Appendix

Opinion Trumps Fact: Entry and Competition in Online Political News

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A Predicting the opinion level of a political news article

A.1 Overview

This appendix details the construction of the paper's key dependent variable, *Opinion*. For each article, *Opinion* is a number $[0, 1]$ interpreted as the probability that the article would be judged "highly opinionated" by a group of human evaluators.

A.2 Labeling training data

We drew a random sample of 1,000 English-language political news articles from NewsAPI.ai and recruited 1,024 U.S. participants on CloudResearch.[32] Each participant read and rated 10 articles. After excluding respondents who failed reCAPTCHA or finished in under five minutes, 990 remained. Articles received a median of 10 ratings. Articles with < 5 ratings were dropped, leaving 967 articles.

For each article–rater pair, raters answered three 7-point Likert questions (and one yes/no item) about the article's opinionation. Items included both positively and negatively framed statements and were randomized in order. Because these are *ordinal* responses, we estimated a one-factor *polychoric* factor model. We first computed a polychoric/tetrachoric correlation matrix for the mixed ordinal/binary items, then fit a single-factor model (minres) to obtain per-rating regression factor scores s_{ir} and item loadings.

To remove rater severity and unrelated taste, we residualized the factor scores on rater fixed effects and a flexible spline in self-reported taste and then averaged within article:

$$\tilde{s}_{ir} \;=\; s_{ir} \;-\; \hat{\beta}^{\top}\mathbf{b}(\text{taste}_{ir}) \;-\; \hat{\alpha}_r, \qquad S_i \;=\; \text{Z-score}\left(\frac{1}{n_i}\sum_{r}\tilde{s}_{ir}\right),$$

where S_i is the article-level *Survey Opinion Score*. Compared to summing Likert items or applying PCA to numeric encodings, factor analysis on the polychoric matrix (i) respects ordinal spacing, (ii) down-weights weak items, and (iii) targets a common latent opinion construct rather than total variance.[33]

Single-rater reliability was moderate (ICC ≈ 0.36). With many raters per article, the reliability of the article mean was near-perfect (ICC of the mean ≈ 1.00). Disagreement across raters followed an inverse-U in S_i, peaking near the center and lowest in the tails (see Figure A.1a). To reduce label noise from ambiguous mid-range cases, we defined a high-confidence binary target with **Positive** = top quartile of S_i and **Negative** = the complement.[34] Figure A.1b illustrates the distribution of S_i and the upper quartile.

A.3 Model training

Text and tokenization. For each article, we concatenated the title and body, tokenized with the `bert-base-uncased` tokenizer, truncated/padded to a maximum sequence length of 512 tokens, and created attention masks.

Architecture. We fine-tuned a BERT encoder with a single linear classification head on the pooled [CLS] representation. The head included dropout ($p = 0.3$) and a 2-class output. Parameters of both the encoder and head were updated during training.

Training protocol. We class-balanced the training data via down-sampling of the majority class. We split the balanced dataset into train/validation/test (75/12.5/12.5). Optimization used AdamW (learning rate 2×10^{-6}, batch size 16) with cross-entropy loss for 12 epochs, running on GPU. We monitored validation performance and evaluated on the held-out test set.

Performance. Using the high-confidence (top-quartile) labels, ROC–AUC on the test set is 0.88 (see Figure A.1c and Figure A.1d for the confusion matrix.) Note that using a mean-based label cut reduces ROC–AUC to 0.72, consistent with the inverse-U pattern in rater disagreement.

[32] See Appendix E for the full survey instrument. We quota-matched basic demographics and implemented reCAPTCHA and speed checks.

[33] Polychoric FA targets a latent trait with measurement error and ordinal inputs; PCA on numeric Likert codes does not. When a single dimension dominates, PCA's first component and a one-factor FA score are similar; we prefer FA for construct validity and ordinal robustness.

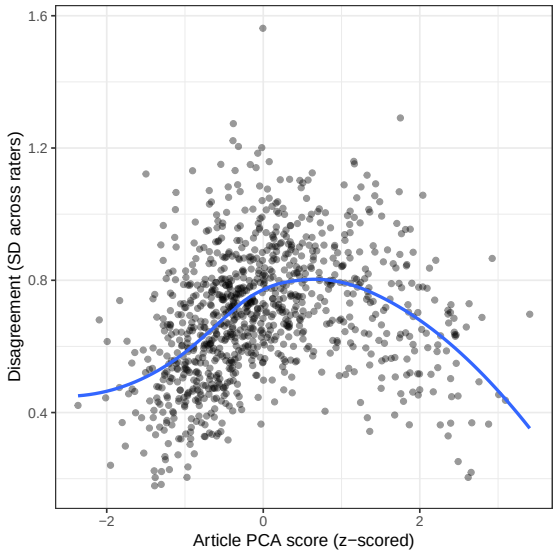
[34] In robustness checks using a mean-based threshold, predictive performance declines as expected (see below).

Output and interpretation. The trained model outputs a softmax score $p_i \in [0, 1]$ for the positive class. We use this as our continuous *Opinion* measure:

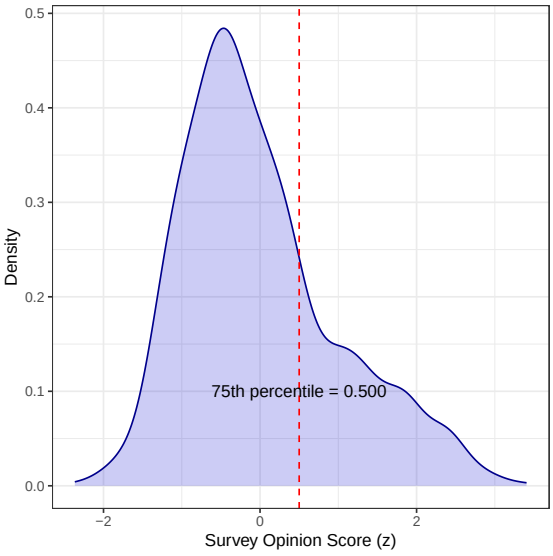
$$\text{Opinion}_i \approx P(\text{labelled "opinionated" by a majority of human raters} \mid \text{text}_i)\,,$$

where "opinionated" corresponds to being in the top quartile of S_i. For large-scale inference, we then applied the model to the full corpus of articles.

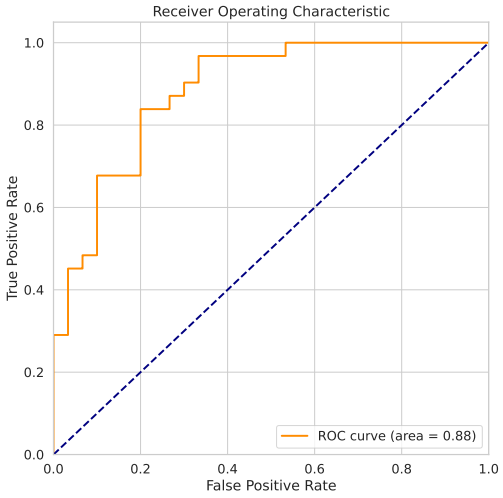
Figure A.1: NLP Opinion Model Performance



