due to framing.

To further explore the relevance of framing, we run our main regressions but adding topic shares from the newspaper articles as an additional set of covariates.[25] As shown in Appendix Table C.14, the estimates are largely unchanged, providing descriptive evidence that the changes in local newspaper content are predominantly driven by framing. However, the coefficients are around 20% smaller in magnitude, suggesting that broad topics do play a minor role.[26]

6.2. Cable news media slant influences local news content

A second mechanism question on slant contagion is what parts of the newspaper content are shifting to be more like cable TV news. One possibility is that slant diffusion works via production costs, making it cheaper for local news outlets to produce articles by borrowing content (either directly or by picking up the same stories that the channels cover). Another possibility is that slant diffusion works by shifting the news preferences of readers, in which case the slanted content would also spill over into originally produced

[25] That is, we use the topic model trained on cable news transcripts to assign to each newspaper article its topic shares for each of the 128 topics. We then aggregate the topic shares at the newspaper level, giving us an indication of how much a newspaper generally focuses on a given topic.

[26] Our preferred specification (third column; with all controls) implies that if Fox News viewership (relative to averaged CNN and MSNBC viewership) increases by one standard deviation in county js where newspaper ijs circulates, the FNC similarity of the newspaper content increases by 0.26 standard deviations (the same coefficient is 0.32 in Table 4 without topic controls).

material.[27] Local news is a content category where direct borrowing of material is not possible, given the national focus of the cable news channels. Thus, to elucidate this issue we study whether cable news exposure influences articles in the local news section.

To distinguish local news from non-local (that is, national or international) news, we proceed as follows. For every topic out of the 128 topics, we manually label whether the topic is more likely to cover local as opposed to non-local news (see Appendix Section B.6). We then impose the criterion that a newspaper article snippet is classified as local news if, cumulatively, more than 50% of its topic share(s) cover topics labelled as local. We validate this approach as capturing local news content via blind annotation of 2,000 newspaper article snippets.[28]

To analyze the local-news issue, Table 5 replicates our main regression specification but using three alternative outcomes. Column 1 shows the effect of instrumented FNC viewership (relative to CNN and MSNBC) on the share of local news. There is no effect, adding further evidence that cable-news exposure does not change the broad topics covered. Next, column 2 shows that there is a positive and significant effect on non-local (national and international) news, with a coefficient even larger than our main estimate. The large effect on non-local content is intuitive given that these are the topics often covered by cable news outlets, so direct borrowing of content by local newspapers is possible. Finally, column 3 shows the effect on the textual slant of local news articles, for which direct borrowing is not possible. There is nonetheless a positive and statistically significant effect, with point estimates almost identical to our main results.[29]

[27]The features of the institutional setting make direct influence of journalists, either through production costs or ideological preferences, an unlikely mechanism for the observed 2SLS effects. A journalist can easily access cable news and borrow material, regardless of local channel position. Because journalists are relatively sophisticated news consumers, they generally have strong pre-existing news preferences and would not be nudged by the instrument. Martin and Yurukoglu (2017) discuss this issue in the context of voting, where one would expect cable news to influence swing voters who don't have a strong partisan commitment. Ash and Poyker (2019) make a similar point in the context of judges: cable news influences criminal sentencing through voters and judicial elections, rather than persuading judges directly.

[28]We recruited annotators on Upwork, as we did for the human validation of the slant measure (see Appendix Section B.2). The annotators were not given any topic information; they simply read the newspaper article snippet. 74 out of the 2,000 articles could not be labelled as either local or non-local (it was unclear). We found that the topic-based predictions come with an accuracy of 81% relative to the human annotation. Since most news is local news, we also check other metrics for the local category. The F1-score is 86%, while precision and recall are 88% and 84%, respectively.

[29]Note that most of the newspaper article snippets are local news (71% are local news according to human annotation, and 75% according to our topic-model-based categorization). Therefore, the sample underlying Table 5 is similar to the one in Table 4.

Table 5: Cable News Effects on Newspaper Content: (Non-)Local News

Dep. variable:	Local share$_{ijs}$	Slant$_{ijs}$	Slant$_{ijs}$
FNC viewership (rel. CNN/MSNBC)	0.039	0.377***	0.295**
	(0.032)	(0.134)	(0.131)
K-P First-Stage F-Stat	34.147	34.147	34.147
N observations	3781	3781	3781
Non-local articles		X	
Local articles			X
State FE	X	X	X
Demographic controls	X	X	X
Channel controls	X	X	X
Newspaper language controls	X	X	X

Notes: 2SLS estimates, only considering local news articles. Cross-section with newspaper-county-level observations weighted by newspaper circulation in each county. In the first, column, the dependent variable is the share of articles in a newspaper categorized as local. In column 2 and 3, the dependent variable is newspaper language similarity with FNC (the average probability that a snippet covering local news from a newspaper is predicted to be from FNC). In column 2, we only include non-local newspaper articles when aggregating the slant measure at the newspaper-level. In column 3, only local newspaper articles are considered. The right-hand side variable of interest is FNC viewership relative to averaged CNN and MSNBC viewership. All columns include state fixed effects and demographic controls as listed in Appendix Table A.2, channel controls (population shares with access to each of the three TV channels), and controls for generic newspaper language features (vocabulary size, avg. word length, avg. sentence length, avg. article length). Standard errors are multiway-clustered at the county and at the newspaper level (in parenthesis): * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Thus, slant contagion works on both local and non-local news content. The effect on local news is notable because it means that cable news influences the original content of local outlets. An interpretation of these results is that contagious slant is not working just by reducing the costs of news production; in addition, local news producers are responding to the shifted partisan slant preferred by cable-exposed readers, even for local content. Thus, the results are consistent with demand-side effect of cable news media slant. See Appendix C.12 for some additional descriptive analysis consistent with demand side effects.

6.3. Cable news media slant polarizes local newspapers

Finally, we investigate effect heterogeneity with respect to the prior partisan commitments of local newspapers. We distinguish three groups of outlets based on 1996 U.S. presidential election endorsements: (1) those that endorsed the Republican candidate Bob Dole, (2) those that endorsed the Democrat candidate Bill Clinton, and (3) those that did not endorse either candidate.[30] We think of endorsements as a signal for whether the pre-FNC/MSNBC political leaning of a newspaper was relatively conservative or liberal. The non-endorsers can be seen as politically neutral.[31]

Table 6 shows the heterogeneity analysis by endorsements, where we re-estimate our main specification but on different subsets of newspapers. Column 1 limits the analysis to Democrat-endorsing newspapers, and we find a *negative* and significant coefficient, suggesting that newspapers with a more liberal leaning become *less* FNC-like in their reporting when more exposed to FNC (relative to MSNBC and CNN). In column 3, we subset on newspapers that endorsed the Republican candidate. These newspapers behave the same as the main sample – a positive coefficient means the more right-wing newspapers adopt more FNC-like language. Meanwhile, when looking at newspapers with no endorsements or where no endorsement data is available (column 2), there is no effect of cable media slant on newspaper content.

These results suggest that cable channel exposure might polarize local news content, in the sense that right-leaning newspaper outlets follow FNC but move away from MSNBC/CNN, whereas left-leaning outlets follow MSNBC/CNN while moving away from FNC. To explore this possibility in more detail, we run an alternative regression

[30]In this latter group we include newspapers where we could not find an explicit endorsement.

[31]Note that 1996 endorsements are pre-FNC/MSNBC and so independent of channel positioning. Our main results are virtually unchanged when including the 1996 endorsement of a newspaper as a control.

Table 6: Cable News Effects on Newspaper Content (2SLS): By Historical Endorsements

Dep. variable: $\text{Slant}_{ijs}=\Pr(FNC\|\text{Text}_{ijs})$	(1)	(2)	(3)
FNC Viewership (rel. to CNN/MSNBC)	-0.463*	0.062	0.259**
	(0.246)	(0.160)	(0.116)
K-P First-Stage F-Stat	10.586	19.708	16.070
N observations	872	1858	1040
Endorsed Democrat	X		
No (Known) Endorsement		X	
Endorsed Republican			X
State FE	X	X	X
Demographic controls	X	X	X
Channel controls	X	X	X
Newspaper language controls	X	X	X

Notes: 2SLS estimates. Cross-section with newspaper-county-level observations weighted by newspaper circulation in each county. The dependent variable is newspaper language similarity with FNC (the average probability that a snippet from a newspaper is predicted to be from FNC). The right-hand side variable of interest is instrumented FNC viewership relative to averaged CNN and MSNBC viewership. In column 1 we only include newspapers that endorsed the Democratic Presidential candidate in 1996 (pre-FNC era). In column 2, we focus on newspapers that did not endorse either candidate (or for which endorsement data is not available). Column 3 considers only newspapers that endorsed the Republican candidate. All columns include state fixed effects, demographic controls as listed in Appendix Table A.2, channel controls (population shares with access to each of the three TV channels), and generic newspaper language features (vocabulary size, avg. word length, avg. sentence length, avg. article length). Standard errors are multiway-clustered at the county and at the newspaper level (in parenthesis): * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

specification that separates out the effects of FNC and MSNBC/CNN. Specifically, we run reduced-form specifications with Slant_{ijs} as the outcome but including two separate treatment variables: (1) the absolute channel position of FNC and (2) the average absolute channel positions of CNN and MSNBC.[32] We find that the effects measured in Table 6 are indeed driven by right-leaning newspapers following FNC when it has a lower channel position and left-leaning newspapers moving away from FNC when it has a lower channel position. Higher exposure to the liberal channels MSNBC/CNN has no effect on the content of left-leaning newspapers, while right-leaning newspapers tend to

[32]Note that the coefficient signs are reversed in the reduced form specification due to a negative first stage. A positive coefficient implies that a lower position of a channel leads to less adoption of slant.

move away from the liberal channels.[33]

Overall, this evidence suggests that exposure to FNC (and to a lesser degree, CNN and MSNBC) has polarized local newspaper language. Newspapers with a right-wing partisan leaning in the pre-FNC/MSNBC era adopt right-wing cable news language in response to FNC viewership increases. Instead, left-wing papers become more left-wing. This dynamic could arise from a market positioning effect (Mullainathan and Shleifer, 2005; Gentzkow et al., 2014). That is, the conservative papers situate themselves to accommodate FNC-viewer news preferences. In turn, liberal papers respond and situate to accommodate non-FNC-viewer news preferences. This type of ideological positioning process is consistent with demand-side mechanisms.

