Media Cross-Amplification and Public Opinion: Evidence from Television Coverage of Social Media

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Abstract

I study how social media messages are amplified by television news and how this amplification shapes public opinion. Using high-frequency data on President Trump's tweets and cable transcripts, I show that Trump's tweets caused near-immediate shifts in cable coverage, providing causal evidence of agenda-setting power. Linking text-on-screen data to a large public opinion survey, I find that broadcasts of Trump's tweets causally shifted viewers' approval of Trump and their 2020 voting intentions, widening gaps across TV audiences. Additional evidence shows that this mechanism is not specific to Trump, with cable news actively amplifying online statements by other prominent U.S. politicians.

Keywords: *social media, cable news, agenda-setting, amplification, public opinion*
JEL Codes: D72, L82, Z13

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1. Introduction

Politicians increasingly use social media to communicate with the public. These platforms allow political messages to spread rapidly and enable politicians to reach audiences without relying on traditional media intermediaries. A growing literature documents that such messages can shape political attitudes and behavior among social-media users (e.g., Fujiwara et al., 2024). However, a majority of U.S. adults do not rely on social media as their primary source of political information, turning instead to television (TV) news (Pew, 2021). If TV outlets actively cover politicians' online activity, social-media messages may reach a much broader share of the electorate and shape political attitudes offline.

Despite the potential importance of this channel, we know relatively little about the indirect effects of social media that operate through TV. Recent work shows that social-media discussion can shape TV coverage of conflict-related events (Hatte et al., 2023), documenting an important channel through which online communication affects TV news. However, it remains unknown whether political content posted on social media has similar effects on TV coverage, and whether TV amplification of such content causally changes public opinion. This paper addresses these questions by studying how political messages issued on social media reshape TV news coverage, and how this reshaping affects the political views of TV audiences.

I make two main contributions. First, by linking political messages posted on social media to minute-by-minute TV transcripts, I show that online political statements causally alter TV coverage in real time. Second, by linking televised coverage of social-media messages to timestamped survey responses, I show that this amplification causally affects public opinion – exposure to social-media posts through TV shifts approval ratings and voting-related attitudes. These effects are heterogeneous across outlets and widen opinion gaps between viewers. Together, these results show that the political effects of social media are not confined to online environments, but spill over offline through TV, shaping both the information environment and the political attitudes of audiences.

To study these dynamics, I draw on Donald J. Trump's use of Twitter and its coverage by major U.S. cable outlets – CNN, Fox News and MSNBC. While Trump may be an atypical political figure in terms of style and online visibility, the mechanisms studied here should not be interpreted as Trump-specific. The patterns documented in this paper appear characteristic of politicians whose social-media communication generates substantial online visibility. Consistent with this, I show that posts issued by other prominent U.S. politicians also receive significant cable news coverage, though less rapidly. Thus, the paper sheds light on a broader class of contemporary political communication, rather than on President Trump alone.

The paper proceeds in two parts. In the first part, I study how TV news outlets respond, in real time, to political statements made on Twitter by Donald Trump. In the second part, I investigate how this coverage affects how TV audiences evaluate Trump politically, not only as President but also as a presidential candidate.

To study whether cable news outlets actively responded to Trump tweets, I combine the text and timing of each tweet with timestamped transcripts from CNN, Fox News, and MSNBC. This allows me to implement a high-frequency design that tracks how the subjects covered on TV shift in the minutes before and after a tweet is posted.

I find that cable outlets began shifting their attention toward the issues raised in Trump's tweets within minutes of posting. Comparing the two hours after a tweet with the same interval before, coverage of the tweeted issue increased by about one minute, roughly doubling the amount of attention that issue would receive otherwise. Importantly, this pattern is present across all three major cable networks – CNN, Fox News, and MSNBC.

The interpretation of these patterns as causal relies on two identifying assumptions. The first is that Trump's tweets were not systematically caused by cable news segments, which would generate concerns about reverse causality. To examine this, I estimate a series of event-study specifications that track how cable news content evolved in the minutes before each tweet. Across specifications, I find no evidence that Trump regularly tweeted in reaction to ongoing TV coverage.