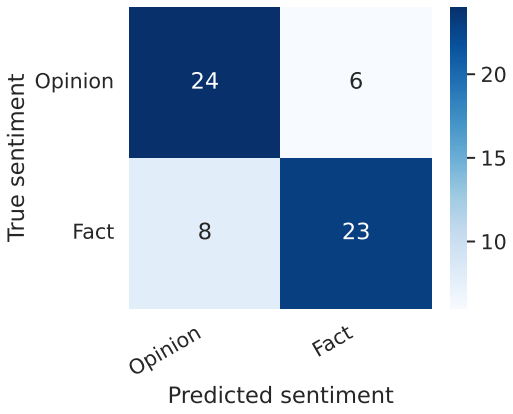
(a) Individual rater disagreement



(b) Distribution of Survey Score S_i



(c) ROC-AUC Curve



(d) Confusion Matrix of out-of-sample test performance

Figure A.2: Annotated distribution of article opinion scores

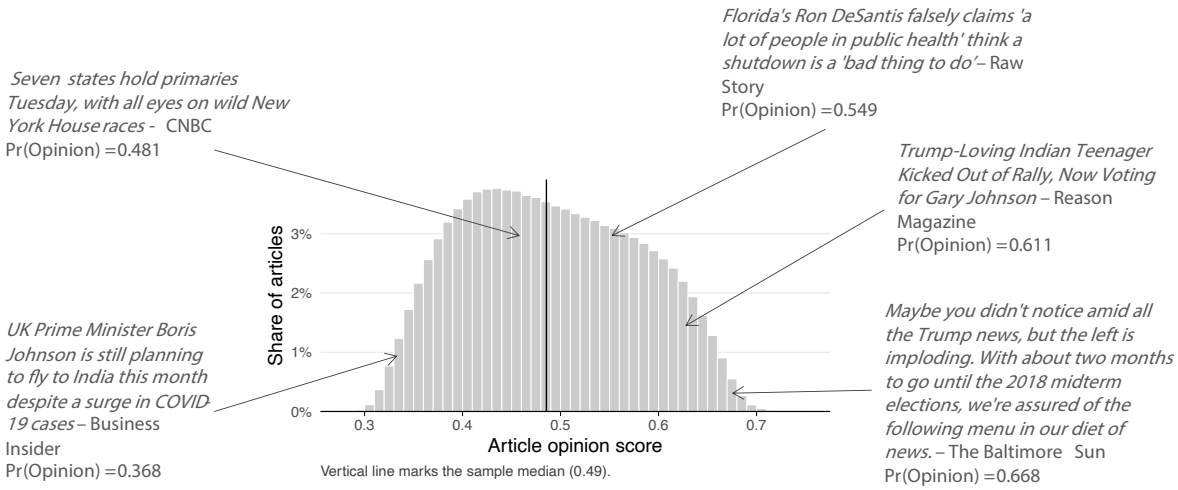


Figure A.3: Linear regression coefficient estimates for a selection of word tokens which are associated with fact and opinion

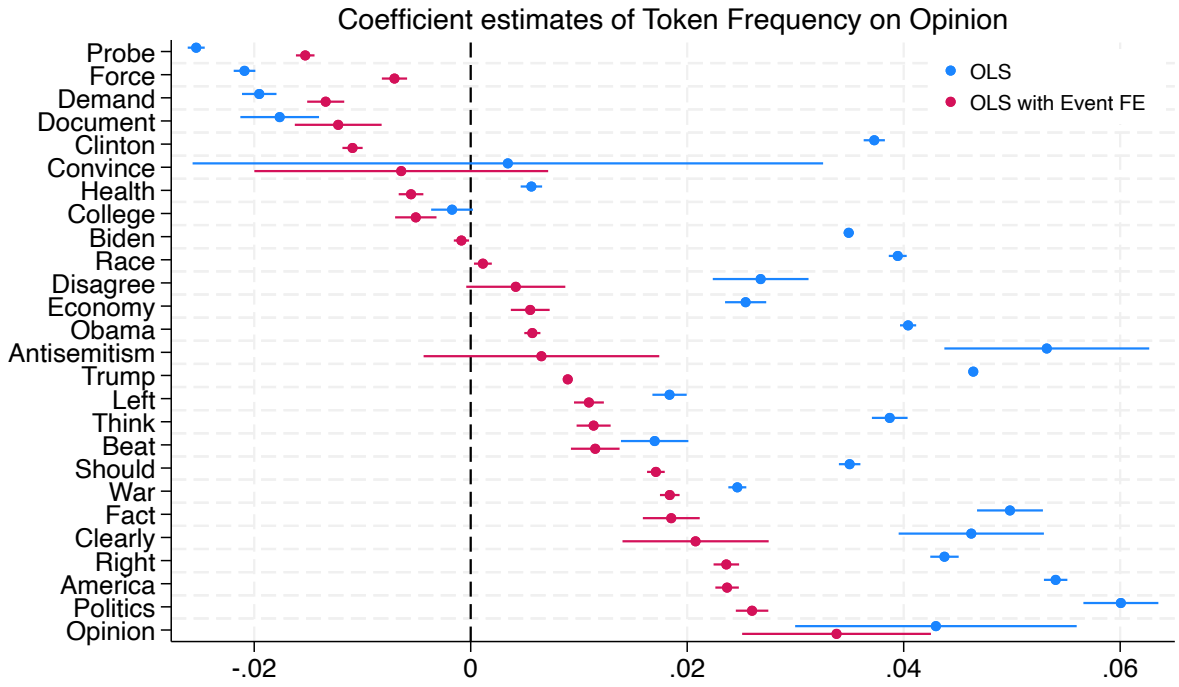


Table A.1: Articles in the top decile of Fact

URI	Pr(Opinion)	Firm	Date	Title	First Sentence of Body
1080647667	0.142	Northwest Arkansas Democrat Gazette	06/03/2019	Civilians, fighters still filter out of ISIS pocket in Syria	OUTSIDE BAGHOUZ, Syria – Hundreds of people left the last area held by the Islamic State group Tuesday in Syria and gathered in a reception area to be searched and screened by U.S.-backed fighters.
434247149	0.128	Daily News	07/05/2016	33 protesters arrested in clash with San Francisco deputies	SAN FRANCISCO » Authorities say 33 people were arrested at San Francisco's City Hall during a protest calling for the firing of the city's police chief.
224848268	0.139	NBC Right Now	06/11/2014	NATO leader in Afghanistan vows continued support	KABUL, Afghanistan (AP) - The head of NATO paid an unannounced visit to Kabul on Thursday, where he vowed that the Western alliance would continue supporting the country after foreign combat troops withdraw at the end of the year.
861358957	0.138	CNN International	03/05/2018	At least 81 killed by high-intensity dust storms in India	Chat with us in Facebook Messenger. Find out what's happening in the world as it unfolds.
6076129357	0.126	Newser	21/05/2020	FBI Suspects Terrorism in Base Shooting	(Newser) - A shooting at a Texas naval air station that wounded a sailor and left the gunman dead is being investigated as "terrorism-related," the FBI said Thursday. The shooting began around 6:15am at Naval Air Station-Corpus Christi. The shooter tried to speed through a gate at the base in a vehicle, but security personnel put up a barrier in time to stop him, US officials said. The man then got out of the car and opened fire, striking and wounding a Navy sailor who is a member of the security force at the base, the AP reports. During the exchange of gunfire, the shooter was killed by security personnel, the officials said. Investigators were working to determine whether a second person of interest was at large in the community.
6347996146	0.126	Seattle Pi	17/12/2020	Italy: 18 fishermen seized by Libya in fishing dispute freed	Foreign Minister Luigi Di Maio said he and Premier Giuseppe Conte went to Benghazi to bring the Sicily-based fishermen back.
6285657530	0.138	Conservative News Today	06/11/2020	Decision Desk HQ calls Penn for Biden, projecting him victor amid Trump camp litigation: 'Election is not over'	Former Vice President Joe Biden has been projected to become the 46th president of the United States by Decision Desk HQ after reportedly overtaking President Donald Trump's sizable lead in Pennsylvania Friday morning.
6285497743	0.111	Green Bay Press-Gazette	06/11/2020	Four people treated for injuries after early morning fire in Green Bay	GREEN BAY- Four people were treated for injuries Friday after an early morning house fire.
209273401	0.127	San Francisco Gate	09/09/2014	California school slaying suspect indicted	OAKLAND, Calif. (AP) – Prosecutors say a grand jury has indicted a man accused of killing seven people at a small Northern California Christian college.
198646031	0.133	abc11 News	20/07/2014	Police identify suspect in Spring Lake shooting	Spring Lake police have issued an arrest warrant for a Fayetteville man in connection with a fatal shooting early Saturday morning.

