Media Slant is Contagious

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Abstract

This paper examines the diffusion of media slant, specifically how partisan content from national cable news affects local newspapers in the U.S., 2005-2008. We use a text-based measure of cable news slant trained on content from Fox News Channel (FNC), CNN, and MSNBC to analyze how local newspapers adopt FNC’s slant over CNN/MSNBC’s. Our findings show that local news becomes more similar to FNC content in response to an exogenous increase in local FNC viewership. This shift is not limited to borrowing from cable news, but rather, local newspapers’ own content changes. Further, cable TV slant polarizes local news content.

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1. Introduction

Scientific consensus and conventional wisdom agree: Media bias is widespread. Media outlets often feature content in a way that is favorable to a particular political party or ideological perspective (e.g., Groseclose and Milyo, 2005; Harmon and Muenchen, 2009; Gentzkow and Shapiro, 2010; Puglisi and Snyder, 2011). These biases in reporting can impact public opinion (e.g., Chiang and Knight, 2011; Djourelova, 2023), and in particular, there is extensive evidence that higher exposure to Fox News (FNC) boosts Republican vote shares and other conservative interests (DellaVigna and Kaplan, 2007; Martin and Yurukoglu, 2017; Ash et al., 2021; Ash and Galletta, 2023).

One unanswered question motivated by these findings is whether biased news messaging can spread to and distort other news outlets’ content. This issue is policy-relevant since media regulation in democracies typically aims at providing consumers with a competitive news market, with a wide, unrestricted choice among independent news sources. After all, diverse news sources only translate into diverse reporting if they are independent in their news making.

This work studies cross-media influence in the context of U.S. cable TV news channels – Fox News, CNN, and MSNBC – which have a well-documented partisan slant. When there is higher viewership of a cable news channel among a newspaper’s readers, is the associated partisan slant reflected in that newspaper’s content? Our word defines slant in relative terms – whether a piece of content resembles Fox News rather than CNN or MSNBC.

The first step in answering this question is to measure the similarity between cable news and 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 from 2005 through 2008. We combine these texts with transcripts of 40,000 episodes from Fox News, 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 the associated predictions with human annotations.

We apply our model to the local newspaper article corpus. For each article, we have a text-based metric reflecting the similarity to content from FNC shows relative to CNN and MSNBC shows. We aggregate the article similarities at the newspaper level. We add
metadata on newspaper circulation, television channel positioning, ratings, and political and demographic covariates.

Then, we investigate whether relative similarity to content 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 reporting. For 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 the relevance of the first stage and the instrument exogeneity. In particular, the instrument is uncorrelated with other local characteristics predictive of viewership or of the relevant dimensions of local newspaper content.

We find that media slant is contagious. Higher cable news network viewership increases the influence of a network’s content on local newspaper articles: 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. Our estimated local average treatment effects survive various 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 the mechanisms, we ask whether local newspapers weave the FNC- or CNN/MSNBC-like slant into their original reporting (i.e., a shift in their own reporting) or whether the effects could be driven by copy-pasting. First, we devise a topic-based procedure to distinguish local news from non-local (that is, national or international) news. Analyzing local and non-local news separately, we find that cable news influences both kinds of content. Since cable TV shows cover national or international stories, the observed diffusion of media slant is not only direct borrowing of content from the cable TV channels. Instead, cable news exposure also shifts the original local reporting of the newspapers.

Finally, we investigate whether cable news has polarized local news content. We split newspapers into three groups: those that have historically endorsed Democrats, those who have historically endorsed Republicans, and those without or with mixed endorsements. In response to exposure to FNC, historically Republican newspapers became
more conservative (FNC-like), while historically Democrat newspapers became more liberal (CNN/MSNBC-like). Thus, media slant from cable news seems to encourage outlets to re-position themselves on the ideological spectrum following 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). This literature provides good evidence that mass media shift election outcomes and readers’ policy preferences. First, Gentzkow et al. (2011) and Drago et al. (2014) report that the opening of local newspapers boosts voter turnout. Chiang and Knight (2011) show that a newspaper endorsement for a presidential candidate shifts voting intentions in favor of this candidate. Djourelova (2023) 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.

Regarding Fox News in particular, there is a body of research documenting its political and societal impact – beyond shifting votes (DellaVigna and Kaplan, 2007; Martin and Yurukoglu, 2017; Ash et al., 2021; Li and Martin, 2022). It has also been shown that cable news can affect voter knowledge (Hopkins and Ladd, 2014; Schroeder and Stone, 2015), fiscal policy decisions (Ash and Galletta, 2023), as well as behaviors during the COVID-19 pandemic (Bursztyn et al., 2021; Ash et al., 2020; Simonov et al., 2022). We add to this work by looking at the influence of partisan narratives using text analysis and looking at the spillover effects on other news outlets.

Our main contribution to the debate on media bias lies in showing how news media outlets are interconnected. Recent contributions on cross-media influence document the influence of social media on traditional media (Cagé et al., 2020a; Hatte et al., 2021), and that news outlets copy-paste from each other extensively (Cagé et al., 2020b). We document explicitly how media bias from one media organization can causally spill over to other media organizations. Hence, our work identifies an additional potential channel.

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1For surveys on the empirical and theoretical literature, see Puglisi and Snyder (2015) and Gentzkow et al. (2015), respectively.

2Prominent contributions on the mass media’s persuasive effects around the world include Adena et al. (2015), DellaVigna et al. (2014), or Yanagizawa-Drott (2014). Prat and Stroemberg (2013) and Stroemberg (2015) provide surveys on the mass media’s political effects.
through which partisan media affects political and social outcomes.