The second assumption is that short-run changes in TV coverage around a tweet are not driven by other events that might simultaneously affect Trump's tweeting and cable news broadcasts. This omitted-variable concern is relevant in a setting where online statements and news events can occur close in time. For example, a sports event may prompt both a tweet from Trump and a news segment from TV outlets, creating a spurious correlation between both. Focusing on within-hour changes in TV coverage helps address this issue, since external events that could influence both tweeting and news coverage are unlikely to shift within such narrow windows. As an additional check, I collect an exhaustive dataset of online news to classify Trump's tweets based on whether each post was related to "neighboring" news events and estimate separate reactions for related and unrelated tweets. In both cases, cable outlets shift coverage within minutes of a tweet, indicating that correlated news shocks are not driving the results.

Taken together, these findings show that Trump exercised short-run agenda-setting power over cable news: his tweets caused measurable shifts in the content that TV channels aired in the minutes, and hours, following each tweet.

I provide three additional insights. First, the average tone of cable coverage remained relatively neutral when responding to tweets, suggesting that, in the short run, outlets relayed the content in a news-style manner rather than through evaluative language. Second, I document that although the effects are largest during Trump's presidency, similar real-time reactions also occur during his presidential candidacy in 2016. Third, I extend the analysis to widely followed Democratic and Republican members of Congress and find no comparable short-run agenda-setting effects for these politicians. This suggests that the agenda-setting power documented above was specific to Donald Trump.

The second part of the paper studies how cable news coverage of President Trump's tweets affected public opinion during 2020. To do so, I use a novel dataset reporting the texts displayed on-screen by TV outlets. I first document every instance in which President Trump's tweets were explicitly shown on cable news during 2020. I then link these broadcasts to a large public opinion survey. In particular, I use a unique set of survey questions to implement a high-frequency differences-in-differences strategy.

More specifically, I compare the approval ratings of President Trump across two groups of news consumers in the hours before and after a cable outlet broadcasts a Trump tweet. For example, when CNN covers a Trump tweet, I compare the approval ratings of CNN viewers with those of individuals who do not watch cable TV, both before and after the broadcast. This comparison provides a causal estimate of the effect of covering a Trump tweet on public opinion under a parallel-trends assumption. I assess this assumption by estimating event-study regressions that compare the approval-rating dynamics of each group (viewers of a given outlet vs. non-viewers) prior to the showing of a Trump tweet.

I find that a broadcast of a Trump tweet by CNN caused CNN viewers to worsen their ratings of Donald Trump by about 7 percent, relative to their pre-broadcast comparison with non-viewers. This effect corresponds to a persuasion rate of roughly -1.7 percent, indicating that a small but measurable fraction of CNN viewers changed their opinion of Trump after seeing the tweet covered on TV.

A series of robustness exercises support this estimate. First, effects are unchanged when restricting attention to broadcasts featuring tweets unrelated to "neighboring" news events, alleviating concerns that correlated news shocks could be driving the results. Second, a placebo test using tweet posting times – rather than showing times – shows no shifts in approval during these periods, ruling out concerns related to misreported media consumption. Third, this pattern extends to a more consequential outcome: voting intentions for Trump in 2020 decline among CNN viewers following a broadcast, Fox News and MSNBC viewers remain unaffected. These exercises reinforce the interpretation that cable news coverage of Trump's tweets has a significant impact on public opinion.

The magnitude of this effect, however, varies with when a broadcast occurs. Having in mind that cable news audiences are substantially larger during primetime (Pew, 2021), I allow for heterogeneous effects by timing of coverage. While I do not find an average effect for Fox News or MSNBC, there appears to be a primetime effect: (1) the worsening of Trump's ratings among CNN viewers is mainly driven by broadcasts during primetime, and (2) an average primetime showing of a Trump tweet by Fox News causes Fox News viewers to improve their ratings of the President.

Taken together, these findings suggest that the amplification of social media content by cable outlets can meaningfully affect the political opinions of TV audiences, potentially contributing to their polarization. I interpret these results as operating through two interacting mechanisms: priming and framing. The priming effect reflects audience composition—CNN and Fox News attract viewers with systematically different political preferences, and coverage of Trump's tweets activates these pre-existing attitudes. The framing effect reflects differences in how outlets report the tweets. Sentiment analysis shows that Fox News adopts a more positive tone than CNN when covering Trump's tweets during primetime. Topic analysis further indicates that, during this period, CNN devoted more attention to tweets about the coronavirus pandemic, while Fox News placed greater emphasis on attacks on Biden, "election integrity" claims, and MAGA-related messaging.