Table A.2: Articles in the top decile of Opinion

URI	Pr(Opinion)	Firm	Date	Title	First Sentence of Body
545240625	0.832	La Crosse Tribune	11/11/2016	Daniel Seehafer: Veterans deserve more action, less talk	The votes have been tallied, promises made and history recorded. Now begins the difficult task of delivering on the promises made to the American people. As the newly elected state commander of the Wisconsin American Legion, it is my duty to focus on the needs of the tens of thousands of Wisconsin men and women who have fought nobly for this country and fight on their behalf. So, while we recognize their sacrifices on Veterans Day, this simple observance is hardly where our responsibility to them begins and ends. As a community, state and nation, we must work harder and longer to more thoroughly and effectively deliver services to these deserving veterans.
267198358	0.858	Vox	06/04/2015	Jeb Bush once registered as a Hispanic voter. Was it a mistake?	The New York Times reported this morning that Jeb Bush identified himself as "Hispanic" on a Florida voter registration form in 2009:
153307506	0.879	Al-Monitor	24/01/2014	Anniversary of Egypt's uprising is a chance for renewal	Today is the third anniversary of the uprising that brought the downfall of Egyptian President Hosni Mubarak's regime.
164646057	0.858	New York Post	05/03/2014	Hyper-liberal de Blasio is Gov. Cuomo's best asset	The further to the left the mayor goes, the more reasonable the governor looks.
818003820	0.842	Kennebec Journal and Morning Sentinel	22/02/2018	From 'duck and cover' to 'active shooter' - CentralMaine.com	As I sit here thinking of the 14 high school students shot dead, three teachers shot dead, 14 others wounded, and thousands of others suffering, there has not been a single word from my congressman, Bruce Poliquin.
250035275	0.844	Portland Press Herald	14/02/2015	Governor quits amid scandal over fiancee's contract work	PORTLAND, Ore. – When the end finally came, the most ubiquitous politician in the history of Oregon had all but disappeared from public view.
939718485	0.904	Mediaite	05/09/2018	Tweet for Everything: Trump Tweeted Praise for Bob Woodward Just Last Year	There's a recurring joke on the internet where every time Donald Trump says something politically controversial, somehow there's always a tweet from his past where he says the opposite is true.
215139475	0.908	Washington Post	03/10/2014	Grimes ad features Bill Clinton as a not-quite attack dog	Bill Clinton has never met a"g" he didn't want to drop.
6195297466	0.854	Alternet.org	27/08/2020	'You've absolutely failed': Former Trump DHS official delivers damning takedown of president's leadership skills	A new video from Republican Voters Against Trump was released on Wednesday. Like former chief of staff for the Department of Homeland Security Miles Taylor's video, this one features Elizabeth Neumann, Trump's former assistant Secretary for Threat Prevention at the DHS. Neumann was one of the DHS officials who spoke on the threat of domestic terrorism with the House back in June 2019. It was a hearing that highlighted the rise of the white supremacist and white nationalist movements in our country and abroad, and the dangers they posed to our democracy.
247259816	0.907	POLITICO	06/02/2015	Putin Has Asperger's Don't Flatter Him	As the father of an child with the syndrome and a Russia expert, I can tell you the Pentagon report couldn't be more wrong.

Table A.3: Highlighting the difference between embedded context and individual tokens: Opinionated and Factual articles containing the word "Fact"

URL	Opinion Score	Title	Excerpt
http://www.commondreams.org/views/2016/02/12/bernie-sanders-changing-hillary-clinton-one-day-and-one-debate-time	0.6127	Bernie Sanders Is Changing Hillary Clinton One Day (and One Debate) at a Time	"...in **fact**, Kissinger's actions in Cambodia, when the United States bombed that country, overthrew Prince Sihanouk, created the instability..."
http://www.commondreams.org/views/2015/04/29/give-em-hell-bernie	0.6616	Give 'Em Hell, Bernie	"...it's a **fact** that the Beltway-media cognoscenti who decide these things make access to money the primary factor in determining viability..."
http://www.nytimes.com/2014/11/14/opinion/paul-krugman-china-coal-climate.html?_r=0	0.6119	China, Coal, Climate	"...the agreement between China and the United States on carbon emissions is, in **fact**, a big deal..."
http://www.metroweekly.com/2015/08/kentucky-county-clerk-defies-court-order-to-issue-marriage-licenses/	0.29996	Kentucky county clerk defies court order to issue marriage licenses	"...this argument ignores the **fact** that Plaintiffs have strong ties to Rowan County..."
https://www.bizpacreview.com/2019/08/24/fl-teacher-baker-acted-after-school-shooter-advice-792728	0.29648	FL teacher 'Baker Acted' after school shooter advice	"...he shook his head and said that he, in **fact**, would not want that now..."
https://wsvn.com/news/us-world/police-officer-wounded-1-dead-in-tennessee-school-shooting/	0.29079	Police: Officer wounded, 1 dead in Tennessee school shooting	"...the governor said the increased penalties mean that 'we in **fact** will be strengthening laws'..."

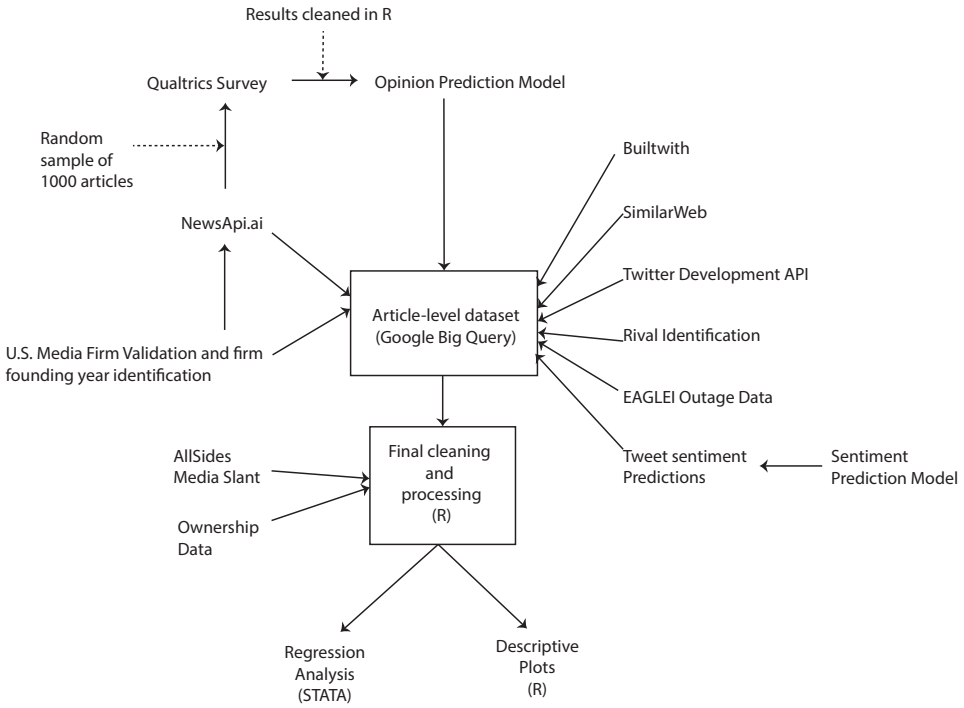
Table A.4: The top 15 most covered events in our sample