The diffusion of national partisan priorities into local news is important because local newspapers 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 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 content.

Methodologically, our approach combines natural language processing (NLP), machine learning, and causal inference (see Gentzkow et al. 2019a and Ash and Hansen 2022 for overviews of text-data-based work in economics). Regarding text-as-data approaches to measuring partisanship, the most related work is Gentzkow and Shapiro (2010), showing a correlation in local news slant and local partisan preferences (see also Gentzkow et al., 2019b). Our innovation is in combining text-based slant measurement with a causal research design.

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

Our data comes from cable news channels and local newspapers. The resulting panel is from 2005 through 2008, the years for which we can construct cable news viewership by locality. For summary statistics, see Table A.2.

Local newspaper article excerpts. Our analysis starts with a corpus of local newspaper articles. Our source is the news aggregation site NewsLibrary, from which we get the headlines and first 80 words of all published articles for various local U.S. newspapers for 2005-2008. We focus on the first 80 words since, at the time of our data construction
(06-08/2019), our subscription allowed us to access these article previews at large.\textsuperscript{3} We programmatically read through the snippets and extract the newspaper name, the headline, the plain article text, and the article date (for an example of an article snippet, see Appendix Figure A.1). Our main dataset contains 16 million article snippets from 305 unique newspapers. Appendices A.1 to A.3 provide more information on the sample.

**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 (for a list of the included shows, see Section A.4). We have several scripts that read through the transcripts to filter out metadata and other non-speech content.

While the newspaper article snippets contain the article’s first 80 words (approximately), the transcripts tend to be longer. We, thus, segment the transcripts into 80-word snippets – to match the length of the newspaper article snippets. That is, we make sure our text-based slant prediction works well on short transcript snippets before applying it to 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 rating data). Our main analyses thus include 3,781 observation units at the newspaper-county level (see Section 4). The AAM also provides information on the newspapers’ headquarters location, which we exploit in additional analyses (Section 5.2).

Appendix A.2 describes an alternative method to match newspapers to counties (not relying on the AAM data, but based on the newspaper’s name). This procedure results in fewer observation units – namely, 682. However, this alternative sample represents slightly more underlying newspaper articles (24 million instead of 16 million). We use this alternative sample in robustness checks. Since the audited county-level circulation data allows for more precise county match(es) for each newspaper, we use the 3,781-

\textsuperscript{3}Full articles – available on a pay-per-piece basis – were prohibitively expensive given our broad coverage in time and space.
observation-unit-sample for the main analysis.

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 Ash and Galletta (2023) and aggregate 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 (see Table A.2), measured at the zip code level. To get aggregate county values, we weigh them by zip code population.

3. Measuring Media Slant

This section describes how we construct the language measures used as outcomes in our regression analysis. We aim to capture the textual similarity between (i) the newspaper article snippets and (ii) the TV show transcripts. Therefore, we implement a supervised machine-learning approach to predict if a newspaper article’s content resembles that from a particular TV station (FNC or CNN/MSNBC).4

3.1. Text pre-processing and featurization

First, we preprocess the newspaper articles and TV transcripts, stem all words, and form bigrams (two-word phrases), see details in Appendix B.1.

4The approach is related to Gentzkow et al. (2019b), who also use a regularized linear model with n-gram inputs. Our different approach reflects a different scientific objective. Gentzkow et al. (2019b) 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).
Let $M$ be the set of transcript documents (snippets indexed by $m$). We group CNN and MSNBC together (for a simple notation, we refer to the CNN/MSNBC label as CNN). 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 $FNC_m = 0$ 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 $F^b_k$ 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

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

The frequency threshold excludes infrequent bigrams that 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. Supervised learning models using n-grams are rarely sensitive to specific pre-processing and featurization choices (e.g., Denny and Spirling, 2018).

3.2. Classifying transcripts by TV source

We 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 it in the test set.

We take two steps to pre-process the features further, 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 $\chi^2$ 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 $B^b_m$ be the frequency of bigram $b$ in transcript $m$ (and $B_m$ the vector of frequencies for transcript $m$, of length $|S| = 2000$).

\(^5\)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.
Our classification method is a penalized logistic regression (Hastie et al., 2009). We parametrize the probability that a transcript is from Fox News as

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

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

\[
J(\psi) = -\frac{1}{M^*} \sum_{m=1}^{M^*} \left( FNC_m \log(\hat{FNC}_m) + (1 - FNC_m) \log(1 - \hat{FNC}_m) \right) + \lambda |\psi|_2
\]

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. Regularization strength is calibrated by the hyperparameter \( \lambda \geq 0 \), selected using a 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 evaluate the classifier’s performance in the test set, obtaining an accuracy of 0.73 (with a standard deviation of 0.02 across five folds). This performance is much better than guessing (i.e., an accuracy of 0.5 in the balanced sample) and comparable with other work in this literature.\(^6\) Table 1 shows good precision and recall across the two categories.

Next, we compare our model to human judgment. Human annotators (U.S. college students) guessed 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 58% of the time (if guessing randomly, their agreement rate would be 25%). Thus, our machine-learning model resembles human annotations. The 80-word snippets contain significant information about the source network, and our text-based model captures it. Appendix B.3 further describes the human validation.