Lastly, I provide additional evidence on the external validity of these results by examining whether the amplification of online political statements by cable news extends beyond Twitter and beyond Donald Trump. First, using a more recent version of the text-shown-on-TV dataset, I document all instances in which Trump's Truth Social handle appeared on-screen in 2024 and find levels of coverage comparable to those devoted to his tweets in 2020. This shows that TV outlets continued to amplify Trump's online statements even after his transition from Twitter to Truth Social. Second, I identify all showings between 2020 and 2024 in which cable outlets displayed the Twitter handles of U.S. members of Congress and find a non-trivial number of such coverages, concentrated among widely followed Democratic and Republican politicians. This indicates that the coverage of politicians' social media posts is not unique to Trump but applies more broadly to prominent political figures.

Importantly, this analysis does not focus on the short-run reactions studied in the first part of the paper. Instead, it relies on a fuller text-shown-on-TV dataset that captures coverages occurring hours after a post. When considering this broader window, I find that social media posts issued by other politicians are also covered by cable news outlets, to an extent comparable to Donald Trump's.

This paper contributes to four strands of literature. The first is the agenda-setting power literature (McCombs and Shaw, 1972, 1993). The paper relates to a recent strand of work that studies the dynamics of agenda-setting on social media. Barberá et al. (2019) show that U.S. members of Congress, on Twitter, are more likely to follow news coverage. Gilardi et al. (2022) instead investigate how politicians' social media posts relate to both online and offline news. These studies rely on correlation-based methods to examine how politicians' online statements relate to news coverage. I provide a first causal account of a politician's agenda-setting power.

Second, the paper contributes to a strand of literature that studies the effects of cable news on outcomes as varied as voting behavior (e.g., DellaVigna and Kaplan, 2007 and Martin and Yurukoglu, 2017), judicial decisions (Ash and Poyker, 2024), health behaviors (Bursztyn et al., 2023), local government expenditure (Galletta and Ash, 2023), and local news production (Widmer et al., 2020). More specifically, the current study sheds light on a potential mechanism through which cable news can persuade different actors – namely, the amplification of extreme content that may shape societal perceptions about specific matters, groups, or views (à la Bursztyn et al., 2020).

Third, the paper contributes directly to a literature that investigates the effects of social media on political outcomes such as, protest participation (Enikolopov et al., 2020), political polarization (Allcott et al., 2020; Levy, 2021), voting behavior (Fujiwara et al., 2024), and politicians' responsiveness to voters (Bessone et al., 2022). These studies focus on measuring the political impact of social media on its direct users. I provide the first causal quantification of the spillover effects of social media onto offline audiences.

Fourth, a strand of the literature has studied the effects of social media on non-political outcomes.[1] This paper is closely related to work examining the effects of social media on news production (Cagé et al., 2022; Hatte et al., 2023). In particular, the paper is closest to Hatte et al. (2023), who show that the reporting of conflict events by U.S. cable outlets is shaped by how these events are discussed on social media. The first part of this paper provides a similar insight by showing that social media events – here, political statements rather than conflict-related discussions – cause changes in cable news coverage. Relative to Hatte et al. (2023), I additionally measure how these editorial decisions, shaped by social media, affect public opinion.[2]

The rest of the paper is organized as follows: Section 2 shows how cable outlets covered President Trump's tweets minutes after these tweets were posted; Section 3 goes on and investigates the effect of these coverages on cable news audiences; Section 4 concludes.

2. Effect of Trump's Tweets on TV News Coverage

In this section, I document how U.S. cable news actively covered President Trump's tweets in real-time, both before and during Donald J. Trump's presidency. Section 2.1 describes the data sources and variables. Section 2.2 outlines the empirical strategy. The main results are described in Section 2.3. Robustness checks are presented in Section 2.4.

[1] For instance, hate crime (Müller and Schwarz, 2023, 2021) and mental health (Braghieri et al., 2022).

[2] In doing so, I also contribute to a recent strand of literature that studies the impact of media on public opinion using large-scale survey data (Melnikov, 2021; Djourelova, 2023).

Section 2.5 extends the analysis along different routes.

2.1 Data

2.1.1 Sources

U.S. cable news transcripts. Timestamped transcripts for the three main cable news stations in the U.S. - CNN, Fox News and MSNBC. This dataset covers close to the universe of shows broadcasted from January 2015 to January 2021 by each of these stations. Transcripts scraped from the TV News Archive (Link).