Event URI	Number of Articles	Event Start Date	Mean Opinion	Event Description
937946	1513	2021-01-06	0.271	President Donald Trump's supporters storm the U.S. Capitol building following his address, causing significant chaos and violence. The situation prompts evacuations, a curfew in Washington D.C., and the halt of Congressional proceedings to certify the election results. Four people are reported dead amidst the unrest.
1929882	1336	2016-02-13	0.568	Supreme Court Justice Antonin Scalia passed away, leaving a vacancy in the court. Despite Republican opposition, President Obama intends to nominate a successor.
2213648	1251	2016-06-05	0.626	Hillary Clinton becomes the presumptive Democratic presidential nominee in the 2016 primaries, winning the New Jersey and California primaries. Despite this, rival candidate Bernie Sanders refuses to acknowledge her victory.
2295705	1360	2016-05-06	0.623	Donald Trump officially named Indiana Governor Mike Pence as his running mate in the 2016 U.S. Presidential election. The decision drew a range of reactions. Pence's political life and unknown public profile were also discussed.
2306149	1256	2016-07-16	0.716	During the 2016 Republican National Convention, Ted Cruz was booed for refusing to endorse Donald Trump. Trump's speech emphasized his promise to restore safety in America.
2533149	1788	2016-10-06	0.667	The event is the second Presidential debate between Hillary Clinton and Donald Trump, under the shadow of a controversy arising from Trump's crude comments about a married woman.
2594367	1357	2016-10-28	0.379	FBI Director, James Comey, announced a renewed investigation into Hillary Clinton's emails shortly before the 2016 U.S. election, sparking controversy and accusations of political bias. The new emails were not sent by Clinton, but were found during an unrelated investigation.
3025928	1955	2017-04-03	0.323	The US launched missile strikes on Syria, triggering international reactions. This action was a response to a suspected chemical attack. It strained US-Russia relations as Russia froze communications with the US following the strikes. The move provoked debates on its strategic implications and effectiveness.
3119254	1496	2017-05-07	0.456	President Donald Trump controversially fired FBI Director James Comey, drawing comparisons to a similar event in 1993. Comey's dismissal came amidst FBI's ongoing investigation on Russia's interference in the 2016 U.S. elections, triggering bipartisan calls for an independent probe. The White House defended the decision.
3187018	1548	2017-06-05	0.456	The articles cover the event of former FBI Director James Comey's testimony to the Senate Intelligence Committee, discussing his interactions with President Donald Trump. Topics include Trump's exercise of executive privilege and responses to Comey's statements.
3274852	1432	2017-07-11	0.503	The articles cover the event of Donald Trump Jr.'s meeting with a Russian-American lobbyist during the 2016 presidential campaign, which sparked controversy due to allegations of possible collusion between the Trump campaign and Russia.
3305531	1355	2017-07-23	0.502	The Trump administration has been considering replacing Attorney General Jeff Sessions, with President Trump expressing dissatisfaction. Meanwhile, Jared Kushner, Trump's son-in-law, is defending the controversial meeting with the Russians. Evangelical leaders and Republican lawmakers are rallying in support of the administration.
4277743	1478	2018-09-16	0.411	The articles cover the accusations against Supreme Court nominee Brett Kavanaugh of sexual misconduct dating back to his high school years, the subsequent investigations and hearings, and the public and political reaction to the allegations.
4297645	2585	2018-09-24	0.417	The event is a Senate Judiciary Committee hearing where Judge Brett Kavanaugh and Dr. Christine Blasey Ford testified about Ford's allegations of sexual assault against Kavanaugh during their high school years, impacting Kavanaugh's Supreme Court nomination.
5110086	1207	2019-09-22	0.493	The articles are covering the impeachment inquiry against US President Donald Trump, triggered by a whistleblower report. It discusses the process of impeachment, reactions of various political factions, Trump's interactions with Nancy Pelosi, and the potential political implications for the Democrats.

B Data

B.1 Pipeline

Figure B.1: Dataset construction pipeline



B.2 Description of Variables

Variable	Measure	Description of Measure	Data Source(s)
Opinion	The extent to which a human evaluator would rate an article as being opinionated	The predicted probability that article i is opinionated.	NewsAPI and Qualtrics survey for human-coded labels
Entrant	New media firms	A dummy variable set to 1 if firm j is less than five years old at the time of publishing article i at time t. In additional models we also define entrant as less than 3, 7, 10, and 15 years old at the time of publishing article i.	ChatGPT4 API, NewsAPI, and manual validation
Firm Age	Years since founding	The age, in years, of firm j on date t.	ChatGPT4 API, NewsAPI, and manual validation
Tweets	Twitter engagement	A count of tweets which mention article i on date t.	Twitter
Average Tweet Length	Average Tweet Length	The average character length of all tweets and retweets which mention article i.	Twitter

Retweets	Twitter engagement	A count of all retweets that mention article i on date t.	Twitter
Replies	Twitter engagement	A count of all replies to tweets that mention article i on date t.	Twitter
Webpage Visits (1000s)	News webpage engagement	The count—in thousands—of the number of unique visits to the webpage of firm j during date t.	SimilarWeb
Advertising Technologies	The use of ad networks	A count of the number of advertising networks identified on the webpage of firm j on date t.	BuiltWith
Political Slant	Firms leaning to the left or right of the political spectrum	A dummy variable equal to one if firm j is classified as left or right leaning; zero otherwise	AllSides
Repeat Readers	The share of yesterday's readers returning today	For outlet i on day t, let n_{it}^{today} denote the number of unique users visiting the outlet on day t, and let $n_{it}^{\text{yesterday}}$ denote the number of unique users on day $t-1$. Let I_{it} denote the number of users active on both days. We define repeat readership using the Jaccard similarity index: $\text{Repeat Readership}_{it} = \frac{I_{it}}{n_{it}^{\text{today}} + n_{it}^{\text{yesterday}} - I_{it}}$, whenever the denominator is positive, and zero otherwise. This measure captures the fraction of users who return on consecutive days relative to the total distinct users across both days, which we use as a proxy for audience stability.	ComScore
Rival Engagement	Intensity of competition	The sum of all tweets recorded during the seven-day period prior to date t mentioning articles published by competitors to firm j.	Twitter, NewsAPI
Rival Outage Exposure	Extent to which a rival's audience is effected by power outtages	See Appendix C	Comscore, EAGLE-I
Own Engagement	Social media engagement with the focal firm's content	The sum of tweets to articles published by the focal firm j in the last 7 days.	Twitter, NewsAPI
Number of Rivals	Count of competitors	A simple count of the number of firms active within the last 30 days of firm j publishing article i	NewsAPI
Print Version	Firms that produce print versions of their articles	A dummy variable set to one if firm j is classified as publishing articles in print; zero otherwise	ChatGPT4 API, NewsAPI, and manual validation
Analytic Technologies	The use of other online web development tools	A count of technologies firm j uses on their website at time t. These technologies include: audience measurement, conversion optimization, AB testing, site optimization, among others.	BuiltWith
Hate Speech	The extent to which a tweet contains hate speech	The average probability for all tweets and retweets associated with article i that the content is classified as containing hate speech.	NewsAPI and TweetNLP
Anger	The extent to which a tweet expresses anger	The average probability for all tweets and retweets associated with article i that the content is classified as expressing anger.	NewsAPI and TweetNLP
Sadness	The extent to which a tweet expresses sadness	The average probability for all tweets and retweets associated with article i that the content is classified as expressing sadness.	NewsAPI and TweetNLP
Joy	The extent to which a tweet expresses joy	The average probability for all tweets and retweets associated with article i that the content is classified as expressing joy.	NewsAPI and TweetNLP
Optimism	The extent to which a tweet expresses optimism	The average probability for all tweets and retweets associated with article i that the content is classified as expressing optimism.	NewsAPI and TweetNLP
Article Year	Year of publication	The year in which article i was published.	NewsAPI
Annual Article Count	Annual Article Count	The total number of articles published by firm j in a given year.	NewsAPI