\(^6\)The prediction accuracy for partisan affiliation in U.K. parliament by Peterson and Spirling (2018) is 60% and 80%, depending on the time period. According to Gentzkow et al. (2019b), one can correctly guess a speaker’s party based on a one-minute speech with 73% in the U.S. Congress (2007–2009). Kleinberg et al. (2017) obtain an AUC of 0.71 in predicting recidivism from criminal defendant characteristics.
Table 1: Test-Set Prediction Performance for Identifying Cable News Source

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

*Notes:* Confusion matrix for test-set predictions. The top left gives true positives for the CNN/MSNBC class; the bottom right gives true positives for the FNC class; the top right gives false negatives for CNN/MSNBC; the bottom left gives false negatives for FNC. The on-diagonal cells have most of the mass and are quite balanced.

We now examine which bigrams are most important for classification. An advantage of logistic regression is its interpretability: The estimated coefficients of the trained model, \( \hat{\psi}_b \), provide a ranking across the 2,000 predictive bigrams for their relative contribution to the predictions. Table B.1 shows some bigram examples with positive (predictive for FNC transcripts) or negative (predictive for CNN/MSNBC) values of \( \hat{\psi}_b \), and Table B.2 provides a longer list. Prominent figures like Sean Hannity (predictive of FNC) or Anderson Cooper (predictive of CNN/MSNBC) appear among the bigrams. FNC 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.

3.3. Text similarity between newspapers and TV stations

We now take our model 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 \( FNC \), \( \hat{FNC} \), for snippet \( n \) is hence:

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

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

Since newspaper articles do not come with labels, we cannot evaluate accuracy in predicting their content. However, we provide some interpretive validation in Appendix C, listing the news article snippets with very high and low \( \hat{FNC}_n \). The topical and rhetorical content of the article snippets reflects intuitions about the ideological com-
mitments of the networks. In Table B.3, 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 closest to CNN/MSNBC (Table B.4) are about campus groups supporting gay rights, the AIDS crisis in Africa, President Bush's responsibility for the financial crisis, or HIV in the gay community.

We now have $\hat{FNC}_n$ as a similarity measure between TV channel content and newspaper article $n$'s content. To link the article-level data to the newspaper-level or the count-level datasets, we aggregate by taking the mean values of the contained news articles. Hence, we define $\text{Slant}_{ijs}$ 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 cable news viewership data. Our main dataset covers 305 newspapers circulating in 12.4 counties on average (the median is six counties), resulting in the aforementioned 3,781 observations. Figure B.2 shows the distribution of FNC content similarity for the 305 unique newspapers in our main dataset (i.e., $\text{Slant}_{ijs}$).

3.4. Topic model

When studying the mechanisms in Section 6, we require topic labels for the news articles – to classify them as either local or non-local news. We use the Latent Dirichlet Allocation (LDA) topic modeling approach of Blei et al. (2003). We build the topic model based on a random sample of 1 million newspaper article snippets, specifying 128 topics. The topics are labeled manually based on the associated words (see Appendix B.6). We then use the trained model to assign topic(s) to all newspaper articles.

4. Econometric Framework

4.1. Instrumental variables specification

The main outcome variable is $\text{Slant}_{ijs}$, the textual similarity to Fox News for newspaper $i$ circulating in county $j$ in state $s$ (see Section 3.3 above). $\text{Slant}_{ijs}$ is a relative...

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7LDA is the standard approach for topic modeling in social science (e.g., Hansen et al., 2018; Bybee et al., 2020). We use the online variational Bayes (VB) implementation by Hoffman et al. (2010). To select the number of topics, we started with 32 and doubled the topic number until they became largely interpretable to humans.
measure. It is interpretable as the average predicted probability that the articles of a newspaper came from FNC, rather than CNN or MSNBC. We are interested in the causal effect of relative local viewership of FNC compared to CNN/MSNBC on this outcome. Hence, our main treatment variable, Viewership$_{ja}$, is the county-level Fox News viewership relative to the averaged county-level CNN and MSNBC viewership: FNC Viewership - 0.5×(MSNBC viewership+CNN viewership).\(^8\)

We specify the relationship between slant and viewership linearly:

\[
\text{Slant}_{ijs} = \alpha_s + \theta \text{Viewership}_{ja} + X_{ij} \beta + \epsilon_{ijs}
\]

where \(\theta\) is the causal parameter of interest. The regression includes state fixed effects (\(\alpha_s\)), a vector of county and newspaper controls (\(X_{ij}\)), and an error term (\(\epsilon_{ijs}\)). The covariate set \(X_{ij}\) varies across specifications but can include demographic controls (see 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 likely produces biased \(\theta\) estimates. Many political and economic factors may correlate with both Fox News viewership and newspapers featuring Fox-like content – any pre-existing ideological preferences of the county. Therefore, we use an instrumental variable.

Inspired by Martin and Yurukoglu (2017), we use cable network channel positioning to construct an instrument Position$_{ja}$ that affects Viewership$_{ja}$ 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., Ash and Galletta, 2023), 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$_{ja}$ as the county-level FNC channel position relative to the averaged channel position of MSNBC and CNN: FNC

\(^8\)This specification for the treatment is different from Martin and Yurukoglu (2017) and reflects our outcome that is also measured in relative terms. Robustness checks report the specification of non-relative FNC viewership.
Position - 0.5×(MSNBC Position+CNN Position). Our first stage is

\[ \text{Viewership}_j \alpha + \delta \text{Position}_j + X_{ij} \beta + \eta_{ij} \]  

(3)

where the other terms are as above.

Combining the first stage (3) and Equation (2), we can procure causal estimates for the local average treatment effect \( \theta \) using two-stage least squares (2SLS). To facilitate the coefficient interpretation, 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 or, for robustness checks, by state.

We use weighted regressions since most newspapers serve more than one county, and 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.  