Tweets by @realDonaldTrump. Timestamped tweets posted by Donald J. Trump's Twitter account, @realDonaldTrump (Link).[3] This dataset covers the universe of tweets posted by Donald J. Trump from January 2015 to January 2021. Made available by the Trump Twitter Archive (Link).

Tweets by U.S. newspapers. Text and timestamp for the universe of tweets posted by a comprehensive subset of U.S. national newspapers, from January 2015 to January 2021. The list of newspapers has as origin CrowdTangle (Link) while the tweets were collected through the Twitter API (Link).

Tweets by U.S. congress-members. Text and timestamps for the universe of tweets posted by U.S. congress-members (MOCs) from June 2017 to July 2023, by Tweets from Congress (Link). Additionally, historical time series for each MOC's Twitter follower counts, scraped from the Wayback Machine (Link).

2.1.2 Variables

2.1.2.1 Trump Tweets

In order to study cable news' coverage of President Trump's tweets, I first count how many tweets were posted by Donald J. Trump at a *quarter-hourly frequency* (i.e., every 15-minutes). To focus exclusively on original statements issued by the President, I do not count retweets. In addition, to filter out statements of little general interest, I exclude "short" tweets (e.g., tweets that are mainly composed of URLs or sentences such as "*MAKE AMERICA GREAT AGAIN*"). In total, President Trump posted 19,294 tweets from 2015 to 2020. These statements accounted for 15,456 15-minute periods in which at least one Trump tweet was posted. The number of tweets posted by President Trump increased significantly over time, in particular during his presidency – from $\approx$ 2,500 tweets in 2017 to $\approx$ 4,000 tweets in 2020 (see Online Appendix Table A.1.1.1).

[3]President Trump's personal Twitter account. This account was created in March, 2009. It issued a first set of tweets in May, 2009. It was permanently suspended by Twitter on January 8, 2021.

2.1.2.2 Coverage Measures

In what follows, I describe the different measures that I use to assess how cable news outlets covered the issues tweeted by President Trump.

Extent of coverage. To rate cable news coverage from an extensive margin, I count how many 3-word expressions (trigrams) were shared between the text of TV transcripts and Donald Trump's tweets, the minutes before and after the posting of a tweet. This measure rests on the implicit assumption that a sudden increase in the use of a tweet-related trigram, the minutes after a tweet is posted, can be interpreted as indicative of an outlet being covering the tweet to which that trigram belongs to.[4] On average, the outlet that tended to share most trigrams with President Trump's tweets, minutes before and after a tweet was posted, was Fox News (see Online Appendix Table A.1.2.1). Overall, the similarity between cable news transcripts and Donald Trump's tweets was largest during 2018 (see Online Appendix Figure A.1.2.1).

Intensity of coverage. To quantify the intensity of coverage of cable news outlets, I measure the amount of minutes that TV networks spent on tweet-related news. This measure accounts both for those minutes preceding and following an explicit mention of a tweet-related issue. To take into account that the addressing of a given topic is composed of three stages: a build-up, an explicit mention and, both a conclusion and a transition to another issue.[5] As with the extent of coverage, Fox News was the network that spent most time on average discussing those issues tweeted by Trump, minutes before and after a tweet was posted (see Online Appendix Table A.1.3.1). CNN spent more time on tweet-related issues during 2017; Fox News and MSNBC instead covered these issues more intensely during 2019 (see Online Appendix Figure A.1.3.1).

Sentiment of coverage. To describe the sentiment in coverage of President Trump's tweets, I measure the tonality of tweet-related coverages by cable news outlets, the minutes before and after a tweet was posted. As before, I take as tweet-related coverages those transcripts close to a mention of an expression tweeted by President Trump. I rate the tone of coverage through a sentiment measure based on a set of dictionaries validated by experts in Linguistics and Psychology (Pennebaker et al., 2015). [6] In general, Fox News was the network that covered the issues tweeted by President Trump most positively (i.e., relative to CNN and MSNBC; see Online Appendix Table A.1.4.1). In addition, all cable news outlets seem to have covered tweet-related issues in an abnormally sentimental fashion during 2018 (see Online Appendix Figure A.1.4.1).

[4]In Online Appendix A.1.2, I provide a formal definition for "*extent of coverage*", together with descriptive statistics and examples of television transcripts with high extents of coverage of Trump tweets.