7. Conclusion

This paper documents that partisan news messaging by large media organizations can spill over to other news outlets. Specifically, we document that the news messaging by U.S. cable TV channels influences local news reporting. Regarding the TV channels, we focus on two poles: on the one hand the Fox News Channel (which is typically seen as conservative), and, on the other hand CNN and MSNBC (known to lean liberal). Based on TV show transcripts from these channels, we build a machine learning model that predicts whether a given piece of text resembles FNC rather than CNN/MSNBC. We then use this model to construct a novel measure of partisan slant in local newspapers: the predicted similarity of their content with FNC versus CNN/MSNBC.

Using exogenous variation in TV channel viewership at the county level, we show that higher FNC viewership leads to more FNC-like language in local news – and vice versa for CNN/MSNBC. Furthermore, we build on the fact that the TV channels address a national audience: We present some evidence that the newspapers shift the slant in their own local stories, rather than copy-pasting national or international stories. Moreover, we find that the exposure to the TV channels leads to a polarization of local news,

[33] Appendix Table C.16 shows the same polarizing trends when looking at Republican vote shares in the pre-FNC/MSNBC era: It replicates Table 6 but instead of pre-FNC/MSNBC era newspaper endorsements, distinguishes observations by the county-level Republican vote share terciles (lowest tercile in the first column, second tercile in middle, and highest tercile in the last column). Again, the relative FNC exposure coefficient is negative in the first column, positive and relatively small in the second column (coefficients in columns 1 and 2 are not significant), before turning significant, positive, and large in the last column.

where outlets that had already been pro-Republican in the pre-FNC/MSNBC era shift more towards FNC-like language. In contrast, outlets with a historically pro-Democrat leaning move towards CNN/MSNBC-like language in response to higher FNC exposure. These findings add to concerns regarding increasing political polarization in the U.S. and beyond (e.g., Campbell, 2018; Carothers and O'Donohue, 2019).

These results add to the literature on the political effects of biased news. We provide new evidence on how partisan media influences not just voting and policy, but also the content of other media organizations. Our results highlight that media outlets or technologies cannot necessarily be considered independent from each other. In addition, future work must allow for secondary indirect effects of partisan media. Such effects could work on voting and other outcomes by reshaping news landscapes and influencing the content of other media providers.

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A. Data Appendix

A.1. Newspaper articles

First, some more info on NewsLibrary. For each article, the NewsLibrary provides the newspaper name, the headline, the date, the byline (if any), and (approximately) the first 80 words of the article.

In principle, NewsLibrary encompasses around 4,000 unique titles for 2005-2008. However, for many titles, there are only a handful of articles available: around 1,500 titles contain less than 1,000 snippets (for all four years combined). In all our analyses, we only consider titles with more than 1000 articles. Also, many titles are not local newspapers in the sense that they cannot be assigned to a county (e.g., the "Army Communicator" or the "Air & Space" magazine). Furthermore, NewsLibrary often lists different editions of the same title separately. For instance, "Augusta Chronicle, the (GA)", "Augusta Chronicle, the: Web Edition Articles (GA)", and "Augusta Chronicle, the: Blogs (GA)" are listed separately. While our initial corpus covers all 2,618 titles with >1,000 articles (amounting to almost 50 million article snippets, see Section A.3), our main analyses focus on 305 titles for which county-level circulation data is available (see Section 2). We also collapse different editions of the same outlet (as in the Augusta Chronicle example) to one observation because the Alliance for Audited Media circulation data is typically not available separately for different editions of the same title. The 16 million articles mentioned in the main text refer to the outlets used in our main regression analyses.

A.2. Alternative county matching of newspapers

For robustness, we also apply an alternative matching procedure which covers more newspaper titles, but which only provides total circulation instead of county-specific circulation. First, we obtain the main county for each newspaper title based on the newspaper name and geographical information provided by NewsLibrary (e.g., *The Call (Woonsocket, RI)* or the *Albany Democrat-Herald (OR)*), the U.S. Newspaper Directory, or a manual web search. For the circulation, we use more broad-based, but less granular data: we assign total circulation (as of 2004) according to the Inter-University Consortium for Political and Social Research (ICPSR) to this main county. Hence, each newspaper is now only assigned to one county, where its total circulation is assumed to accrue. With this matching approach, we have a dataset of 682 unique newspaper titles and 24 million article snippets. As Appendix Table C.7 shows, with the alternative matching, the coefficients are again statistically significant and around three to four times larger than in the main Table 4.

A.3. Filtering and number of article snippets

Table A.1 gives an overview of the number of articles collected and how we obtain the number of articles used in our main analyses and robustness checks.

Table A.1: Number of Articles Collected and Filtering

Filtering	**# Articles**	**Results**
No filtering: raw scrapes	49,891,120	None (not possible: no county assignment)
County assignment as in App. A.2 and total circulation data available (ICPSR)	23,979,516	Table C.7
County assignment as in Sec. 2 and county-level circulation data available (AAM)	16,098,537	All other tables

A.4. Summary statistics

Table A.2: Summary Statistics

Variable	Mean	Std. Dev	Min	Max	N
Newspapers (and newspaper language)					
Probability FNC	0.434	0.029	0.38	0.655	3781
Circulation	5067.311	18487.863	1	390687.8	3781
Vocabulary size	0.026	0.023	0.007	0.146	3781
Word length	7.221	0.288	6.292	8.321	3781
Sentence length	35.846	6.826	18.858	69.036	3781
Article length	447.782	112.426	193.957	918.617	3781
# collected articles	83289.858	57642.203	1067	286027	3781
News channels					
FNC channel position 2005-2008	42.647	11.502	5	74.625	3781
CNN channel position 2005-2008	30.299	10.408	1	66.306	3781
MSNBC channel position 2005-2008	45.138	13.006	4	128.5	3781
Position (Fox News-0.5(MSNBC+CNN))	4.928	11.219	-48.042	54.75	3781
Position (Fox News - MSNBC)	-2.491	13.641	-81.417	55	3781
Position (Fox News - CNN)	12.347	12.769	-39	59.618	3781
Ratings % Fox News 2005-2008	0.539	0.354	0	5.475	3781
Ratings % MSNBC 2005-2008	0.14	0.384	0	13	3781
Ratings % CNN 2005-2008	0.303	0.229	0	3.7	3781
Ratings (%Fox News - 0.5(%MSNBC - %CNN))	0.318	0.411	-7.600	5.412	3781
Ratings (%Fox News - %MSNBC)	0.399	0.512	-12.55	5.45	3781
Ratings (%Fox News - %CNN)	0.236	0.377	-2.65	5.375	3781
Share pop. access to FNC	0.934	0.106	0.039	1	3781
Share pop. access to MSNBC	0.891	0.174	0.004	1	3781
Share pop. access to CNN	0.962	0.067	0.055	1	3781
Demographic Controls					
Population 2000	210572.061	509458.494	712	9818535	3781
Republican vote share 1996	0.426	0.098	0.093	0.79	3781
White	0.858	0.139	0.057	0.993	3781
Black	0.077	0.116	0	0.795	3781
Asian	0.014	0.028	0	0.359	3781
Hispanic	0.064	0.114	0.002	0.973	3781
Male	0.493	0.014	0.433	0.627	3781
Age 10-19	0.16	0.016	0.088	0.277	3781
Age 20-29	0.12	0.03	0.047	0.327	3781
Age 30-39	0.144	0.017	0.082	0.23	3781
Age 40-49	0.153	0.013	0.096	0.213	3781
Age 50-59	0.116	0.012	0.063	0.177	3781
Age 60-69	0.082	0.017	0.035	0.173	3781
Age 70-79	0.066	0.018	0.013	0.172	3781
Age 80-89	0.039	0.013	0.003	0.121	3781
Urban	0.538	0.284	0	1	3781
High school	0.342	0.072	0.111	0.527	3781
Some college	0.263	0.049	0.108	0.424	3781
Bachelor	0.125	0.053	0.028	0.397	3781
Postgraduate	0.068	0.04	0.013	0.31	3781
Land area	309.047	405.331	1.768	6812.404	3781
Population density	4.454	1.706	-1.08	10.307	3781
Mean log. income	10.794	0.231	10.105	11.597	3781
Gini index	0.429	0.036	0.335	0.604	3781
Occ. management and professional	29.63	6.791	16.6	61.3	3781
Occ. service	15.466	2.809	8.1	31.9	3781
Occ. sales and office	24.449	2.978	13.6	32.6	3781
Occ. farming, fishing, and forestry	1.43	1.722	0	24.9	3781
Occ. construction, extraction, and maintenance	10.818	2.644	2.3	24.5	3781

B. Methods Appendix

Here, we present additional material related to the measurement of cable news slant.