Figure B.2: Media Firms Founded per Year

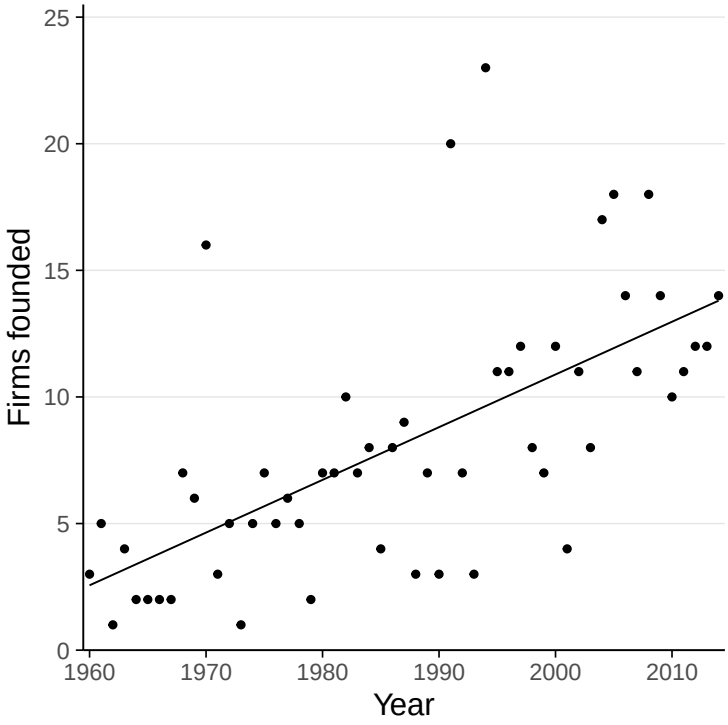


Table B.1: Article-Level Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Opinion	1.00																							
Entrant (< 5 years old)	0.08	1.00																						
Firm Age	-0.07	-0.17	1.00																					
Tweets	0.04	0.01	0.02	1.00																				
Average Tweet Length	0.03	0.02	-0.07	0.03	1.00																			
Retweets	0.03	0.02	0.01	0.81	0.02	1.00																		
Replies	0.04	0.00	-0.00	0.40	0.01	0.41	1.00																	
Webpage Visits (1000s)	0.05	-0.13	0.25	0.18	-0.03	0.14	0.12	1.00																
Advertising Technologies	-0.04	-0.34	-0.05	-0.08	-0.06	-0.05	-0.03	-0.12	1.00															
Political Slant	0.08	0.14	-0.18	0.05	-0.04	0.04	0.01	0.25	0.05	1.00														
Repeat Readers	0.02	-0.00	-0.02	0.01	-0.00	0.00	0.01	0.03	0.02	0.00	1.00													
Rival Tweets (prev 7d)	-0.03	0.00	-0.02	0.01	0.04	0.01	0.02	-0.02	0.02	0.03	-0.01	1.00												
Rival Outage Exposure (sum, 7d)	-0.02	-0.01	-0.01	0.00	0.01	0.00	0.02	0.06	-0.04	0.01	-0.00	0.15	1.00											
Focal Tweets (prev 7d)	0.10	-0.07	0.08	0.18	-0.00	0.13	0.11	0.64	-0.19	0.02	0.04	-0.03	0.01	1.00										
N Rivals (30d)	-0.01	-0.04	-0.13	0.08	0.01	0.06	0.08	0.36	-0.03	0.11	0.03	0.40	0.24	0.31	1.00									
Print Version	-0.05	-0.19	0.58	0.01	-0.01	-0.00	-0.04	0.12	0.02	0.06	-0.04	0.03	0.01	-0.06	-0.09	1.00								
Analytic Technologies	0.03	-0.18	0.31	0.07	-0.02	0.04	0.02	0.41	0.32	0.17	0.01	-0.15	-0.08	0.24	-0.06	0.43	1.00							
Hate Speech	-0.00	-0.01	-0.06	0.02	0.03	0.02	0.02	0.01	0.05	0.11	0.01	-0.00	0.00	-0.01	0.04	-0.05	-0.02	1.00						
Anger	0.16	0.02	-0.14	0.08	0.10	0.07	0.06	0.04	0.06	0.18	0.01	-0.02	-0.02	0.05	0.05	-0.11	0.01	0.22	1.00					
Sadness	-0.12	-0.02	0.09	-0.03	-0.10	-0.03	-0.03	-0.00	-0.00	-0.03	-0.00	-0.00	-0.00	-0.04	-0.05	0.06	0.02	-0.05	-0.22	1.00				
Joy	0.07	-0.00	0.04	-0.02	-0.06	-0.02	-0.01	-0.01	-0.01	-0.02	-0.01	0.00	0.00	-0.03	-0.03	0.02	0.00	-0.08	-0.36	-0.10	1.00			
Optimism	0.10	-0.00	0.02	-0.03	0.06	-0.03	-0.02	-0.02	-0.03	-0.03	-0.01	0.01	0.01	-0.02	-0.01	0.04	-0.02	-0.09	-0.36	-0.13	0.27	1.00		
Article Year	-0.08	-0.01	0.01	-0.00	0.07	0.00	0.01	-0.03	-0.10	-0.00	-0.01	0.34	0.17	-0.10	0.26	0.03	-0.42	0.01	-0.07	0.01	0.00	0.05	1.00	
Annual Article Count	0.08	-0.12	-0.12	0.11	-0.00	0.08	0.10	0.48	-0.01	-0.10	0.06	-0.13	0.02	0.65	0.44	-0.25	0.19	0.03	0.08	-0.07	-0.04	-0.03	-0.30	1.00

Table B.2: Summary Statistics split by availability of Political Slant data

	No AllSides Match		AllSides Match	
	Mean	SD	Mean	SD
Opinion	0.492	(0.090)	0.488	(0.088)
Entrant (< 5 years old)	0.039	(0.194)	0.019	(0.137)
Firm Age	72.968	(61.435)	79.450	(62.410)
Tweets	161.306	(801.484)	121.497	(672.025)
Average Tweet Length	119.505	(24.494)	117.656	(25.605)
Retweets	67.203	(479.009)	52.398	(372.244)
Replies	24.052	(159.768)	21.026	(163.166)
Webpage Visits (1000s)	2078.795	(5264.390)	14622.687	(37967.823)
Advertising Technologies	0.700	(0.431)	0.762	(0.450)
Repeat Readers	0.004	(0.020)	0.004	(0.020)
Rival Engagement	181420.190	(110312.272)	184918.223	(107479.357)
Rival Outage Exposure	18.759	(44.003)	19.840	(46.678)
Own Engagement	2633.883	(6720.737)	3184.127	(8070.401)
Number of Rivals	403.443	(132.128)	416.646	(117.384)
Print Version	0.544	(0.498)	0.611	(0.488)
Analytic Technologies	27.738	(11.619)	28.358	(9.768)
Hate Speech	0.023	(0.075)	0.022	(0.072)
Anger	0.206	(0.197)	0.193	(0.190)
Sadness	0.059	(0.112)	0.061	(0.117)
Joy	0.072	(0.127)	0.077	(0.132)
Optimism	0.062	(0.097)	0.062	(0.095)
Article Year	2017.153	(2.120)	2017.245	(2.105)
Annual Article Count	5775.498	(5369.808)	8563.986	(9772.517)

C Instrumental Variable Strategy

In this section, we discuss the construction of the instrumental variable and the main assumptions underlying our identification strategy for estimating the effects of social media engagement with rival content on article opinionation.

C.1 Variable Construction

Social media engagement with rival content. Let a_{jd} denote the count of tweets referencing content from firm j on date d. This captures audience engagement with firm j's articles, for example users sharing or discussing articles published by firm j on Twitter. We aggregate raw tweet data to obtain daily engagement counts for each firm in our sample. For each article i published by focal firm v on date t, let $\mathcal{R}_{vt}$ denote the set of rival firms that published articles covering the same news event within a 30-day window. We construct the rival engagement measure as:

$$X_{vt} = \sum_{j \in \mathcal{R}_{vt}} \sum_{d=t-\tau}^{t-1} a_{jd} \tag{7}$$

where τ defines the lookback window. Our primary specification uses $\tau = 7$ days; we also consider $\tau \in \{3, 14, 30\}$ as robustness checks. This measure captures the cumulative Twitter engagement with rival firms' content in the τ days preceding article publication, excluding the publication date itself. We similarly construct a control for engagement with the focal firm's own content, $X_{vt}^{\text{own}} = \sum_{d=t-\tau}^{t-1} a_{vd}$.

Power outage data. Our instrument exploits plausibly exogenous variation in Twitter engagement with rivals' content arising from power outages in U.S. states where rival audiences are concentrated. We obtain power outage data from the Environment for Analysis of Geo-Located Energy Information (EAGLE-I) platform, maintained by Oak Ridge National Laboratory for the U.S. Department of Energy (Brelsford et al., 2024). EAGLE-I monitors electric utility customer outages by scraping utilities' public outage maps via an automated ETL process at 15-minute intervals. By 2022, the platform covered 456 utilities accounting for approximately 146 million electric utility customers (92% of U.S. customers) across 3,044 of 3,226 U.S. counties and county equivalents. The raw data record the number of customers without power in each county at each 15-minute timestamp.

The EAGLE-I data cover November 2014 through 2023, yielding approximately 11.1 million county-level outage events and a cumulative 8.5 billion customer-hours of disruption. The median outage lasted 90 minutes, with substantial right-skew (75th percentile: 225 minutes; 90th percentile: 495 minutes). Figure C.1 displays the full duration distribution.