4.2. Instrument first stage and validity

Figure C.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). Table C.1 shows coefficients and standard errors in tabular format. 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. The tables below report Kleinbergen-Paap cluster-robust first-stage F-statistics (consistently >30, indicating a well-powered first stage).

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

10 We demonstrate robustness to other weighting schemes, including a variant in line with Martin and Yurukoglu (2017) which weights by the number of households in a locality surveyed by Nielsen.
Beyond relevance, we assume monotonicity, that the exclusion restriction holds, and exogeneity. Monotonicity appears plausible in our context (i.e., that the channel position influences TV viewership in the same direction for all counties, and thus, that higher positions would not systematically increase viewership). For the exclusion restriction, we assume that the channel position affects local news reporting only through its effect on cable news viewership. Third, exogeneity demands that $\text{Position}_{js}$ is uncorrelated with $\epsilon_{ij}$. That is, 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 several checks supporting the exogeneity assumption. Their qualitative research highlights that channel positions have an important arbitrary, historical component with significant inertia and path dependence. Quantitatively, they document an absent correlation of the instrument with Republican vote shares before the introduction of FNC. Similarly, Ash and Galletta (2023) show that the instrument is unrelated to demographic characteristics that predict policy preferences or news channel viewership. We apply the same checks to our newspaper-county-level data, finding no association between channel positions and county characteristics otherwise important for our endogenous regressor or outcome (Appendix C.2). Additionally, a placebo check based on local news from 1995 and 1996 (the pre-FNC/MSNBC era) results in insignificant estimates (Appendix C.3).

5. Results

5.1. Main results

Table 2 shows two-stage-least-squares estimates of the effect of higher FNC viewership on newspaper content similarity with FNC (the average probability that a snippet from a newspaper is predicted to be from FNC based on the bigrams it contains).\textsuperscript{11} 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. Column 2 also includes controls for the share of households with potential

\textsuperscript{11}Appendix C.5 features the reduced form results.
Table 2: Cable News Effects on Newspaper Content (2SLS)

| Dep. variable: Slant<sub>ijs</sub>=Pr(FNC|Text<sub>ijs</sub>) | (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<sub>ijs</sub>. 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.

In all three columns, the estimated treatment effects are positive and statistically significant. The magnitudes across columns are highly similar, ranging from 0.31 in columns 1 and 2 to 0.32 in column 3. Thus, the channel and language controls do not change the estimates relative to the baseline in column 1 with only state fixed effects and demographic controls. 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. 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 slant difference between an 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), a one-standard-deviation decrease in the relative FNC channel position (11

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12 OLS estimates are reported in Appendix C.4.
positions) shifts slant towards FNC by about 3 percent of the difference between FNC and CNN/MSNBC.

5.2. Robustness checks

Our first robustness checks rely on alternative samples. Table C.6 replicates the baseline estimates but only considers newspaper-county observations where the county coincides with where the immediate newspaper owner is based. The effect size doubles relative to the entire sample and is still significant despite a smaller sample.\textsuperscript{13}

Second, we use alternative weighting schemes. The results are robust to weighting by circulation from the pre-FNC/MSNBC era, specifically 1995 (Table C.9). So, our main results are not driven by potential circulation changes due to cable news exposure.\textsuperscript{14} Next, we weight observations by \textit{relative} circulation shares by county, multiplied by the number of surveyed individuals for each county by Nielsen (Table C.10). In using the number of surveyed individuals, we follow Martin and Yurukoglu (2017). Similarly, we also weight observations by \textit{relative} circulation shares by county, multiplied by county population (Table C.11). The results are again positive and statistically significant.

Third, we replicate the main results using different instrument specifications (Table C.12). Instead of FNC’s \textit{relative} to CNN’s/MSNBC’s viewership combined, we take FNC viewership relative to CNN’s and MSNBC’s separately (columns 1/2 and columns 3/4, respectively), or just FNC viewership (columns 5/6). The estimates are positive and overall consistent with our main results, yet not significant in the FNC-vs-CNN specification.

Fourth, we rely 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 circulation data (see Section A.2 for details). The results are fully robust (Appendix C.7).

Finally, our results are still significant when clustering by state (Table C.13) and remain consistently significant when dropping newspapers individually (Figure C.5).

\textsuperscript{13}Meanwhile, the effect is smaller and insignificant when excluding headquarters counties (Table C.7).

\textsuperscript{14}Our main analysis does not use the pre-FNC/MSNBC county-level circulation data 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 where 1995 circulation is available.
6. Mechanisms and Heterogeneity

6.1. Local vs. national or international news content

An important question regarding slant contagion is what parts of the newspaper content shift towards cable TV content. Slant diffusion could work via production costs, such that local outlets borrow content (either directly or by picking up the stories that the channels cover). Alternatively (or additionally), slant could spill over into originally produced material. We study this question with local news – where direct borrowing of material is impossible, given the cable channels’ national focus.