[5]In Online Appendix A.1.3, I provide a formal deifitnion and descriptives for "*intensity of coverage*".

[6]In Online Appendix A.1.4, I provide a formal definition for "*sentiment of coverage*" together with different statistics and examples of abnormally positive and negative coverages of Trump tweets.

2.2 Empirical Strategy

To study how cable news broadcast evolved during the minutes before and after a Trump tweet was posted, I estimate a standard event-study specification:

$$y_{n,w,\tau} = \alpha_{n,w} + \sum_{\eta \in \{C,F,M\}} \sum_{\substack{k=-3, \\ k \neq -1}}^{3} \mathbb{1}\left\{ \substack{n=\eta, \\ \tau=k} \right\} \times \text{tweets}_{w,0} \times \beta^{\eta}_{k} + \varepsilon_{n,w,\tau} \tag{1}$$

where $y_{n,w,\tau}$ denotes an outcome variable specific to network n and relative time period τ of event window w (in what follows, τ corresponds to a 15-minute period). $\alpha_{n,w}$ denotes a network $\times$ window fixed effect, aimed at controlling for underlying macro factors assumed to affect each outlet's coverage differently.[7] $\mathbb{1}\{n = \eta, , k = \tau\}$ is an indicator variable equal to one if network n is network η (CNN, Fox News, or MSNBC) and relative time period τ equals k (where k ranges from –3 to 3, excluding –1). $tweets_{w,0}$ is a treatment variable indicating how many tweets President Trump posted during relative time period 0 of window w. β^{η}_{k} is a standard event-study coefficient, specific to network η and relative time period k. I estimate Eq. 1 via ordinary least squares (OLS) and cluster standard errors at a network $\times$ event-window level.

The coefficient of interest, β^{η}_{k}, should be interpreted differently depending on y. First, if y measures whether a network covered issues addressed in Trump's tweets, then β^{η}_{k} captures the differential change in the number of trigrams shared between network η's transcripts and Trump's tweets, k periods before (or after) a tweet was posted. Second, if y measures how a network covered tweet-related issues in terms of time, then β^{η}_{k} captures the differential change in the number of minutes network η devoted to issues mentioned in Trump's tweets, k periods before (or after) a tweet was posted. Lastly, if y captures how a network covered Trump's tweet-related issues in terms of tone, then β^{η}_{k} measures the differential change in the sentiment of network η's coverage of tweet-related issues, k periods before (or after) a tweet was posted.

The identifying assumptions necessary for β^{η}_{k} to be interpreted as a causal estimate of how President Trump's tweets affected cable news coverage are twofold.

First, President Trump's tweets are assumed not to have been systematically caused by cable news coverage. A practice that would violate this assumption is Donald J. Trump regularly tweeting in reaction to television news segments.[8] Such a pattern would confound the estimation of β^{η}_{k}. In particular, any post-tweet change in coverage could be

[7] This assumption is grounded in past media bias literature: Martin and Yurukoglu (2017), and more recently Kim et al. (2022), document significant differences in the editorial choices of cable outlets.

[8] A practice that appears plausible a priori: several news reports claim that Donald J. Trump cleared significant portions of his schedule, both before and during his presidency, to watch different morning shows from various cable outlets (see, e.g., Axios, 2017, 2019).

caused either by the tweet itself or by the continuation of a pre-tweet news segment that triggered the tweet, and these causes would be indistinguishable. To assess this assumption, I estimate Eq. 1 including pre-tweet coefficients to test whether cable news often exhibited abnormal dynamics in the minutes preceding a Trump tweet – an indication that President Trump may have tweeted in response to cable coverage.

Second, any change in coverage occurring during an event window is assumed to be orthogonal to omitted variables relevant at explaining both cable news coverage and President Trump's tweets. An example is a shooting – an unexpected event that prompts both an immediate reaction by President Trump and coverage by cable outlets. If such an episode occurred within an event window, it would confound the estimation of β_k^η. In particular, a shift in coverage caused by a breaking news event could be mistaken for a shift caused by the tweet. To support this assumption, I study cable news at an intra-hour frequency, to keep other factors relevant at explaining cable news coverage as close to constant as possible .[9]