B.1. Bigrams most predictive for FNC or CNN/MSNBC

Table B.1 lists the 200 bigrams that are most predictive for a transcript being from FNC or CNN/MSNBC, respectively (specifically, the bigrams that come with the largest absolute coefficients in the logistic regression from Section 3).

Table B.1: Top 200 of bigrams predictive for FNC or CNN/MSNBC transcripts

FNC-Related		MSNBC/CNN-Related	
segment tonight	steve thank	situat room	point tonight
fox news	thank sean	anderson cooper	stay welcom
correspond mike	welcom washington	king live	report baghdad
final tonight	join reaction	senior polit	later today
dick morri	come straight	person world	live baghdad
mr oreilli	ahead continu	live pictur	polit analyst
chief white	jim thank	best polit	stay stori
power player	fair balanc	great appreci	york good
david lee	doubl homicid	watch cnn	thank ahead
correspond jim	got run	david shuster	food drug
come panel	whos stand	cnn report	hes author
sean know	wrap thing	hello hello	im join
sean hanniti	georg soro	glenn beck	mari thank
jame thank	laura ingraham	wolf blitzer	real stori
al qaida	record right	jack thank	eastern right
roll tape	deepak satish	join tomorrow	later broadcast
plenti ahead	time left	question hour	let ahead
live vote	jonathan thank	chief medic	washington thank
went record	captur terrorist	thank larri	york stock
join author	karen hanretti	share stori	morn thank
latest polit	casey anthoni	david gergen	day presidenti
jennif thank	chief polit	stori work	quick want
homicid detect	lack better	polit news	pat buchanan
right colonel	join boston	noon eastern	andrew speaker
bring legal	minut left	hello yes	news cnn
brit hume	war stori	im toni	thank lot
later special	play tape	hes join	tonight real
secular progress	later rememb	watch stori	new concern
let screen	right mr	work stori	bit earlier
anyth unusu	ted know	donna brazil	investig unit
headlin come	illeg right	dont away	sure appreci
ahead welcom	dr michael	paul begala	right susan
senat mcconnel	report moment	tonight eastern	thank joe
ill word	michell malkin	ramo compean	want updat
emin domain	senior command	know larri	come situat
live phone	sort thought	thank ed	andrea mitchel
panel stay	regular folk	live today	result poll
mr speaker	drill anwr	spi program	thank toni
thank panel	anywher world	eastern pacif	hello everyon
kiryat shmona	happen join	headlin news	ahead tonight
griffin report	michael reagan	weather center	heart diseas
steve forb	right sir	news debat	happen news
thank major	thank special	david gregori	youll want
mike thank	forens pathologist	pentagon correspond	news follow
second left	tell later	look headlin	new pictur
far left	bring panel	pleas join	talk morn
join los	stay im	shes join	closer look
record good	look come	stay come	ill speak
oclock morn	fair doctrin	good everybodi	bailout plan

FNC-Related		MSNBC/CNN-Related	
oh stop	crimin alien	danc star	stori day
stori wont	search underway	stori stay	hour presid
later program	yes polic	impact world	dow point
thank moment	marriott hotel	bring date	race white
note earlier	left wing	littl ago	transport safeti
record come	special report	ill talk	job lost
amber frey	right panel	health offici	correspond dana
join dalla	dr dobson	winter storm	earlier morn
holiday inn	youll meet	watch unfold	join talk
governor good	light fact	larri king	join tonight
welcom good	homicid investig	lung cancer	atlanta georgia
strong economi	upper incom	hurrican ike	work men
da mike	live scene	hous thank	vinci code
welcom program	killer killer	complet coverag	steve fossett
charl krauthamm	welcom aboard	right ed	stori follow
undermin presid	hezbollah hama	listen senat	receiv copi
right sean	murder scene	tom cruis	mind busi
appreci guy	franklin graham	come hour	continu watch
come continu	atm card	great thank	talk tomorrow
news correspond	later polic	develop news	littl clip
public radio	jim know	thank time	im chris
sneak peek	media research	associ editor	short break
dr perper	captain thank	war room	john dean
code pink	time pleas	let listen	bird flu
drew peterson	john kelli	good morn	right larri
guilt associ	headlin new	talk live	begin tonight
welcom come	senat schumer	pictur come	lot join
legitim point	westchest counti	new studi	look stori
brett favr	liber want	larri thank	hold news
correspond jeff	madison wisconsin	miss soldier	thank updat
execut editor	abl determin	toni know	jone industri
live aruba	black panther	report thank	day news
ward churchil	aruban polic	polit director	weve hear
elect decemb	scott peterson	poll tonight	drug cartel
dispos bodi	join san	thank david	shes watch
mark thank	inform tonight	senior editor	chris matthew
gloria allr	doctor thank	meantim let	let stori
ladi thank	congressman good	thank report	live white
sir come	arm control	new number	end video
chief thank	frantic search	day number	poll believ
privat jet	judg instruct	big board	look thought
father pfleger	american media	sever weather	snow new
loui farrakhan	murder right	valeri wilson	thank want
beth holloway	duke case	let head	war middl
ninth circuit	gaza strip	flight cancel	hi everybodi
senat graham	chief prosecutor	expect hear	thank brian
ad quot	interview fox	american idol	big number
respect law	rais good	let play	winner loser
guest say	byron york	harri potter	report pentagon

B.2. Human validation of NLP model

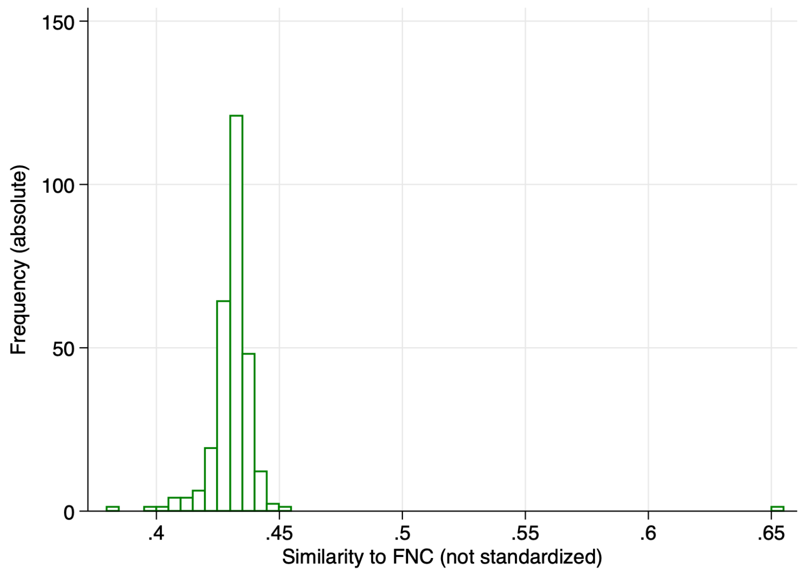
We evaluate the accuracy of human guesses on whether an 80-word TV transcript snippet is from FNC or CNN/MSNBC. This section provides some more detail on this validation step. We extract a random sample of 1,000 TV transcript snippets and ask three individual freelancers to guess whether each snippet is from FNC or CNN/MSNBC.

The individuals were recruited from the freelancing platform Upwork. When selecting the individuals, we imposed these three filtering criteria: must (i) live in the United States, (ii) be socialized in the U.S. (e.g., born and raised in the U.S.), and (iii) show good literacy (defined by properly reading our instructions, i.e., returning a valid working sample, see below). The initial job post read as follows: "We have a file with 1,000 very short excerpts of news reports. You will read them and spontaneously (based on your intuition) decide if you think a given excerpt was published by Fox News or by CNN. In the process of labelling, do not google or engage in any other form of research. Just give us your spontaneous impression based on how you perceive news reporting by the two channels in your everyday life." All freelancers who replied to this post within a day were requested to submit a working sample of 10 snippets. We recruited the first three individuals who submitted the requested working sample. The hired freelancers received the file with the reminder: "Please indicate whether you think the text is from Fox News or CNN. We would like to remind you that you mustn't do research of any kind when assessing the excerpts. Your labels should be based on your spontaneous guess and nothing else." All individuals had or were in the process of acquiring a college degree. They were based in Point Pleasant (WV), Malvern (PA), and Houston (TX).

The accuracy scores of the freelancer's guesses are 0.73, 0.78, and 0.78, respectively. The average false-positive rate (a freelancer guesses a CNN/MSNBC snippet to be from FNC) is slightly higher (at 0.14) than the false-negative rate (0.08). The three freelancers agree on whether a snippet appears to be from FNC or from CNN/MSNBC in 58% of cases (if they guessed randomly, they would agree in 25% of cases). We derive two conclusions from this exercise. First, even if cut into 80-word snippets, TV transcripts still contain information that allows a reader to infer the channel. Second, our classifier approximates the performance of humans.

B.3. Distribution of Fox News similarity in newspapers

Figure B.1: Distribution of Local Newspaper Content Similarity with FNC



Notes: Histogram (bin width 0.005) of newspaper-level predictions. The figure shows the absolute frequency (unique newspaper counts) against the average value of FNC similarity by newspaper ($\widehat{FNC}_j$). For most newspapers, we predict that – on average – a snippet resembles FNC with a probability between 0.40 and 0.45.

B.4. Example articles by Fox News similarity

Table B.2: Newspaper articles that are most similar to Fox News Channel shows

The Free Lance-Star (Fredericksburg, VA), 2 January 2008
98% similarity to FNC
Regarding their recent op-ed ["The Pentagon should stay out of Africa," Dec. 14], I am afraid Danny Glover and Nicole Lee are victims of misinformation about U.S. Africa Command. AFRICOM is not part of a "U.S. military expansion," nor will it involve placing many "American troops on foreign soil." Rather, AFRICOM marks recognition of the growing importance of Africa and reallocates responsibility for U.S. security interests accordingly. The U.S. Department of Defense assigns [...]