To distinguish local from non-local (national or international) news, we proceed as follows. We manually label each of the 128 topics from the newspaper corpus (see Section B.6) as more likely to cover local than non-local news. We then classify a newspaper article snippet as local news if, cumulatively, more than 50% of its topic share(s) cover topics labeled as local. We validate our approach via blind human annotations of 2,000 newspaper article snippets. The topic-based predictions come with an accuracy of 81% relative to the human annotation, suggesting that our approach performs well in identifying local articles.\footnote{We recruited the annotators on Upwork, as or the human validation of the slant measure (see Section B.3). The annotators were not given any topic information; they read the newspaper article snippet and decided whether it covered local or other news. Since most news is local, we also check other metrics for the local category. The F1-score is 86%, while precision and recall are 88% and 84%, respectively.}

Table 3 replicates our main regression specification but uses 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. Next, column 2 points to 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 (potentially in addition to slant spillovers into the newspaper’s own content). Finally, column 3 shows the effect on the slant of local news articles, for which direct borrowing is impossible. Nonetheless, there is a positive and significant effect, with point estimates almost identical to our main results.\footnote{Most of the article snippets are local news (71% according to human annotation, and 75% according to our topic-model-based categorization). Therefore, the sample underlying Table 3 is similar to the one in Table 2.}
Table 3: Cable News Effects on Newspaper Content: (Non-)Local News

| Dep. variable: | Local share\textsubscript{ij} | Slant\textsubscript{ij} | Slant\textsubscript{ij} |
|---------------|------------------|-----------------|-----------------|
| FNC viewership (rel. CNN/MSNBC) | 0.039 (0.032) | 0.377*** (0.134) | 0.295** (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 content. The latter effect is notable because it means that cable news influences the local outlets’ original content. This requires that cable TV shifts either readers’ or journalists’ preferences – or both.\(^\text{17}\)

### 6.2. Cable news media slant polarizes local newspapers

Finally, we investigate effect heterogeneity regarding the prior partisan commitments of local newspapers. We distinguish three outlet groups 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.\(^\text{18}\) Endorsements signal whether the pre-FNC/MSNBC political leaning of a newspaper was relatively conservative or liberal. The non-endorsers can be seen as politically neutral.\(^\text{19}\)

Table 4 re-estimates our main specification on different newspaper subsets. Column 1 focuses on Democrat-endorsing newspapers, where we find a significantly *negative* coefficient, suggesting that liberal-leaning newspapers become *less* FNC-like in their reporting when more exposed to FNC (relative to CNN/MSNBC). Column 3 subsets on Republican-endorsing newspapers. Those behave the same as the main sample, i.e., they adopt more FNC-like content. For newspapers with no (known) endorsements (column 2), no effect emerges.

Accordingly, cable channel exposure might polarize local news content, such that right-leaning news outlets follow FNC but move away from MSNBC/CNN, whereas left-leaning outlets follow MSNBC/CNN while moving away from FNC. We explore this possibility by running an alternative regression specification that separates the effects of FNC and MSNBC/CNN in Table C.18. Specifically, we run reduced-form specifications with Slant\(_{ijt}\) 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.\(^\text{20}\) The effects from Table 4 are, indeed, driven by right-leaning newspapers following FNC when it has a lower channel position and left-leaning newspapers moving away. Higher exposure to the two liberal-leaning channels does not affect the content of

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\(^\text{17}\)Appendix C.13 provides descriptive evidence on shifting reader preferences likely being a more salient mechanism than shifting journalist preferences.

\(^\text{18}\)This latter group includes newspapers where we could not find an explicit endorsement.

\(^\text{19}\)1996 endorsements are pre-FNC/MSNBC and, thus, independent of channel positioning.

\(^\text{20}\)The reduced form coefficient signs reverse due to the negative first stage. A positive coefficient implies that a lower channel position leads to less slant contagion.
left-leaning newspapers, while right-leaning newspapers tend to move away. Table C.17 shows the same polarizing trends when looking at county-level Republican vote shares in the pre-FNC/MSNBC era.

Overall, exposure to FNC (and, to a lesser degree, CNN and MSNBC) seems to polarize local news content: Republican-leaning newspapers adopt right-wing cable news content in response to FNC viewership increases. Instead, Democrat-leaning papers become more left-wing. This dynamic is consistent with a market positioning effect (Mullainathan and Shleifer, 2005; Gentzkow et al., 2014), where the conservative papers accommodate FNC-viewers’ news preferences. In turn, liberal papers accommodate non-FNC-viewers’ news preferences. Such an ideological positioning is consistent with demand-side mechanisms.
7. Conclusion

We document that partisan news messaging by large media organizations can spill over to smaller outlets. Specifically, the news messaging by U.S. cable TV channels influences local news reporting. Our evidence suggests that the newspapers shift the slant in their own local content, where direct copy-pasting from the TV channels is not possible (since the latter are nationally-oriented). Moreover, the exposure to the TV channels leads to a polarization of local news, 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).
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Online Appendices

A. Data Appendix

A.1. Newspaper articles

First, we provide 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. We focus on the first 80 words since, at the time of our data construction (June-August 2019), our subscription allowed us to access these article previews at large.\(^{21}\) An example of such a newspaper snippet is shown in Figure A.1.

![Figure A.1: Example of a local newspaper article snippet](image)

**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. […]*

In principle, NewsLibrary encompasses around 4,000 unique outlets for 2005-2008. However, for many outlets, there are only a handful of articles available: around 1,500 outlets contain less than 1,000 snippets (for all four years combined). In all our analyses, we only consider outlets with more than 1,000 articles. Also, many outlets 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 outlet separately. For instance, “Augusta Chronicle, the

\(^{21}\)Full articles were available on a pay-per-piece basis, which was prohibitively expensive given our broad coverage in time and space.
A.2. Alternative county matching of newspapers

For robustness, we also apply an alternative matching procedure that covers more newspapers but only uses total instead of county-specific circulation. First, we obtain the main county for each newspaper outlet 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 only assigned to one county, where its total circulation is assumed to accrue. This matching approach produces a dataset of 682 unique outlets and 24 million article snippets. As Table C.8 shows, with the alternative matching, the coefficients are significant and three to four times larger than in the main Table 2.