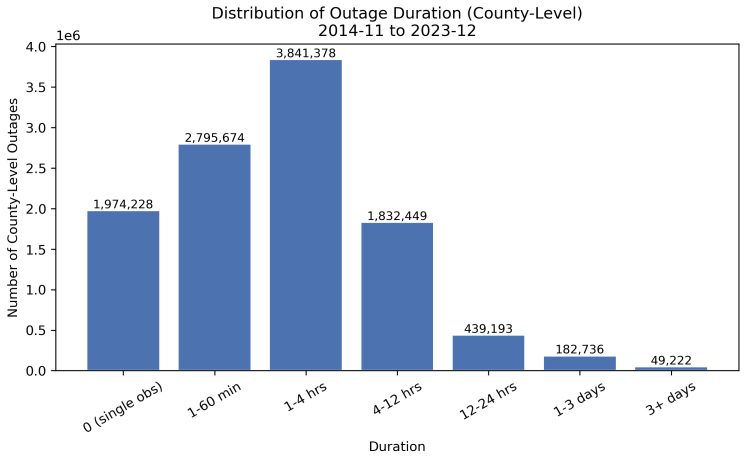


Figure C.1: Distribution of outage duration (county-level events), November 2014–December 2023.

Outages are geographically widespread but unevenly distributed. Figure C.2 maps outage frequency by county across the continental United States. Texas, Georgia, North Carolina, Virginia, and Ohio are the most affected states by event count. The geographic variation, driven by differences in weather exposure, grid infrastructure, and vegetation, provides the identifying variation for our instrument after weighting by audience geography.

Figure C.3 displays the monthly time series of outage frequency and customer-hours affected. Outage frequency and severity exhibit clear seasonal patterns, with peaks during summer months (heat-driven grid stress) and winter

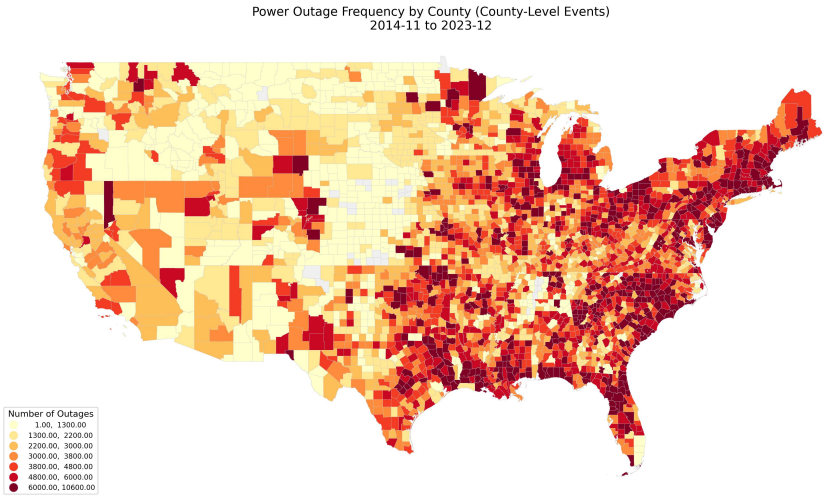


Figure C.2: Power outage frequency by county (county-level events), November 2014–December 2023.

storms. The annual number of events grew from approximately 780,000 in 2015 to over 1.5 million by 2020. These temporal patterns motivate the inclusion of month and year fixed effects in our specifications, which absorb predictable seasonal and secular variation in outage intensity.

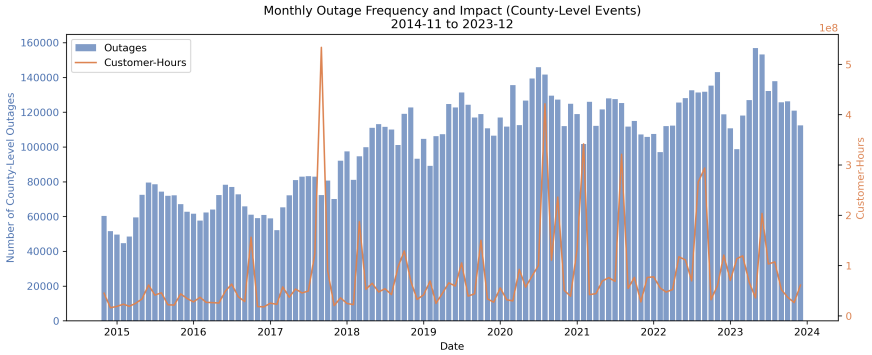


Figure C.3: Monthly outage frequency and customer-hours affected (county-level events), November 2014–December 2023.

Audience-weighted power outage exposure. We aggregate these county-level records to the state-date level, converting each 15-minute snapshot of customers out into customer-hours, and summing across all intervals and counties within a state-day. For each state s and date d, we normalize by state population:

$$I_{sd} = \frac{H_{sd}}{P_{s,\text{year}(d)}} \tag{8}$$

where H_{sd} denotes total person-hours of power outage in state s on date d, and $P_{s,\text{year}(d)}$ is the population of state s in the corresponding year. We cumulate this measure over a rolling τ-day window (excluding the current day), $I_{s,t}^{(\tau)} = \sum_{d=t-\tau}^{t-1} I_{sd}$.

To translate state-level outages into firm-level exposure, we weight by audience geography. Using Comscore web traffic data, we compute the share of firm j's audience located in state s:

$$w_{js} = \frac{n_{js}}{\sum_{s'} n_{js'}} \tag{9}$$

where n_{js} is the number of observed web sessions from users in state s accessing firm j's content. Firm j's audience-weighted outage exposure is then:

$$E_{jt} = \sum_{s} w_{js} \cdot I_{s,t}^{(\tau)} \tag{10}$$

The instrumental variable aggregates this exposure across all rivals of the focal firm:

$$Z_{vt} = \sum_{j \in \mathcal{R}_{vt}} E_{jt} \tag{11}$$

Last, because multiple articles by the same firm may share the same rival set and engagement measures on a given date, we aggregate the data to the firm-date level before estimation. Specifically, we collapse article-level observations by taking means of the outcome variable (article opinion) and all covariates within each firm-date cell. The unit of observation in our regressions is therefore firm v on date t.

Regression specifications. The baseline OLS specification estimates:

$$\bar{Y}_{vt} = \beta \log(X_{vt}) + \mathbf{W}_{vt}'\boldsymbol{\gamma} + \delta_t + \varepsilon_{vt} \tag{12}$$

where $\bar{Y}_{vt}$ is the mean opinion score for articles published by firm v on date t, $\mathbf{W}_{vt}$ is a vector of controls including $\log(X_{vt}^{\text{own}})$, $\log(N_{v,\text{year}(t)})$ (focal firm's annual article count), and $|\mathcal{R}_{vt}|$ (number of rivals), and δ_t represents time fixed effects (day-of-week, month, and year). Standard errors are clustered at the firm level. The 2SLS specification instruments for $\log(X_{vt})$ using Z_{vt}:

First Stage:

$$\log(X_{vt}) = \pi Z_{vt} + \mathbf{W}_{vt}'\boldsymbol{\lambda} + \delta_t + \nu_{vt} \tag{13}$$

Second Stage:

$$\bar{Y}_{vt} = \beta \widehat{\log(X_{vt})} + \mathbf{W}_{vt}'\boldsymbol{\gamma} + \delta_t + \varepsilon_{vt} \tag{14}$$

To examine heterogeneity by firm age, we instrument both $\log(X_{vt})$ and its interaction with an entrant indicator D_v (equal to one if the firm is five years old or younger), using Z_{vt} and $D_v \times Z_{vt}$ as instruments:

$$\bar{Y}_{vt} = \beta_1 \widehat{\log(X_{vt})} + \beta_2 \left(D_v \times \widehat{\log(X_{vt})} \right) + \mathbf{W}_{vt}'\boldsymbol{\gamma} + \delta_t + \varepsilon_{vt} \tag{15}$$

C.2 Instrument Relevance

The instrument's relevance relies on the notion that power outages in states where a news firm's audience is concentrated reduce Twitter engagement with that firm's content (and political news consumption in general). Power outages disrupt social media activity through several reinforcing channels. Most directly, outages disable home Wi-Fi routers and local network infrastructure, cutting off the primary means through which most users access the internet at home. Even when cellular networks remain operational, users facing uncertain outage durations have strong incentives to conserve smartphone battery life for essential communications (calls, texts, and emergency alerts) rather than browsing news or engaging on social media. Outages also shut down desktop computers and unplug charging stations, further limiting the devices available for online activity. Beyond connectivity, outages impose practical demands (checking on neighbors, managing perishable food, securing alternative lighting and heating) that crowd out discretionary media consumption. The cumulative effect is a sharp, temporary reduction in the volume of news reading and social media engagement among affected populations.