The Sacramento Bee (CA), 19 May 2007
97% similarity to FNC
Don Kercell thinks he's earned a second chance. The Contractors State License Board does not agree. And therein lies a tale of choices and consequences; crime and punishment; addiction and rehabilitation; public protection and personal redemption – and second chances. Kercell is a 48-year-old resident of Rio Linda. In his youth, he discovered two things. One was that he had a talent for working with concrete. The other was methamphetamine. [...]

Joplin Globe, the (MO), 28 April 2007
95% similarity to FNC
Bush vows to veto any attempts by Dems to force troop pullout CAMP DAVID, Md. – President Bush warned Congress Friday that he will continue vetoing war spending bills as long as they contain a timetable for the withdrawal of American troops from Iraq. Speaking a day after the Democratic-controlled Congress approved legislation that requires that a troop drawdown begin by Oct. 1, Bush said – as he has before - he will veto it because of that demand. He [...]

The Commercial Appeal (Memphis, TN), 16 June 2008
83% similarity to FNC
WASHINGTON – One momentous case down, another equally historic decision to go. The Supreme Court returns to the bench Monday with 17 cases still unresolved, including its first-ever comprehensive look at the Second Amendment's right to bear arms. The guns case – including Washington, D.C.'s ban on handguns – is widely expected to be a victory for supporters of gun rights. Top officials of a national gun control organization said this week that they expect the handgun ban to be [...]

Table B.3: Newspaper articles that are most similar to CNN and MSNBC shows

The Sun (San Bernardino, CA), 21 March 2005
3% similarity to FNC
REDLANDS - A week after a state judge ruled that banning gay marriage is unconstitutional, students at University of Redlands will celebrate the milestone along with continued efforts to raise awareness of the gay community.The PRIDE Alliance, a campus group devoted to promoting tolerance on campus for gay, lesbian, bisexual and transgender students, will celebrate PRIDE Week at the university through Friday. A series of events is scheduled to raise awareness on campus and in the [. . .]

Robesonian, the (Lumberton, NC), 12 October 2007
4% similarity to FNC
About $18 billion a year has been drained from Africa by nearly two dozen wars in recent decades, a new report states, a price some officials say could've helped solve the AIDS crisis and created stronger economies in the world's poorest region."This is money Africa can ill afford to lose," Liberian President Ellen Johnson Sirleaf wrote in an introduction to the report by the British charity Oxfam and two groups that seek tougher controls on small arms, Saferworld [. . .]

Denver Examiner (CO), 26 September 2008
5% similarity to FNC
John McCain and Barack Obama will indeed debate tonight at 7 p.m at the University of Mississippi, moderated by Jim Lehrer. The debate is scheduled to focus on issues of foreign policy, but given the economic meltdown of the last two weeks, and the Bush administration's proposed $700 billion bailout plan, Politico is reporting that Lehrer might add in some questions on the economy. Also, Rich Lowry from National Review is reporting that everyone at Ole Miss "hates" McCain for [...]

Long Beach Press-Telegram (CA), 22 June 2006
6% similarity to FNC
There is finally some good news about the most sinister drug on the black market: crystal methamphetamine. Nationwide demand and production is down, according to federal drug cops. Meth, which has been linked to the spread of HIV in Long Beach's gay community, is still out there, but law enforcement officials say plenty of busts are reducing supplies. We hope that treatment is part of the equation nationwide as it is California, where voters agreed to put more users in treatment than in [. . .]

B.5. Topics from the transcript-based LDA model

Table B.4: Transcript-Based LDA Topic Model: List of 128 Topics

Most frequent tokens	Topic label
victim destroy katrina crowd relief	disaster
station ride regular stern dinner	infrastructure
know mean like thing dont	opinion
worst scenario chavez bowl cuba	communism
governor state california mexico alert	state governments
year ago old jail time	crime
car sunni shia militia say	islam
im know right say ok	no label
tape context say pop sat	scandals
key saudi stronger arabia plame	foreign intelligence service
shouldnt object option greatest fault	no label
arizona missouri wisconsin ice home	us states
deal ship port big built	ports and nautics
money spend want make know	money
girl young boy yearold sexual	child protection
god pain plant bless exist	god and christian religion
ahead date pope straight new	god and christian religion
father son daughter dna super	family
hezbollah profit rocket quarter rapid	terrorism
human exit right male gap	internet
life heart lay react rid	lifestyle and health
pakistan british london britain musharraf	international politics
right look eye blood like	health and accidents
shes woman mother mom know	motherhood
progress union dream boat equal	unions and labor
group air citizen learn defend	no label
iran nuclear weapon iranian say	international politics
confirm wilson memo hide mr	international politics
travel bus gate seat broken	travel
school student teacher high class	schools
alan drive driver detect contract	economy
africa know deepak tj stadium	international politics
nice rumsfeld donald trump stone	defense
killer rock birth pro scientist	crime
lawyer prosecutor say attorney appeal	judiciary
palestinian meet ban item gaza	middle east
war iraq world terror american	military and war
faith duke jesus shame christ	god and christian religion
miss search suspect disappear aruba	crime

Notes: The 128 topics from the transcript-based model and their labels. The first columns shows the most frequent tokens for each topic. The second column lists the manually chosen topic labels. Sometimes, two or more topics are similar and receive the same label. For 28 out of 128 topics, no obvious label emerges. Table continued on the next page.

Most frequent tokens	Topic label
children die husband wife space	family
social account gore benefit invest	social insurance
truth pardon fourth alabama campus	judiciary
edward lieberman colorado connecticut neck	crime
thank come right join sir	events
vote voter democrat state republican	democracy and voting
pay billion dollar cost tax	economy
protest research stem complex cell	protests
reverend embarrass pastor speech sharpton	god and christian religion
white say africanamerican staff bush	racial issues
elect june day year turnout	democracy and voting
afghanistan chief withdraw tactic troop	military and war
hi stage hello studio hollywood	no label
interview politician talk hair say	politics
palin sarah japan alaska yard	tea party
fish steroid cabinet say youth	no label
word nbc news page right	no label
wear cloth dress shirt look	lifestyle and health
price gas higher fuel oil	oil and oil products
murder attorney death general professor	crime
appoint voter veto anger know	politics
percent care health say number	healthcare
ph glad sergeant corp art	military and war
million cut fund store budget	economy
inform threat warrant collect time	no label
mayor guard corrupt new nation	politics
shoot newsroom live atlanta da	no label
terrorist qaeda attack terror bin	terrorism
kid book parent right know	family
radio leadership republican talk host	politics
north south carolina korea korean	no label
saw bomb train scene film	no label
visit honor flag sight winner	honoring america
game play saddam san trial	no label
storm west coast wind florida	weather
kick ring scream jew fat	crime
bush prime rate mr say	international politics
closer shelter right juror louisiana	local politics
child avail ticket patient various	no label
prison sex offend colonel rice	imprisonment
plane angel los airport crash	aviation
sponsor pitch inject bat flipflop	baseball
yes dont know right like	no label
ive phone video know got	no label

Notes: The 128 topics from the transcript-based model and their labels. The first columns shows the most frequent tokens for each topic. The second column lists the manually chosen topic labels. Sometimes, two or more topics are similar and receive the same label. For 28 out of 128 topics, no obvious label emerges. Table continued on the next page.

Most frequent tokens	Topic label
democrat republican clinton mccain campaign	national politics
site web internet post email	internet
dog mass smoke cold thing	no label
women men speaker pelosi indiana	politics
reagan accept gay director ronald	national politics
state unit iraq govern iraqi	international politics
door georgia sheriff bear born	no label
vice cheney dick red jersey	national politics
law freedom religion protect right	freedom
hate brain coulter lunch compel	hate
gun lie sound small like	guns and shooting
job china buy american product	economy
confess column repair trick dispatch	celebrity news
east lebanon syria camp hezbollah	international politics
hes romney perform mitt know	no label
question border answer ask agent	border control
status abc brutal sold ton	no label
court rule record legal standard	judiciary
obama barack mccain clinton campaign	national elections
said say know didnt talk	no label
congress worker program member guest	politics
iraq troop iraqi soldier kill	military and war
home friend like feel felt	home and neighbours
credit bank card oj simpson	economy
fight forth distinct loud shoulder	no label
fbi strike depart homeland new	homeland security
media list theyll know cop	media
forward crime commit intent say	crime
push trail planet sooner right	no label
need joran drill sloot bail	no label
land occur board flight wing	aviation
cancer treatment english brand aint	healthcare
tax cut tire talk hes	taxation
ad doctor dr say treat	healthcare
grand schiavo pray walter feed	no label
tonight poll new tomorrow news	no label
oil barrel oprah nifong say	oil and oil products
think dont know want thing	no label
hour player ohio box alcohol	no label
test special sunday eastern come	no label
area weather flood rain island	weather
drug letter say use tool	drugs
amend control stake cbs award	no label
street market wall stock apart	infrastructure
food rush model tree limbaugh	agriculture

Notes: The 128 topics from the transcript-based model and their labels. The first columns shows the most frequent tokens for each topic. The second column lists the manually chosen topic labels. Sometimes, two or more topics are similar and receive the same label. For 28 out of 128 topics, no obvious label emerges. Table continued on the next page.