A.3. Filtering of the 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.
| 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.8 |
| County assignment as in Sec. 2 and county-level circulation data available (AAM) | 16,098,537 | All other tables |
### A.4. Included prime-time TV shows

| Fox News Channel       | CNN                        | MSNBC                                  |
|------------------------|----------------------------|----------------------------------------|
| Fox News Edge          | Anderson Cooper 360        | All In with Chris Hayes                |
| Fox News Sunday         | Campbell Brown             | Ashleigh Banfield On Location          |
| Glenn Beck              | CNN Live Today             | Buchanan & Press                       |
| Hannity                 | CNN News Room              | Countdown with                         |
|                        |                            | Keith Olbermann                        |
| On the Record with Greta van Susteren | CNN Tonight               | Donahue                                |
|                        |                            |                                        |
| O’Reilly Factor         | Connie Chung Tonight       | Hardball with Chris Matthews           |
| Special Report with Bret Baier | Crossfire             | Live with Dan Abrams                   |
| Special Report with Brit Hume | Erin Burnett OutFront    | Morning Joe                            |
| The Edge with Paula Zahn | Glenn Beck               | Politics Nation                        |
| The Five                | Greenfield at Large        | Race for the White House               |
|                        |                            | / 1600 Pennsylvania Av.                |
| The Kelly File          | John King, USA             | Rita Cosby Live and Direct             |
| Your World with Neil Cavuto | Larry King Live           | Scarborough Country                     |
|                        | Moneyline and Lou Dobbs Tonight | The Ed Show                           |
|                        | News Night with Aaron Brown | The Last Word with Lawrence O'Donnell  |
|                        | Parker Spitzer             | The News with Brian Williams           |
|                        | Paula Zahn Now / Live from the Headlines | The Rachel Maddow Show                |
|                        | Piers Morgan               | The Savage Nation                      |
|                        | The Point with Greta Van Susteren | Tucker                               |
|                        | The Situation Room with Wolf Blitzer |                                  |
|                        | Wolf Blitzer Reports       |                                        |
### A.5. 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 | 0.268 | 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 | 13.067 | 4 | 128.5 | 3781 |
| Position (Fox News - 0.5(MSNBC - CNN)) | -2.491 | 13.641 | -81.417 | 55 | 3781 |
| Position (Fox News - MSNBC) | 12.347 | 13.641 | -81.417 | 55 | 3781 |
| Position (Fox News - CNN) | -2.491 | 13.641 | -81.417 | 55 | 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 | 0.902 | 0.067 | 0.055 | 1 | 3781 |
| **Demographic Controls** | | | | | |
| Population 2000 | 210572.061 | 589458.494 | 712 | 981535 | 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 | 0.013 | 0.047 | 0.327 | 3781 |
| Age 30-39 | 0.144 | 0.017 | 0.082 | 0.23 | 3781 |
| Age 40-49 | 0.133 | 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 | -1.068 | 10.307 | 3781 |
| Mean log. income | 10.794 | 0.231 | 0.231 | 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. Text pre-processing

We preprocess all texts (i.e., TV channel transcripts and newspaper articles). We convert them to lowercase and remove non-meaningful stopwords (like and 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 (phrases of two words).

B.2. Bigrams most predictive for FNC or CNN/MSNBC

Table B.1 shows some selected bigram examples with positive (predictive for FNC transcripts) or negative (predictive for CNN/MSNBC) values of $\hat{\psi}_b$. Table B.2 provides a more comprehensive list – the 200 bigrams most predictive for a transcript being from FNC or CNN/MSNBC, respectively. That is, the list is ordered such that the FNC-related bigrams are the 200 bigrams with the largest absolute coefficients in the logistic regression from Section 3). Conversely, CNN/MSNBC-related ones are the 200 bigrams with the most negative coefficients.

Table B.1: 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).
Table B.2: Top 200 of bigrams predictive for FNC or CNN/MSNBC transcripts

| FNC-Related | MSNBC/CNN-Related |
|-------------|--------------------|
| segment tonight | situat room |
| fox news | fox news |
| correspond me | correspond me |
| final tonight | final tonight |
| dick mori | dick mori |
| nr orelli | nr orelli |
| chief white | chief white |
| power player | power player |
| david lee | david lee |
| correspond jim | correspond jim |
| come panel | come panel |
| sean know | sean know |
| sean hanniti | sean hanniti |
| jame thank | jame thank |
| al quida | al quida |
| roll tape | roll tape |
| plenty ahead | plenty ahead |
| live vote | live vote |
| went record | went record |
| join author | join author |
| latest polit | latest polit |
| homicidal detect | homicidal detect |
| right colonel | right colonel |
| bring legal | bring legal |
| brit hime | brit hime |
| later special | later special |
| secular progress | secular progress |
| let screen | let screen |
| anyth unusu | anyth unusu |
| headlin come | headlin come |
| ahead welcom | ahead welcom |
| senat macconnel | senat macconnel |
| emin domain | emin domain |
| live phone | live phone |
| panel stay | panel stay |
| nr speaker | nr speaker |
| kiryat shmona | kiryat shmona |
| griffin report | griffin report |
| steve forb | steve forb |
| thank major | thank major |
| mike thank | mike thank |
| second left | second left |
| far left | far left |
| join los | join los |
| record good | record good |
| o'clock morn | o'clock morn |