Because our instrument aggregates audience-weighted outage exposure across rival firms, it captures exogenous negative shocks to the overall level of social media engagement with rival content. When outages disproportionately strike states where a rival's readership is concentrated, the rival experiences a drop in Twitter engagement that is unrelated to the content it produces or the editorial decisions of other firms.

Column (4) of Table 5 reports the first-stage estimates. The coefficient on rival outage exposure is negative and statistically significant at the 1% level. The point estimate is small in magnitude, which is expected given that our outage intensity measure (person-hours per capita) and the dependent variable (log rival tweet counts) operate on very different scales. The Kleibergen-Paap cluster-robust first-stage F-statistic is 1,311.4, far exceeding conventional thresholds for weak instruments. The large F-statistic likely reflects the substantial sample size (over 526,000 firm-date observations) combined with the broad geographic coverage of the EAGLE-I outage data.

C.3 Conditionally Unconfounded Instrument

Unconfoundedness of the instrument requires that there are no unmeasured common causes between the instrument (audience-weighted power outage exposure affecting rivals) and the endogenous variable (Twitter engagement with rival content), and between the instrument and the second-stage outcomes of interest. We discuss these assumptions and provide supporting evidence.

Power outages are driven by weather events, equipment failures, and grid capacity constraints, factors that are plausibly unrelated to editorial decisions or news content characteristics. To account for systematic differences across time periods, we condition all models on day-of-week, month, and year fixed effects. Because power outages exhibit strong seasonal patterns (e.g., summer heat waves strain grid capacity, winter storms damage power lines), month fixed effects absorb the predictable cyclical component of outage intensity. Year fixed effects account for secular trends in grid reliability, and day-of-week fixed effects capture weekly patterns in both outage incidence and social media usage. The identifying variation in our instrument therefore comes from deviations in outage exposure relative to the expected level for a given month, year, and day of week. Standard errors are clustered at the firm level to account for within-firm correlation. Within these controls, outage events should be orthogonal to unobserved determinants of article opinionation.

A potential concern is that power outages may be correlated with newsworthy events (e.g., hurricanes that both cause outages and generate news coverage). Note, however, that our sample is restricted to political news articles, so weather-related coverage does not enter the analysis. We further address this concern as follows. The instrument captures outages affecting *rivals'* audiences, not the focal firm's audience. A remaining threat would be that outages in rivals' audience states also overlap geographically with the focal firm's readership, creating a direct effect on the focal firm's own engagement. We account for this by controlling for the focal firm's own Twitter engagement ($\log(X_{vt}^{\text{own}})$) in all specifications (see Table 5). This control absorbs any direct effect of outages on the focal firm's readership, ensuring that the instrument operates only through its effect on rival engagement. After conditioning on own engagement, outages in states where the focal firm's audience is concentrated do not provide additional variation in the instrument, because the instrument is constructed using rivals' audience weights, not the focal firm's.

To further support the unconfoundedness assumption, Table C.2 presents balance tests examining the correlation between the instrument and observable firm characteristics. Each column regresses a pre-determined covariate on the instrument, conditioning on the same controls used in the main 2SLS specification (number of rivals, log firm-year articles, log own engagement, and time fixed effects). The instrument is uncorrelated with entrant status, political slant (any, left, or right), print edition availability, and readership stability, with no coefficient statistically significant at conventional levels. The one exception is the number of analytics tools (column 6), which shows a small but statistically significant negative association with the instrument.[35]

C.4 Exclusion Restriction

The exclusion restriction posits that audience-weighted power outages affecting rivals influence the focal firm's content decisions only through their effect on Twitter engagement with rival content. Formally:

$$\text{Cov}(Z_{vt}, \varepsilon_{vt} \mid \mathbf{W}_{vt}, \delta_t) = 0 \tag{16}$$

A threat to this assumption could arise if power outages directly affect the focal firm's editorial process. For instance, if outages in rivals' audience states also affect the focal firm's own readership or operations, the instrument could influence outcomes through channels other than rival engagement. This concern is mitigated by the geographic specificity of our instrument construction: by weighting outages by *rivals'* audience shares (and controlling for the focal firm's own Twitter engagement), we isolate variation that operates through rivals rather than through the focal firm itself.

Another possibility is that outages shift the overall news agenda in ways that affect article characteristics. For example, major weather events might crowd out political coverage or change the mix of topics available for reporting. As noted above, our sample is restricted to political news, limiting the scope for weather-driven agenda effects. In addition, the time fixed effects (month, year, day of week) absorb seasonal and cyclical variation in news coverage patterns. We also control for the number of rivals $|\mathcal{R}_{vt}|$, which accounts for changes in the competitive environment on a given date.

C.5 Summary of Key Variables

Table C.1 summarizes the key variables used in the instrumental variable analysis.

[35] Adding the number of analytics tools as an additional control in the main 2SLS specification leaves the coefficient on rival engagement virtually unchanged. Results available upon request.

Table C.1: Summary of Key Variables

Variable	Definition	Equation
$\bar{Y}_{vt}$	Mean opinion score for firm v on date t	—
X_{vt}	Rival tweet count in prior τ days	(7)
X_{vt}^{own}	Focal firm tweet count in prior τ days	—
Z_{vt}	Sum of audience-weighted outage exposure across rivals	(11)
I_{sd}	State-date outage intensity (person-hours / population)	(8)
w_{js}	Share of firm j's Comscore audience in state s	(9)
E_{jt}	Firm j's audience-weighted outage exposure	(10)
D_v	Entrant indicator (firm age ≤ 5 years)	—
$\lvert\mathcal{R}_{vt}\rvert$	Number of rivals for focal firm v on date t	—
$N_{v,\text{year}(t)}$	Focal firm's article count in year of t	—

Table C.2: IV Balance Test: Instrument and Observable Firm Characteristics

	(1) Entrant	(2) Any Slant	(3) Left Slant	(4) Right Slant	(5) Print Version	(6) Analytics Tools	(7) Repeat Readers
Rival Outage Exposure	0.0000	-0.0000	-0.0000	0.0000	0.0000	-0.0015**	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0006)	(0.0000)
Observations	526,398	209,122	209,122	209,122	526,398	506,128	360,771
Adjusted R-squared	0.021	0.150	0.068	0.068	0.040	0.189	0.001

Standard errors clustered by firm in parentheses.
Each column regresses the dependent variable on the instrument (Rival Outage Exposure) with the same controls as the main 2SLS specification: number of rivals, log firm-year articles, log own engagement, and day-of-week, month, and year fixed effects.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: Each column regresses a pre-determined firm characteristic on the instrument (Rival Outage Exposure), conditioning on the same controls as the main 2SLS specification: number of rivals, log firm-year articles, log own engagement, and day-of-week, month, and year fixed effects. Standard errors, shown in parentheses, are clustered at the firm level. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

D Robustness Analysis

Table D.1: Which firms produce Opinion? Alternate measures of New Entrant

	Opinion					
	(1)	(2)	(3)	(4)	(5)	(6)
Entrant ($\leq$ 3 years)	0.0176**					
	(0.0084)					
Entrant ($\leq$ 5 years)		0.0116**				
		(0.0051)				
Entrant ($\leq$ 7 years)			0.0071*			
			(0.0041)			
Entrant ($\leq$ 10 years)				0.0060**		
				(0.0030)		
Entrant ($\leq$ 15 years)					0.0034	
					(0.0030)	
ln(Firm Age)						-0.0006
						(0.0013)
ln(Annual Article Count)	-0.0014	-0.0014	-0.0014	-0.0014	-0.0015	-0.0016
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0011)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Event FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,777,389	4,777,389	4,777,389	4,777,389	4,777,389	4,771,282
Adj R-squared	0.437	0.437	0.437	0.437	0.437	0.437