B.6. Topics from the newspaper-based LDA model

Table B.5: Newspaper-Based LDA Topic Model: List of 128 Topics

Most frequent tokens	Topic label	Local news
davi broker morgan stanley princeton	international economic actors	0
plant garden winter farmer flower	farmers	1
dairi payn lilli liabil utica	no label	0
probat fine suspend penalti ppg	crime	1
collin prayer omaha floyd billi	small city names	1
ice indiana chip hall fame	food	1
light marshal lane bennett home	local happenings	1
law immigr illeg enforc clinton	border control	0
harrison intellig counsel harper island	no label	0
park water lake land river	nature and infrastructure	1
springfield indian martinez tribe riley	local happenings	1
paul pope novel decatur roman	names	1
health care medic hospit center	healthcare	1
airport said nuclear plane iran	aviation and terrorism	0
oregon wine meter sullivan wildlif	nature and infrastructure	1
rate credit class flag glass	economy	0
secur report exchang act date	no label	0
offic agenc number address post	post	1
navi laker naval salina reagan	no label	0
walker nevada dear easter mother	family	1
bird boulder rent rumor wagner	farmers	1
weather snow temperatur day degr	weather	1
club golf channel cour rain	sports and associations	1
ford busi small negoti sewer	no label	0
new announc cancer technolog program	technology	0
phillip perri campbel crawford year	names	1
right left disabl miller list	healthcare	1
current estim ratio consensus low	international economic actors	0
school high student graduat colleg	education	1
art museum artist paint exhibit	arts and culture	1
drink mental said jacksonvil sleep	alcoholism	1
pound donat blood baker weigh	charities	1
harbor sioux alt nichol wheeler	no label	0
concert israel orchestra drill isra	no label	0
compani million inc financ bank	economy	0
like time year get day	no label	0
salem african sex violenc offend	crime (international)	0
event annual celebr saturday award	holidays	1
daytona ranger wyom walsh bengal	no label	0

Notes: The 128 topics and their labels. The first columns shows the most frequent tokens for each topic. The second column lists the manually chosen topic labels. Sometimes, two or more topics are similar and receive the same label. For 22 out of 128 topics, no obvious label emerges. The last column captures whether we label the topic to be indicative of local rather than non-local (national, international) news. Table continued on the next page.

Most frequent tokens	Topic label	Local label
recycl mitchel firework merchant berlin	no label	0
girl boy basketb team tournament	sports and associations	1
iowa coloni fork delta cousin	no label	0
hurrican storm orlean katrina scout	disaster	1
polic said man offic report	crime	1
church servic fort wayn king	religion	1
beach bond sacramento barri borough	local infrastructure	1
davenport coleman consolid newark freeman	small city names	1
cross chapter heart royal kati	no label	0
rapid cedar huntington myer dispatch	no label	0
pierc warner celtic augustin year	local services	1
news page editor letter mail	media	1
jewish griffin supplement year penguin	nature	1
coach team season footbal game	sports and associations	1
ring hopkin waterloo peanut philippin	no label	0
santa idaho mph wind powel	weather	1
fayettevil newport rhp montreal alarm	small city names	1
holland cole bedford missionari zion	local happenings	1
food chicken appl fresh recip	food	1
ashland mapl boyd ash birmingham	small city names	1
film movi inch screen jone	television	0
die home funer born son	family	1
book children child read parent	family	1
stock share trade type date	economy	0
palm charg kent beach counti	crime	1
estim consensus buy hold sell	economy	0
govern pari lebanon attack said	international policitics	0
manag new build applic develop	economy	0
los que del las por	spanish word parts	0
san final chicago sport new	no label	0
serv marin vega utah bend	military	0
team game first state win	sports and associations	1
meet counti center inform call	local events	1
card jackson comput ident check	assets	0
point score run game win	sports and associations	1
inmat jail aberdeen blind counti	no label	0
estim current previous next report	economy	0
ridg oak cape fli flint	local surroundings	1
danc fish swim lesson pool	leisure	1
island rhode jacob hanov hilton	no label	0
circl rod roof turkey fbi	no label	0
architect pipe middletown year benson	local infrastructure	1
world global ship warm africa	climate change	0
bridg traffic truck transport interst	traffic and infrastructure	1

Notes: The 128 topics and their labels. The first columns shows the most frequent tokens for each topic. The second column lists the manually chosen topic labels. Sometimes, two or more topics are similar and receive the same label. For 22 out of 128 topics, no obvious label emerges. The last column captures whether we label the topic to be indicative of local rather than non-local (national, international) news. Table continued on the next page.

Most frequent tokens	Topic label	Local label
shaw chili year resolv aug	no label	0
state bill hous tax feder	national politics	0
anderson wichita granddaught victoria alexand	names and family	1
windsor bow elgin perkin sanford	no label	0
call phone confer mine press	international policitics	0
nelson horn wore said ordinari	local happenings	1
kansa oakland smith sport network	small city names	1
monro sept col nobl camden	no label	0
citi board council counti plan	local politics	1
year baseb new like first	sports and associations	1
drove said furnitur gun mckinney	crime	1
site com www web onlin	internet	0
bush muslim bee year abort	national politics	0
anim dog human pet cat	pets	1
railroad riversid rail jul fairfield	infrastructure	0
real estat new jersey coff	real estate	1
mar space broadcast alert maryland	space and technology	0
mobil breakfast hair lopez rutger	local services	1
minist china said prime foreign	international policitics	0
tree cup egg salt sugar	food	1
percent year increa counti rate	economy	0
store shop question answer box	shopping	1
bull get think time want	no label	0
drug librari possess marijuana dec	drugs	1
hole shot round par dame	sports and associations	1
eve watson woodland wade poster	local infrastructure	1
price year gas oil get	oil and oil products	0
race vote elect voter ballot	local politics	1
music show perform band theater	arts and culture	1
mart wal beer penn zoo	local services	1
alabama casino portland auburn memphi	local infrastructure	1
fire firefight depart burn said	fire and firefighters	1
court judg charg counti attorney	crime	1
ticket gay arlington gordon victor	local services	1
wilson wrestl olymp stewart warren	sports and associations	1
peterson aurora spur hancock dawson	local services	1
youth camp day peoria summer	local events	1
supervisor petit counti signatur cumberland	local politics	1
farm syracus intersect road paso	small city names	1
restaur cook smoke food eat	food	1
war iraq militari veteran armi	military and war	0
peopl get map mani exerci	daily life	1
consum montana store destin fare	shopping	1
ride year hor old dad	local services	1
presid democrat republican elect state	national politics	0

Notes: The 128 topics and their labels. The first columns shows the most frequent tokens for each topic. The second column lists the manually chosen topic labels. Sometimes, two or more topics are similar and receive the same label. For 22 out of 128 topics, no obvious label emerges. The last column captures whether we label the topic to be indicative of local rather than non-local (national, international) news.

C. Results Appendix

C.1. First stage results

Table C.1: Cable TV Position Effects on Viewership (First Stage)

Dep. variable: FNC Viewership$_{ijs}$ (rel. to CNN/MSNBC)	(1)	(2)	(3)
FNC Position (rel. to CNN/MSNBC)	-0.113***	-0.113***	-0.114***
	(0.019)	(0.019)	(0.020)
N observations	3781	3781	3781
State FE	X	X	X
Demographic controls	X	X	X
Channel controls		X	X
Newspaper language controls			X

Notes: First stage estimates. Cross-section with newspaper-county-level observations weighted by newspaper circulation in each county. The dependent variable is FNC viewership (relative to averaged CNN and MSNBC viewership). The right-hand side variable of interest is the channel position of FNC, relative to the averaged position of CNN and MSNBC viewership. All columns include state fixed effects and demographic controls as listed in Appendix Table A.2. Column 2 also includes channel controls (population shares with access to each of the three TV channels). Column 3 controls for generic newspaper language features (vocabulary size, avg. word length, avg. sentence length, avg. article length). Standard errors are multiway-clustered at the county and at the newspaper level (in parenthesis): * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C.2. Placebo: Content Similarity in 1995/96

Table C.2: Placebo Cable News Effects on Newspaper Content (2SLS)

Dep. variable: $\text{Slant}_{ijs}=\Pr(FNC\|\text{Text}_{ijs})$	(1)	(2)	(3)
FNC Viewership (rel. to CNN/MSNBC)	-0.133	-0.078	-0.302
	(0.456)	(0.424)	(0.714)
K-P First-Stage F-stat	18.265	18.276	13.654
N observations	1143	1143	1143
State FE	X	X	X
Demographic controls	X	X	X
Channel controls		X	X
Newspaper language controls			X

Notes: 2SLS estimates. Cross-section with newspaper-county-level observations weighted by newspaper circulation in each county. The dependent variable is newspaper language similarity with FNC (the average probability that a snippet from a newspaper is predicted to be from FNC) **in 1995/1996** (pre-FNC era). The text similarity scores use the 2005-2008 TV transcripts (same as the main analysis) because FNC and MSNBC did not yet exist in 1995-1996. The right-hand side variable of interest is instrumented FNC viewership relative to averaged CNN and MSNBC viewership. All columns include state fixed effects and demographic controls as listed in Appendix Table A.2. Column 2 also includes channel controls (population shares with access to each of the three TV channels). Column 3 controls for generic newspaper language features (vocabulary size, avg. word length, avg. sentence length, avg. article length). Standard errors are multiway-clustered at the county and at the newspaper level (in parenthesis): * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C.3. OLS results

Table C.3 shows OLS results for regressions of predicted Fox News similarity for newspaper ijs, Slant_{ijs}, on TV channel viewership. Column 1 looks at FNC viewership relative to averaged MSNBC and CNN viewership. It hence shows the OLS estimates that mirror the 2SLS results in the main Table 4 (specifically, column 3). In columns 2 and 3, we look at FNC viewership relative to CNN and MSNBC separately. Column 4 focuses on absolute FNC viewership. All columns include state fixed effects and demographic controls as listed in Appendix Table A.2, channel controls (population shares with access to each of the three TV channels), and controls for generic newspaper language features (vocabulary size, avg. word length, avg. sentence length, avg. article length). The OLS coefficients are positive, as the 2SLS coefficients, though smaller in magnitude and only significant for absolute FNC viewership.