| | | |
|----------------|----------------|
| fox news | fox news |
| correspond me | correspond me |
| final tonight | final tonight |
| dick mori | dick mori |
| nr orelli | nr orelli |
| chief white | chief white |
| power player | power player |
| david lee | david lee |
| correspond jim | correspond jim |
| come panel | come panel |
| sean know | sean know |
| sean hanniti | sean hanniti |
| jame thank | jame thank |
| al quida | al quida |
| roll tape | roll tape |
| plenty ahead | plenty ahead |
| live vote | live vote |
| went record | went record |
| join author | join author |
| latest polit | latest polit |
| homicidal detect | homicidal detect |
| right colonel | right colonel |
| bring legal | bring legal |
| brit hime | brit hime |
| later special | later special |
| secular progress | secular progress |
| let screen | let screen |
| anyth unusu | anyth unusu |
| headlin come | headlin come |
| ahead welcom | ahead welcom |
| senat macconnel | senat macconnel |
| emin domain | emin domain |
| live phone | live phone |
| panel stay | panel stay |
| nr speaker | nr speaker |
| kiryat shmona | kiryat shmona |
| griffin report | griffin report |
| steve forb | steve forb |
| thank major | thank major |
| mike thank | mike thank |
| second left | second left |
| far left | far left |
| join los | join los |
| record good | record good |
| o'clock morn | o'clock morn |
| FNC-Related | MSNBC/CNN-Related |
|------------|------------------|
| oh stop    | dace star        |
| stori wont | stori stay       |
| later program | yes polic      |
| thank moment | marriott hotel |
| note earlier | left wing     |
| record come | special report  |
| amber frey | right panel     |
| join dalia | dr dolson      |
| holiday inn | youll meet    |
| governor good | light fact   |
| welcom good | homicid investig |
| strong economi | upper incom |
| da mike | live scene     |
| welcom program | killer killer  |
| chari kranthanam | welcom aboard |
| undermin presid | hebollah hama  |
| right sean | murder scene   |
| appre ci guy | franklin graham |
| come contin | atm card       |
| news correspond | later polic |
| public radio | jim know     |
| sneak peek | media research |
| dr perper | captain thank  |
| code pink | time pleas     |
| drew peterson | john kelli |
| guilt associ | headlin new   |
| welcom come | senat schumer |
| legititum point | westchest counti |
| brett favr | liber want    |
| correspond jeff | madison wisconsin |
| execut editor | abl determinin |
| live aruba | black panther |
| ward churchil | aruban polic |
| elect decemb | scott peterson |
| dispos boli | join san      |
| mark thank | inform tonight |
| gloria allr | doctor thank  |
| lash thank | congressman good |
| sir come | arm control |
| chief thank | frantic search |
| privat jet | juqiq instruct  |
| father pf neger | american media |
| loui farakkhan | murder right |
| beth holloway | duke case     |
| ninth circuit | gaza strip |
| senat graham | chief prosecutor |
| ad quot | interview fox   |
| respect law | rais good     |
| guest say | byron york    |
|                      | harry potter  |
|                      | report pentagon |

33
B.3. 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.4. Distribution of Fox News similarity in newspapers

Figure B.2: 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 ($\hat{FNC}_j$). For most newspapers, we predict that – on average – a snippet resembles FNC with a probability between 0.40 and 0.45.
B.5. Example articles by Fox News similarity

Table B.3: 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.4: 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 […]

37
### 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 immigir 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           |
| hurricane 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 consolari newark freeman                | small city names                 | 1           |
| cross chapter heart royal lati                            | 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 politicits         | 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           |
| circ 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 politics | 0     |
| nelson horn wore said ordinari                            | local happenings | 1     |
| kansas 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 politics | 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 syracuse intersect road paso                          | small city names | 1     |
| restaur cook smoke food cat                                | 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

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

| Dep. variable: FNC Viewership$_{ij}$ (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. Instrument exogeneity

In this Section, we follow Ash and Galletta (2023) to demonstrate that our instrument is unrelated to demographic characteristics that predict policy preferences or news channel viewership. 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 capture the variation in viewership and news content due to pre-existing cultural, economic, and political county characteristics.

Table C.2: Identification checks: Instrument Uncorrelated with Relevant Covariates

| Reduced form | FNC* Viewership (absolute) | Slant$_{ij}$* (rel. to CNN/MSNBC) | FNC* Viewership (relative) | Slant$_{ij}$* |
|--------------|-----------------------------|-----------------------------------|-----------------------------|----------------|
|              | (1)                         | (2)                               | (3)                         | (4)            |
| FNC position (absolute) | -0.022                     | 0.017                             |                             |                |
| (0.043)      | (0.013)                     |                                   |                             |                |
| FNC position (rel. to CNN/MSNBC) | 0.006                      | -0.006                            | 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.

We then regress these predictions on different definitions of our instrument $Position_{ij}$. Table C.2 summarizes 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 predicted values. Overall, these results suggest that channel positions are not associated with county characteristics otherwise important for our endogenous regressor or outcome.
C.3. Placebo: Content similarity in 1995/96

As a placebo check, we estimate our main specifications while calculating the similarity to cable news using local newspaper articles from 1995 and 1996 (i.e., the pre-FNC/MSNBC era); these estimates are insignificant (Table C.3). Hence, reassuringly, there was not a pre-existing Fox-like content dimension in locations that later had a lower Fox channel position. The placebo regressions are based on fewer observations than the main results because some news outlets 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 if we only use the observations entering the placebo regression.

Table C.3: Placebo Cable News Effects on Newspaper Content (2SLS)

| Dep. variable: Slant$_{ij}$=Pr(FNC|Text$_{ij}$) | (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.4. OLS results

Table C.4 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 2 (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 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.

| Dep. variable: Slant\(_{ijs}\)=Pr(FNC|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): \(\hat{FNC}_{ijk}=P(FNC|Text_{ijk})\). 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.5. Reduced form results

Figure C.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 panel (a), the outcome and the instrument are residualized on state fixed effects. The right panel (b) additionally includes 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). There is a clear downward relationship, suggesting that easier access to FNC is associated with more FNC-like content in the local county newspapers. Table C.5 presents reduced-form results in tabular format.