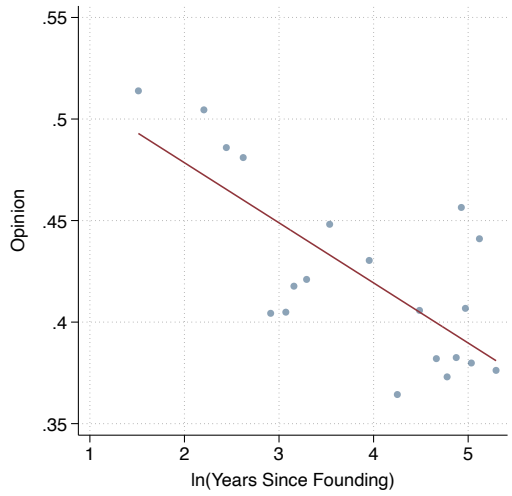
Notes: This table reports the baselines results for the effect of entrant on the opinion level for articles with various measures of entrant. In columns (1) through (5), Entrant is a dummy variable equal to one if firm j is less than 3, 5, 7, 10 or 15 years old respectively (5 years is the measure featured in the main paper). In column (6) the key independent variable is the logarithm of firm age (years since founding on date t). In all models we control for the logarithm of the firms annual article count (a proxy for firm size). Standard errors, shown in parentheses, are clustered at the firm and event levels. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table D.2: The Demand for Opinion: Alternate measures of Twitter Engagement

	ln(Retweets)		ln(Replies)	
	(1)	(2)	(3)	(4)
Opinion	0.9020***	0.8616***	0.4429*	0.4534*
	(0.3098)	(0.3150)	(0.2600)	(0.2652)
Entrant (< 5 years old)		0.3376		0.4692
		(0.3984)		(0.3137)
Opinion $\times$ Entrant (< 5 years old)		0.1928		-0.5114
		(0.8279)		(0.6161)
ln(Annual Article Count)	0.3461***	0.3571***	0.3514***	0.3566***
	(0.0705)	(0.0703)	(0.0642)	(0.0639)
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Event FE	Yes	Yes	Yes	Yes
Observations	225,879	225,879	225,879	225,879
Adjusted R-squared	0.149	0.151	0.209	0.209

Notes: This table reports alternative analyses to Table 3 with different measures of Twitter engagement. In columns (1) and (2) the dependent variable is the count of retweets, and in columns (3) and (4) the dependent variable is the count of replies. Standard errors, shown in parentheses, are clustered at the firm and event levels. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Figure D.1: Firm Age and Opinionation



Notes: This figure shows a binned scatter plot of the relationship between firm age and the probability of producing opinionated news content. The negative trend highlights that younger firms are more likely to produce opinionated articles.

Table D.3: Competitive Dynamics: Robustness to measuring competition over a 30 day window

	Opinion Content			Log(Rival Engagement)	Opinion Content	
	(1) OLS	(2) OLS	(3) OLS	(4) First Stage	(5) 2SLS	(6) 2SLS
Log(Rival Engagement)	0.0022*		0.0020		0.0313***	0.0307***
	(0.0012)		(0.0013)		(0.0072)	(0.0073)
Log(Entrant Rival Engagement)		0.0036***				
		(0.0005)				
Log(Incumbent Rival Engagement)		-0.0009				
		(0.0009)				
Focal Entrant			-0.0420			-0.2017
			(0.0737)			(0.1494)
Focal Entrant × Log(Rival Engagement)			0.0041			0.0158
			(0.0055)			(0.0110)
Rival Outage Exposure				-0.0002***		
				(0.0000)		
Log(Firm-Year Articles)	-0.0108***	-0.0106***	-0.0106***	-0.0440***	-0.0096***	-0.0094***
	(0.0012)	(0.0012)	(0.0012)	(0.0041)	(0.0011)	(0.0012)
Log(Own Engagement)	0.0060***	0.0060***	0.0059***	-0.0021	0.0061***	0.0059***
	(0.0006)	(0.0006)	(0.0006)	(0.0013)	(0.0006)	(0.0006)
Number of Rivals	0.0000*	0.0000	0.0000*	0.0015***	-0.0000*	-0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	602,030	602,030	602,030	602,030	602,030	602,030
Adjusted R-squared	0.044	0.045	0.045	0.824	0.022	0.023
First-stage F					560.9	277.1

*Notes:*In this table, we study the robustness of our results on the effect of rival competition on firm's content strategies to a longer time-window. In this table, our measure of competition, *Rival Engagement*, is the count of social media posts referencing rival content in the prior 30 days. We present OLS results in columns (1)-(3). Column (4) shows the first stage from the 2SLS model. The instrument, *Rival Outage Exposure*, is the sum of audience-weighted power outage intensity across rivals. Columns (5) and (6) report the second stage results. All models include fixed effects at the year, month, and day levels. Standard errors are clustered at the firm level. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table D.4: Exploring Alternative Controls for the News Source

	Opinion	
	(1)	(2)
Opinion Blog	0.0258***	0.0221***
	(0.0034)	(0.0038)
Entrant (< 5 years old)		0.0116**
		(0.0051)
ln(Annual Article Count)		-0.0013
		(0.0010)
Year FE	Yes	Yes
Month FE	Yes	Yes
Day FE	Yes	Yes
Event FE	Yes	Yes
Observations	4,777,389	4,777,389
Adj R-squared	0.436	0.437

Notes: This table investigates the use of an alternative proxy for the source type, using a dummy which flags whether the source URI contains the words 'opinion' or 'blog'. All regressions include year-month, day-of-week, and event fixed effects. Standard errors are clustered at the firm and event levels. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table D.5: Composition of articles, firm type, and ad networks

	Share Opinionated Articles		
	(1)	(2)	(3)
Entrant (age $\leq$ 5)	0.1059***		
	(0.0320)		
Log(Firm-Year Articles)	-0.0024		
	(0.0056)		
Ad Technologies		-0.0484**	-0.0475**
		(0.0188)	(0.0220)
Political Slant		0.1056***	0.1075***
		(0.0204)	(0.0316)
Ad Technologies × Political Slant			-0.0026
			(0.0265)
Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Observations	278,601	278,601	278,601
Adj R-squared	0.012	0.029	0.029

Notes: In this table, we collapse the data to the firm-date level. We only include observations where we have data on political slant from All Sides (which we collect for only 307 firms in our sample) and data on advertising technologies from BuiltWith. The dependent variable is the share of a firm's articles on a given date with article opinion above the sample median. *Ad Technologies* is a count of the distinct ad network technologies active on a media outlet's website on a given day, as recorded by BuiltWith. The variable *Political Slant* is a dummy variable set to 1 if the firm is classified as left- or right-leaning based on AllSides ratings. All models are estimated with OLS, and include fixed effects at the event, year, month, and day of week levels. Standard errors are clustered by firm after collapsing the data to the firm-date level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

E Survey Instrument

Thank you for choosing to participate in our News Perception Survey.
Once you click 'next,' you will be guided through a review of 10 news articles.
Please read each article thoroughly and answer the following questions.
Please be assured that your responses will remain anonymous. Your participation is of great value to this study, and we are grateful for the time.

[Article Text]

Please rate the following statements on a scale of 1 to 7, where 7 is strongly agree, and 1 is strongly disagree:

[POSITIVE VERSION] The article is written in a way which is intended to influence my opinion on the topic.
[OR]
[NEGATIVE VERSION] The article is written in a way which is not intended to influence my opinion on the topic.

○ 1 (Strongly Disagree) ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 (Strongly Agree)

[POSITIVE VERSION] The author's personal views on the topic are expressed in this article.
[OR]
[NEGATIVE VERSION] The author avoids expressing their own personal views on the topic.

○ 1 (Strongly Disagree) ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 (Strongly Agree)

[POSITIVE VERSION] The tone of this article is assertive or authoritative, with subjective language being used, and instances of addressing the reader with commands or suggestions.
[OR]
[NEGATIVE VERSION] The tone of this article is neutral and impartial, with objective language being used. There is a lack of commands or suggestions directed at the reader.

○ 1 (Strongly Disagree) ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 (Strongly Agree)

Notes:

- *Each evaluator is presented with 10 random articles.*
- *Statement order is randomized for each article.*
- *Positive and negative statement versions are randomized.*