Table C.3: Cable News Effects on Newspaper Content (OLS)

Dep. variable: $\text{Slant}_{ijs}=\Pr(FNC\vert\text{Text}_{ijs})$	(1)	(2)	(3)	(4)
FNC Viewership (rel. to CNN and MSNBC)	0.015			
	(0.011)			
FNC Viewership (rel. to CNN)		0.019		
		(0.014)		
FNC Viewership (rel. to MSNBC)			0.012	
			(0.010)	
FNC Viewership (absolute)				0.028**
				(0.013)
N observations	3781	3781	3781	3781
State FE	X	X	X	X
Demographic controls	X	X	X	X
Channel controls	X	X	X	X
Newspaper language controls	X	X	X	X

Notes: OLS estimates. Cross-section with newspaper-county-level observations weighted by newspaper circulation in each county. The dependent variable is newspaper language similarity with FNC (the average probability that a snippet from a newspaper is predicted to be from FNC): $\widehat{FNC}_{jik}=P(FNC|Text_{jik})$. In the first column, the right-hand side variable of interest is FNC viewership relative to averaged CNN and MSNBC viewership. In the second column, it is FNC viewership relative to CNN viewership. In the third, it is FNC viewership relative to MSNBC viewership. Finally, in the fourth column, it is absolute FNC viewership. All columns include state fixed effects and demographic controls as listed in Appendix Table A.2, channel controls (population shares with access to each of the three TV channels), and controls for generic newspaper language features (vocabulary size, avg. word length, avg. sentence length, avg. article length). Standard errors are multiway-clustered at the county and at the newspaper level (in parenthesis): * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C.4. Reduced form results

Table C.4: Cable News Effects on Newspaper Content (Reduced Form)

Dep. variable: Slant$_{ijs}$	(1)	(2)	(3)
FNC Position (rel. to CNN/MSNBC)	-0.036***	-0.035***	-0.036***
	(0.012)	(0.012)	(0.013)
N observations	3781	3781	3781
State FE	X	X	X
Demographic controls	X	X	X
Channel controls		X	X
Newspaper language controls			X

Notes: Reduced form estimates. Cross-section with newspaper-county-level observations weighted by newspaper circulation in each county. The dependent variable is newspaper language similarity with FNC (the average probability that a snippet from a newspaper is predicted to be from FNC). The right-hand side variable of interest is the channel position of FNC, relative to the averaged position of CNN and MSNBC viewership: *Position (FNC - 0.5(MSNBC - CNN))*). All columns include state fixed effects and demographic controls as listed in Appendix Table A.2. Column 2 also includes channel controls (population shares with access to each of the three TV channels). Column 3 controls for generic newspaper language features (vocabulary size, avg. word length, avg. sentence length, avg. article length). Standard errors are multiway-clustered at the county and at the newspaper level (in parenthesis): * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C.5. Sub-samples: Newspaper Headquarters and Other Counties

Table C.5: Cable News Effect on Newspaper Content (2SLS): Newspaper-Headquarter Counties

Dep. variable: $\text{Slant}_{ijs}=\Pr(FNC\|\text{Text}_{ijs})$	(1)	(2)	(3)
FNC Viewership (rel. to CNN/MSNBC)	0.711**	0.701**	0.684**
	(0.288)	(0.287)	(0.287)
K-P First-Stage F-Stat	11.630	11.659	11.982
N observations	263	263	263
State FE	X	X	X
Demographic controls	X	X	X
Channel controls		X	X
Newspaper language controls			X

Notes: 2SLS estimates. Cross-section with newspaper-county-level observations weighted by newspaper circulation in each county. This Table only includes newspaper-county observations where the county coincides with the newspaper headquarters. The dependent variable is newspaper language similarity with FNC (the average probability that a snippet from a newspaper is predicted to be from FNC). The right-hand side variable of interest is instrumented FNC viewership relative to averaged CNN and MSNBC viewership. All columns include state fixed effects and demographic controls as listed in Appendix Table A.2. Column 2 also includes channel controls (population shares with access to each of the three TV channels). Column 3 controls for generic newspaper language features (vocabulary size, avg. word length, avg. sentence length, avg. article length). Standard errors are multiway-clustered at the county and at the newspaper level (in parenthesis): * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.6: Cable News Effect on Newspaper Content (2SLS): Non-Newspaper-Headquarter Counties

Dep. variable: $\text{Slant}_{ijs} = \Pr(FNC \mid \text{Text}_{ijs})$	(1)	(2)	(3)
FNC Viewership (rel. to CNN/MSNBC)	0.132	0.127	0.109
	(0.081)	(0.079)	(0.106)
K-P First-Stage F-Stat	47.698	49.911	46.439
N observations	3507	3507	3507
State FE	X	X	X
Demographic controls	X	X	X
Channel controls		X	X
Newspaper language controls			X

Notes: 2SLS estimates. Cross-section with newspaper-county-level observations weighted by newspaper circulation in each county. This Table only includes newspaper-county observations where the county does *not* coincide with the newspaper headquarters. The dependent variable is newspaper language similarity with FNC (the average probability that a snippet from a newspaper is predicted to be from FNC). The right-hand side variable of interest is instrumented FNC viewership relative to averaged CNN and MSNBC viewership. All columns include state fixed effects and demographic controls as listed in Appendix Table A.2. Column 2 also includes channel controls (population shares with access to each of the three TV channels). Column 3 controls for generic newspaper language features (vocabulary size, avg. word length, avg. sentence length, avg. article length). Standard errors are multiway-clustered at the county and at the newspaper level (in parenthesis): * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C.6. Robustness: Alternative county matching

Table C.7: Cable News Effects on Newspaper Content (2SLS): Alternative Matching Procedure

Dep. variable: Slant_{ijs}=$\Pr(FNC\|\text{Text}_{ijs})$	(1)	(2)	(3)
FNC Viewership (rel. to CNN/MSNBC)	0.859**	1.051**	1.164**
	(0.338)	(0.426)	(0.455)
K-P First-Stage F-Stat	19.704	14.828	13.869
N observations	682	682	682
State FE	X	X	X
Demographic controls	X	X	X
Channel controls		X	X
Newspaper language controls			X

Notes: 2SLS estimates. Cross-section with newspaper-level observations weighted their total circulation. The dependent variable is newspaper language similarity with FNC (the average probability that a snippet from a newspaper is predicted to be from FNC). The right-hand side variable of interest is instrumented FNC viewership relative to averaged CNN and MSNBC viewership. All columns include state fixed effects and demographic controls as listed in Appendix Table A.2. Column 2 also includes channel controls (population shares with access to each of the three TV channels). Column 3 controls for generic newspaper language features (vocabulary size, avg. word length, avg. sentence length, avg. article length). Standard errors are clustered at the state level (in parenthesis): * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C.7. Robustness: Historical circulation weights

Table C.8: Cable News Effects on Newspaper Content (2SLS): 1995 Circulation Weights

Dep. variable: Slant_{ijs}=$\Pr(FNC \mid \text{Text}_{ijs})$	(1)	(2)	(3)
FNC Viewership (rel. to CNN/MSNBC)	0.556***	0.538***	0.561***
	(0.165)	(0.162)	(0.180)
K-P First-Stage F-Stat	21.357	21.311	19.157
N observations	1928	1928	1928
State FE	X	X	X
Demographic controls	X	X	X
Channel controls		X	X
Newspaper language controls			X

Notes: 2SLS estimates. Cross-section with newspaper-county-level observations weighted by newspaper circulation in 1995 (the pre-FNC era) in each county. The dependent variable is newspaper language similarity with FNC (the average probability that a snippet from a newspaper is predicted to be from FNC). The right-hand side variable of interest is instrumented FNC viewership relative to averaged CNN and MSNBC viewership. All columns include state fixed effects and demographic controls as listed in Appendix Table A.2. Column 2 also includes channel controls (population shares with access to each of the three TV channels). Column 3 controls for generic newspaper language features (vocabulary size, avg. word length, avg. sentence length, avg. article length). Standard errors are multiway-clustered at the county and at the newspaper level (in parenthesis): * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C.8. Robustness: Relative circulation weights

Table C.9: Cable News Effects on Newspaper Content (2SLS): Relative Circ. Weights × Sampled Households

Dep. variable: Slant$_{ijs}$=Pr(FNC|Text$_{ijs}$)	(1)	(2)	(3)
FNC Viewership (rel. to CNN/MSNBC)	0.521***	0.509***	0.922**
	(0.173)	(0.172)	(0.442)
K-P First-Stage F-Stat	20.790	20.973	20.801
N observations	3781	3781	3781
State FE	X	X	X
Demographic controls	X	X	X
Channel controls		X	X
Newspaper language controls			X