Figure C.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 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.
Table C.5: Cable News Effects on Newspaper Content (Reduced Form)

| Dep. variable: | Slant\textsubscript{ij,t} | (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     | 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.6. Sub-samples: Newspaper headquarters and other counties

Here, we replicate the baseline estimates but only consider newspaper-county observations where the county coincides with where the immediate owner of the newspaper is based. To do so, 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. Conversely, in Table C.7, we exclude headquarters counties.

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

| Dep. variable: | Slant_{ij}=Pr(FNC|Text_{ij}) | (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 share 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.7: Cable News Effect on Newspaper Content (2SLS): Non-Newspaper-Headquarter Counties

|                      | (1)          | (2)          | (3)          |
|----------------------|--------------|--------------|--------------|
| **Dep. variable:**   | **Slant\_ij\_s = Pr(FNC|Text\_ij\_s)** | **Slant\_ij\_s = Pr(FNC|Text\_ij\_s)** | **Slant\_ij\_s = Pr(FNC|Text\_ij\_s)** |
| 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            | 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.7. Robustness: Alternative county matching

Table C.8: Cable News Effects on Newspaper Content (2SLS): Alternative Matching Procedure

| Dep. variable: $\text{Slant}_{ij} = \Pr(FNC|\text{Text}_{ij})$ | (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                                  |        |       |       |

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.8. Robustness: Historical circulation weights

Table C.9: Cable News Effects on Newspaper Content (2SLS): 1995 Circulation Weights

| Dep. variable: Slant\textsubscript{ij}s = Pr(FNC|Text\textsubscript{ij}s) | (1) | (2) | (3) |
|-----------------------------|-----|-----|-----|
| FNC Viewership (rel. to CNN/MSNBC) | 0.556*** (0.165) | 0.538*** (0.162) | 0.561*** (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 | 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.9. Robustness: Relative circulation weights

Table C.10: Cable News Effects on Newspaper Content (2SLS): Relative Circ. Weights \times\text{Sampled Households}

| Dep. variable: $\text{Slant}_{ijs} = \Pr(FNC|\text{Text}_{ijs})$ | (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   | 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.11: Cable News Effects on Newspaper Content (2SLS): Relative Circ. Weights \times\text{County Pop}

| Dep. variable: $\text{Slant}_{ijs} = \Pr(FNC|\text{Text}_{ijs})$ | (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   | 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): * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 

52
### C.10. Robustness: Absolute and relative FNC viewership

Table C.12: Cable News Effects on Newspaper Content (2SLS): Different Instruments

| Dep. variable: Slant_{ij} = Pr(FNC|Text_{ij}) | (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    | X    | X    | X    |
| Circulation share weights                     | X    | X    | X    | 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 2). 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.11. Robustness: Dropping observations and clustering

Table C.13: Cable News Effects on Newspaper Content (2SLS): State Clustering

| Dep. variable: Slant$_{ij}$=$\Pr(FNC|\text{Text}_{ij})$ | (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.5: Cable News Effects on Newspaper Content (2SLS): Dropping Individual Newspapers

The histogram on the left (bin width 0.005) shows the Viewership coefficients according to our main specification (Table 2, 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.12. Mechanisms: Language features and topics

Table C.14: 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.14, 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. 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 content.

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22 The number of articles scraped is given by the availability on NewsLibrary. It does not seem to follow a pattern: the 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).

23 The insignificance of the coefficients in Table C.14 should not come as a surprise given that the main results in Table 2 barely change when we move from column 2 to column 3 (where generic newspaper language controls are introduced).
Table C.15: Cable News Effects on Newspaper Content (2SLS): Conditioning on Topics

| Dep. variable: Slant_{ij}=Pr(FNC|Text_{ij}) | (1) | (2) | (3) |
|-------------------------------------------|-----|-----|-----|
| FNC Viewership (rel. to CNN/MSNBC)        | 0.223** (0.101) | 0.223** (0.101) | 0.258** (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.
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.

The features of the institutional setting make direct influence of journalists, either through production costs or ideological preferences, a less likely or at least less salient mechanism for the observed 2SLS effects. A journalist can easily access cable news and borrow material, regardless of the local channel position (assuming that journalists are relatively sophisticated news consumers). 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 for judges: cable news influences criminal sentencing through voters and judicial elections rather than persuading judges directly.

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 the 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. Figure C.6 shows that the predicted effect sizes for each outcome are highly correlated across counties (with a Pearson’s correlation of 0.25). Further, Table C.16 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.6: 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.16: The five covariates most associated with a response to the instrument (county-level)

| Strong response of $\text{Slant}_k$ | 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 $\text{Slant}_k$ (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.14. Mechanisms: Slant contagion and polarization

Here, we replicate Table 4, but instead of pre-FNC/MSNBC era newspaper endorsements, we distinguish 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). Qualitatively, we find the same pattern: The relative FNC exposure coefficient is negative in the first column, positive plus 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.

Table C.17: Cable News Effects on Newspaper Content (2SLS): By Historical Republican Vote Shares

| Dep. variable: Slant_{ij}s = Pr(FNC|Text_{ij}s) | (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.18: Polarizing Effect of Cable News: Separate Reduced-Form Effects of FNC and CNN/MSNBC

| Dep. variable: Slant_{ij} = Pr(FNC|Text_{ij}) | (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.