A final identification concern relates to the frequency of President Trump's tweets. Trump tweets were often posted so close together that many event windows overlap in calendar time.[10] Such overlap is problematic for outcomes that are not event-window-specific.[11] In these cases, pre- and post-tweet periods are not distinguishable.[12]

To address this issue, I implement a stacked design following Cengiz et al. (2019). Specifically, I restrict attention to outcomes defined around event-window-specific factors – in this case, coverage measures exclusively focused on the issues addressed in President Trump's tweets, which vary across event windows. This design yields unbiased estimates of β_k^η if and only if the event windows used in Eq. 1 do not overlap simultaneously across calendar time and content.[13] To meet this requirement, I estimate Eq. 1 using only event windows that do not overlap simultaneously across calendar time and content. In theory, this restriction implies that β_k^η should be interpreted as local coefficients, specific to tweets that are not followed closely by content-similar statements. In practice, this

[9]Moreover, to address additional endogeneity concerns driven by omitted variables, in Section 2.4 I leverage an exhaustive self-collected dataset of online news to estimate a version of Eq. 1 that controls for breaking news events.

[10]President Trump posted 19,530 tweets from 2015 to 2020. These map into 15,594 event-windows of which 15,296 (≈98%) overlap in calendar time (taking event windows to be 1h45m intervals, as in Eq. 1).

[11]Examples include coverage measures focused on themes that span across calendar time – for instance, the number of minutes devoted to stories explicitly mentioning "Trump".

[12]For event windows that overlap in calendar time, pre-tweet periods for some windows will be mistakenly classified as post-tweet periods for other windows. This is analogous to a differences-in-differences setting with staggered treatment where newly and already treated units are erroneously compared as treated and untreated (see e.g., Sun and Abraham, 2021).

[13]Here, "content" refers to 3-word phrases tweeted by Donald J. Trump within each event window.

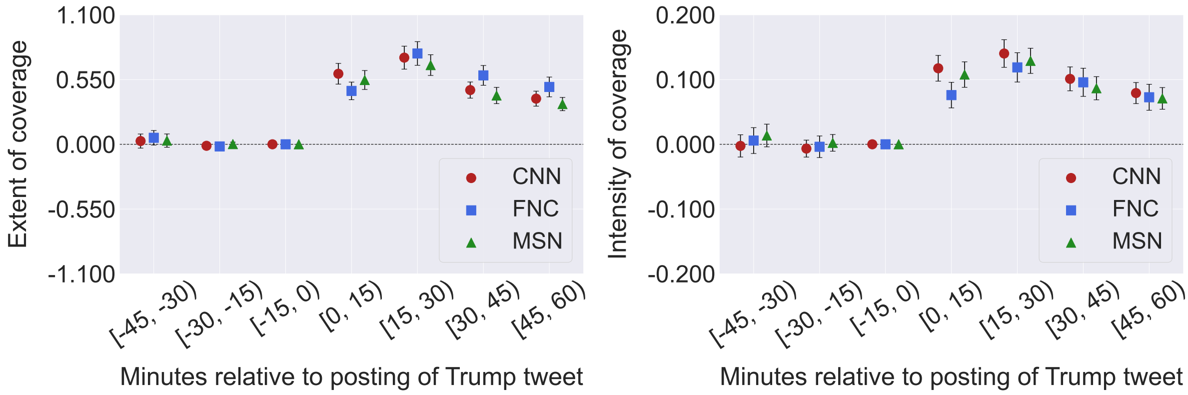
class of posts is representative of Donald J. Trump's tweeting behavior; thus, β_k^η can be interpreted as the effect of an average Trump tweet on cable news coverage.[14]

2.3 Main Results

2.3.1 Extent and Intensity of Coverage

I first study whether President Trump's tweets were picked up by cable news outlets in the minutes after being posted. I then measure the amount of time that cable outlets spent discussing the issues addressed in these same tweets.

Event-studies. Panel 2.3.1a plots the coefficients from an event-study regression where the dependent variable is an extent-of-coverage measure (a textual similarity measure comparing the transcripts of cable news outlets with President Trump's tweets, using trigrams). Panel 2.3.1b instead plots the coefficients from an identical regression in which the dependent variable is an intensity-of-coverage measure (the number of minutes that cable outlets spent discussing tweet-related issues).