Notes: 2SLS estimates. Cross-section with newspaper-county-level observations weighted by their circulation *share* in each county, multiplied by the number of surveyed individuals for each county by Nielsen. The dependent variable is newspaper language similarity with FNC (the average probability that a snippet from a newspaper is predicted to be from FNC). The right-hand side variable of interest is instrumented FNC viewership relative to averaged CNN and MSNBC viewership. All columns include state fixed effects and demographic controls as listed in Appendix Table A.2. Column 2 also includes channel controls (population shares with access to each of the three TV channels). Column 3 controls for generic newspaper language features (vocabulary size, avg. word length, avg. sentence length, avg. article length). Standard errors are multiway-clustered at the county and at the newspaper level (in parenthesis): * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.10: Cable News Effects on Newspaper Content (2SLS): Relative Circ. Weights × County Pop

Dep. variable: Slant$_{ijs}$=Pr(FNC|Text$_{ijs}$)	(1)	(2)	(3)
FNC Viewership (rel. to CNN/MSNBC)	0.436***	0.439***	0.342*
	(0.151)	(0.150)	(0.204)
K-P First-Stage F-Stat	20.773	21.150	20.439
N observations	3781	3781	3781
State FE	X	X	X
Demographic controls	X	X	X
Channel controls		X	X
Newspaper language controls			X

Notes: 2SLS estimates. Cross-section with newspaper-county-level observations weighted by their circulation *share* in each county, multiplied by the county population. The dependent variable is newspaper language similarity with FNC (the average probability that a snippet from a newspaper is predicted to be from FNC). The right-hand side variable of interest is instrumented FNC viewership relative to averaged CNN and MSNBC viewership. All columns include state fixed effects and demographic controls as listed in Appendix Table A.2. Column 2 also includes channel controls (population shares with access to each of the three TV channels). Column 3 controls for generic newspaper language features (vocabulary size, avg. word length, avg. sentence length, avg. article length). Standard errors are multiway-clustered at the county and at the newspaper level (in parenthesis): * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C.9. Robustness: Absolute and relative FNC viewership

Table C.11: Cable News Effects on Newspaper Content (2SLS): Different Instruments

Dep. variable: $\text{Slant}_{ijs}=\Pr(FNC \vert \text{Text}_{ijs})$	(1)	(2)	(3)	(4)	(5)	(6)
FNC Viewership (rel. to CNN)	0.157	0.274				
	(0.143)	(0.365)				
FNC Viewership (rel. to MSNBC)			0.409***	1.073**		
			(0.126)	(0.470)		
FNC Viewership (absolute)					0.075	1.085*
					(0.197)	(0.649)
K-P First-Stage F-stat	39.173	23.314	32.120	23.834	15.011	7.715
N observations	3781	3781	3781	3781	3781	3781
State FE	X	X	X	X	X	X
Demographic controls	X	X	X	X	X	X
Channel controls	X	X	X	X	X	X
Newspaper language controls	X	X	X	X	X	X
Circulation weights	X		X		X	
Circulation *share* weights		X		X		X

Notes: 2SLS estimates. Cross-section with newspaper-county-level observations. In uneven columns, we weight observations by newspaper circulation in each county (following column 3 of Table 4). In even columns, we weight observations by their circulation *share* in each county, multiplied by the number of surveyed individuals for each county by Nielsen. The dependent variable is newspaper language similarity with FNC (the average probability that a snippet from a newspaper is predicted to be from FNC). The right-hand side variable of interest is (i) instrumented FNC viewership relative to CNN viewership: *Viewership (FNC - CNN)*) in columns 1 and 2, (ii) instrumented FNC viewership relative to MSNBC viewership: *Viewership (FNC - MSNBC)*) in columns 3 and 4, and (iii) absolute instrumented FNC viewership: *Viewership FNC*). All columns include state fixed effects, demographic controls as listed in Appendix Table A.2, channel controls (population shares with access to each of the three TV channels), and controls for generic newspaper language features (vocabulary size, avg. word length, avg. sentence length, avg. article length). Standard errors are multiway-clustered at the county and at the newspaper level (in parenthesis): * p < 0.1, ** p < 0.05, *** p < 0.01.

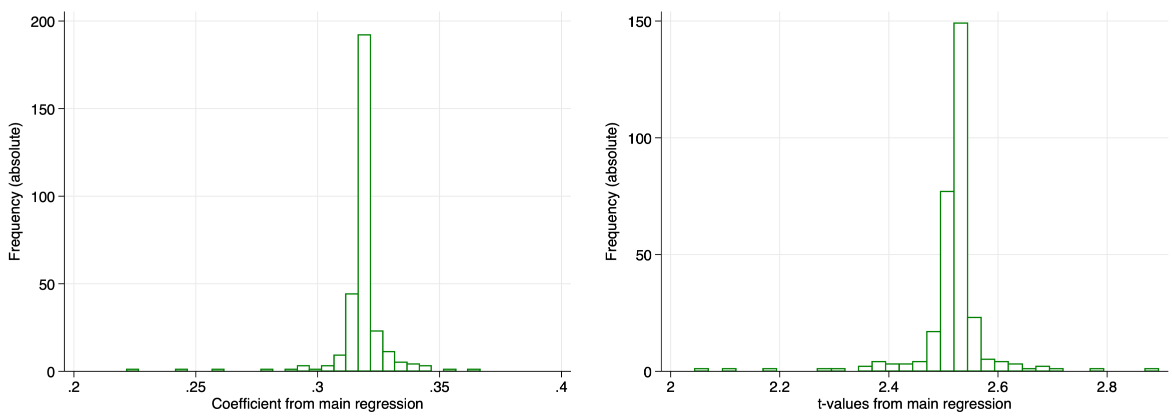
C.10. Robustness: Dropping observations and clustering

Table C.12: Cable News Effects on Newspaper Content (2SLS): State Clustering

Dep. variable: Slant_{ijs}=$\Pr(FNC\|\text{Text}_{ijs})$	(1)	(2)	(3)
FNC Viewership (rel. to CNN/MSNBC)	0.314**	0.311**	0.318**
	(0.120)	(0.117)	(0.135)
K-P First-Stage F-Stat	35.682	36.496	37.544
N observations	3781	3781	3781
State FE	X	X	X
Demographic controls	X	X	X
Channel controls		X	X
Newspaper language controls			X

Notes: 2SLS estimates. Cross-section with newspaper-county-level observations weighted by newspaper circulation in each county. The dependent variable is newspaper language similarity with FNC (the average probability that a snippet from a newspaper is predicted to be from FNC). The right-hand side variable of interest is instrumented FNC viewership relative to averaged CNN and MSNBC viewership. All columns include state fixed effects and demographic controls as listed in Appendix Table A.2. Column 2 also includes channel controls (population shares with access to each of the three TV channels). Column 3 controls for generic newspaper language features (vocabulary size, avg. word length, avg. sentence length, avg. article length). Standard errors are clustered at the state level (in parenthesis): * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure C.2: Cable News Effects on Newspaper Content (2SLS): Dropping Individual Newspapers



The histogram on the left (bin width 0.005) shows the $Viewership_{js}$ coefficients according to our main specification (Table 4, column 3), but leaving out each individual newspaper once. The histogram on the right (bin width 0.025) shows the distribution of the t-values from the same regressions.

C.11. Mechanisms: Language features and topics

Table C.13: 2SLS: Cable News Effects on Text Readability Metrics (2SLS)

Dep. variable	*Vocab. size*	*Len. words*	*Len. sent*	*Len. art*
FNC Viewership (rel. to CNN/MSNBC)	-0.227	0.885	0.154	0.863
	(0.543)	(0.740)	(0.393)	(0.554)
K-P First-Stage F-Stat	36.380	36.380	36.380	36.380
N observations	3781	3781	3781	3781
State FE	X	X	X	X
Demographic controls	X	X	X	X
Channel controls	X	X	X	X
Corpus size control	X	X	X	X

Notes: 2SLS estimates. Cross-section with newspaper-county-level observations weighted by newspaper circulation in each county. The dependent variable is vocabulary size in column 1, average word length in column 2, average sentence length in column 3, and average total article length in column 4. The right-hand side variable of interest is instrumented FNC viewership relative to averaged CNN and MSNBC viewership. All columns include state fixed effects, demographic controls as listed in Appendix Table A.2, channel controls (population shares with access to each of the three TV channels), and a control for the size of the newspaper-specific corpus. Standard errors, multiway-clustered at the county and at the newspaper level, in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In Table C.13, re-run our main specification, but instead of bigram-based similarity with FNC, we regress vocabulary size (normalized by the total size of the corpus, column 1), average word length (column 2), average sentence length (column 3), and average article length (column 4) on instrumented FNC viewership relative to MSNBC and CNN. As before, we include demographic and channel controls. We also account for the size of the newspaper-specific corpus.[34] None of the coefficients are significant or close to significant. These results are consistent with the interpretation that our main results are driven by FNC-specific bigrams that diffuse into local newspaper language.[35]

[34]The number of articles scraped is given by the availability on NewsLibrary. It does not seem to follow a pattern: correlation between corpus size and circulation by newspaper is rather small, around 0.3. The correlation between similarity with FNC and corpus size is, if anything, negative (around -0.21).

[35]The insignificance of the coefficients in Table C.13 should not come as a surprise given that the main results in Table 4 barely change when we move from column 2 to column 3 (where generic newspaper language controls are introduced).

Table C.14: Cable News Effects on Newspaper Content (2SLS): Conditioning on Topics

Dep. variable: Slant_{ijs}=$\Pr(FNC \mid \text{Text}_{ijs})$	(1)	(2)	(3)
FNC Viewership (rel. to CNN/MSNBC)	0.223**	0.223**	0.258**
	(0.101)	(0.101)	(0.107)
K-P First-Stage F-Stat	37.499	37.290	35.341
N observations	3781	3781	3781
State FE	X	X	X
Demographic controls	X	X	X
Channel controls		X	X
Newspaper language controls			X

Notes: 2SLS estimates. Cross-section with newspaper-county-level observations weighted by newspaper circulation in each county. The dependent variable is newspaper language similarity with FNC (the average probability that a snippet from a newspaper is predicted to be from FNC). The right-hand side variable of interest is instrumented FNC viewership relative to averaged CNN and MSNBC viewership. All columns include state fixed effects, demographic controls as listed in Appendix Table A.2, and average topic share controls. Column 2 also includes channel controls (population shares with access to each of the three TV channels). Column 3 controls for generic newspaper language features (vocabulary size, avg. word length, avg. sentence length, avg. article length). Standard errors are multiway-clustered at the county and at the newspaper level (in parenthesis): * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C.12. Mechanisms: Descriptive Evidence on Demand Side

A relevant question is whether the effects of contagious slant are driven by supply or demand – that is, a direct influence on news producers, or else theirs response to changes in reader preferences. Newspaper readers, influenced by their cable news consumption, might demand more slanted news content. On the supply side, owners, editors, or journalists exposed to certain channels may borrow the associated slanted content and push it to consumers.

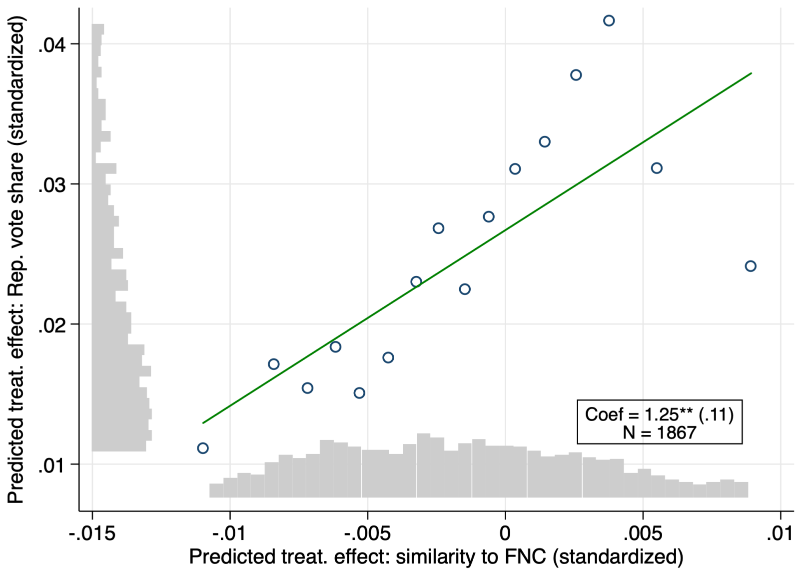
The previous literature has produced mixed evidence, with some work showing that slant across U.S. newspapers reflects the political preferences of readers rather than producers (Gentzkow and Shapiro, 2010), while other work has shown that media owners do influence news content (Gilens and Hertzman, 2000; Martin and McCrain, 2019; Mastrorocco and Ornaghi, 2020; Szeidl and Szucs, 2021). Given the declining revenues in the local news industry during the 2005-2008 time period (Evans, 2009; Rolnik et al., 2019; Djourelova et al., 2021), it could be that newspapers have less leeway to deviate from consumer preferences in favor of producer preferences. On the other hand, lower revenues might also reduce newsmaking resources. Then, borrowing content from national platforms may provide a cheap production alternative to original reporting.

There is good reason to be skeptical of a supply-side mechanism in our case, given that variation comes from shifts in viewership due to channel positioning. Journalists, editors, and others involved in news production are sophisticated news consumers. These individuals will view their preferred cable news shows regardless of local channel position. Thus our instrument will not affect them. Hence, any supply-side mechanism is suspect and would require strong evidence.

Here, we provide some descriptive evidence on the demand side by comparing the effects of cable-channel exposure on news content to the parallel effects on Republican vote share documented in previous work (Martin and Yurukoglu, 2017; Ash et al., 2021). If the contagious-slant effects are driven by responses to a cable news-induced demand shift among readers, we would expect newspapers to react most in counties where the FNC effect on Republican voting is largest. To test for this possibility, we use a machine learning approach to model heterogeneous treatment effects across counties in the response to the channel-position instrument. This generalized model – a causal forest from Athey et al. (2019) – allows the reduced form effect of channel position to vary flexibly with local covariates. After collapsing the data to the county level, we train two models – one with newspaper slant as the outcome, and a second with 2008 Republican vote share as the outcome.

Using the trained causal forests, we predict county-specific treatment effects for both outcomes. Appendix Figure C.3 shows that the predicted effect sizes for each outcome are highly correlated across counties (with a Pearson's correlation of 0.25). Further, Appendix Table C.15 shows that similar covariates predict a strong response for both news similarity and Republican vote share. Overall, these findings suggest that the types of counties who are responsive to cable news exposure in their voting are also responsive in the associated news content similarity. We interpret this result as descriptive evidence for the relative importance of demand-side effects.

Figure C.3: Predicted treatment effects of instrument: similarity to FNC versus Republican votes in 2008



Binned scatterplots (16 bins) of the predicted treatment effect of FNC exposure (relative to CNN) on Republican vote shares in 2008 (standardized) against the predicted treatment effects of same instrument on predicted similarity to FNC (standardized). Cross-section with county-level observations. No controls are included. In grey (next to the axes), we show the distributions of the underlying variables.

Table C.15: The five covariates most associated with a response to the the instrument (county-level)

Strong response of Slant_k	Strong response of voting
% Black population	% High school graduates
% High school graduates	% Republican votes 1996
% Republican votes 1996	% Age group 80s
% Asian population	Gini
% Age group 80s	% Age group 70s

Notes: Covariates most associated with a strong response of newspaper similarity Slant_k (left column) and Republican vote shares (right column) to the instrument. The covariates were identified using heterogeneous treatment effect estimation via instrumental variables as proposed by Athey et al. (2019). The top-listed covariate represents the most associated one, the second covariate the second-most associated one, etc. All effects estimated at the county level. The newspaper-county level similarity values (as used in the main results) are averaged at the county-level weighting each newspaper-county observation by the newspaper circulation.

C.13. Mechanisms: Slant contagion and polarization

Table C.16: Cable News Effects on Newspaper Content (2SLS): By Historical Republican Vote Shares

Dep. variable: $\text{Slant}_{ijs} = \Pr(FNC \mid \text{Text}_{ijs})$	(1)	(2)	(3)
FNC Viewership (rel. to CNN/MSNBC)	-0.280	0.061	0.327**
	(0.305)	(0.092)	(0.127)
K-P First-Stage F-Stat	9.235	18.261	16.627
N observations	1459	1249	1068
Rep. vote share 1996 in 1st tercile	X		
Rep. vote share 1996 in 2nd tercile		X	
Rep. vote share 1996 in 3rd tercile			X
State FE	X	X	X
Demographic controls	X	X	X
Channel controls	X	X	X
Newspaper language controls	X	X	X

Notes: 2SLS estimates. Cross-section with newspaper-county-level observations weighted by newspaper circulation in each county. The dependent variable is newspaper language similarity with FNC (the average probability that a snippet from a newspaper is predicted to be from FNC). The right-hand side variable of interest is instrumented FNC viewership relative to averaged CNN and MSNBC viewership. Column 1 only includes newspaper-county-level observations from counties where the Republican votes share in 1996 (pre-FNC era) lies in the lowest tercile. In column 2, we include observations from counties in the second tercile, and in column 3 from those in the highest tercile. All columns include state fixed effects, demographic controls as listed in Appendix Table A.2, channel controls (population shares with access to each of the three TV channels), and generic newspaper language features (vocabulary size, avg. word length, avg. sentence length, avg. article length). Standard errors are multiway-clustered at the county and at the newspaper level (in parenthesis): * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.17: Polarizing Effect of Cable News: Separate Reduced-Form Effects of FNC and CNN/MSNBC

Dep. variable: Slant$_{ijs}$=Pr(FNC|Text$_{ijs}$)	(1)	(2)	(3)
FNC Position (absolute)	0.067***	0.002	-0.031***
	(0.022)	(0.019)	(0.008)
CNN/MSNBC Position (average)	0.040	0.020	0.031**
	(0.031)	(0.032)	(0.014)
N observations	872	1858	1040
Endorsed Democrat	X		
No (Known) Endorsement		X	
Endorsed Republican			X
State FE	X	X	X
Demographic controls	X	X	X
Channel controls	X	X	X
Newspaper language controls	X	X	X

Notes: Reduced form estimates. Cross-section with newspaper-county-level observations weighted by newspaper circulation in each county. The dependent variable is newspaper language similarity with FNC (the average probability that a snippet from a newspaper is predicted to be from FNC). The two right-hand side variables of interest are (i) the absolute position of FNC viewership (*Position FNC*) and the (ii) average of the absolute positions of CNN and MSNBC (*Position 0.5(CNN+MSNBC)*). In column 1 we only include newspapers that endorsed the Democratic Presidential candidate in 1996 (pre-FNC era). In column 2, we focus on newspapers that did not endorse either candidate (or for which endorsement data is not available). Column 3 considers only newspapers that endorsed the Republican candidate. All columns include state fixed effects, demographic controls as listed in Appendix Table A.2, channel controls (population shares with access to each of the three TV channels), and generic newspaper language features (vocabulary size, avg. word length, avg. sentence length, avg. article length). Standard errors are multiway-clustered at the county and at the newspaper level (in parenthesis): * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.