(a) **Extent of coverage** (b) **Intensity of coverage**

Figure 2.3.1: **Cable outlets' response to Trump tweets – extent and intensity of coverage**. Panels (a) and (b) report event-study coefficients from Eq. 1. Panel (a) uses an extent-of-coverage outcome, defined as the number of 3-word phrases (trigrams) that appear both in a network's transcript and in the tweets posted during the event window. Panel (b) uses an intensity-of-coverage outcome, defined as the number of transcript minutes within a window that contain a matched trigram or lie immediately adjacent to one. Error bars denote 95% confidence intervals based on standard errors clustered at a network × window level.

Both panels suggest two results. First, the average relationship between cable news coverage and President Trump's tweets did not experience any significant changes in the

[14]Tweets that do not overlap across both calendar time and content account for 90% of Donald J. Trump's tweets (see Online Appendix Table A.2.1.1) and closely mimic his within-day tweeting patterns (see Online Appendix Figure A.2.1.1).

minutes preceding a tweet. This result holds on both the extensive and intensive margins. It suggests that President Trump did not typically tweet in reaction to contemporaneous cable news broadcasts, a requirement if the post-tweet coefficients in Eq. 1 are to be interpreted as causal estimates of how a Trump tweet affected cable news coverage

Second, the posting of a Trump tweet caused persistent changes in cable news coverage. In particular, the discussions taking place on cable news outlets converged toward the content of President Trump's tweets within minutes after the posting of a tweet. This finding also holds on both the extensive and intensive margins. It suggests that President Trump was able to shift the coverage of cable outlets through his tweets, thereby exercising agenda-setting power over cable news channels.

Pre-posts. To translate the previous event-study coefficients into coarser and more interpretable estimates, I aggregate the extent and intensity measures into pre- and post-tweet periods. I then estimate the following pre-post specification:

$$\mathrm{y}_{\mathrm{n,w,p}} = \alpha_{\mathrm{n,w}} + \sum_{\eta \in \{\mathrm{C,F,M}\}} \mathbb{1}\left\{ \begin{matrix} \mathrm{n}=\eta, \\ \mathrm{p}=1 \end{matrix} \right\} \times \mathrm{tweets}_{\mathrm{w}} \times \beta^{\eta}_{\mathrm{post}} + \varepsilon_{\mathrm{n,w,p}} \tag{2}$$

where p indicates either a *pre* (= 0) or *post-tweet* (= 1) period (p may correspond to a 45m, 1h30m, or 2h15m period). y, n, w, p denotes an aggregated coverage measure (e.g., an extent-of-coverage measure, aggregated at a 45m frequency). $tweets_w$ is a treatment variable indicating how many tweets President Trump posted during window w. β^{η}_{post} is a post-treatment coefficient specific to network η.

Table 4.1 presents the coefficients from estimating Eq. 2 for the extent and intensity of coverage measures, respectively. In both tables, columns 1 and 5 compare cable news coverage 45 minutes post-tweet to 45 minutes pre-tweet. Columns 2-4 and 6-8 report analogous comparisons for longer time windows: e.g., columns 4 and 8 use 2h15m windows.

As shown in column 8 of Table 4.1, I find that the posting of one Trump tweet about a given issue caused cable outlets to increase their coverage of that issue by approximately 1 minute during the 2h15m following a tweet. In relative terms, this represents a twofold increase in the outlets' tweet-related coverage (relative to baseline). Moreover, I find no differences across outlets in how these reacted to Trump tweets.

2.3.2 Sentiment of Coverage

After establishing that President Trump's tweets tended to be covered by cable news outlets within minutes, I turn to how these tweets were covered, in terms of the tone used by each outlet.

Event-studies. Figure 2.4.2 plots the coefficients from an event-study regression in which the dependent variable is a sentiment-of-coverage measure (the difference between positive and negative words, with each group defined by an external sentiment dictionary).

As before, the figure shows two results. First, the issues addressed in President Trump's tweets were not the subject of abnormally positive or negative coverage in the minutes preceding a tweet. This corroborates earlier findings indicating that Trump's tweets were, on average, independent of past cable news coverage – specifically, he did not tend to tweet about issues that had been the target of unusually charged coverage.

Second, cable outlets used a slightly positive sentiment when reacting to Trump's tweets. Moreover, these channels did not exhibit significantly different tones of coverage across outlets when responding to a Trump tweet. These findings suggest that the immediate coverage of President Trump's tweets by cable outlets was oriented more toward reporting the content of the tweets than toward providing outlet-specific commentary.

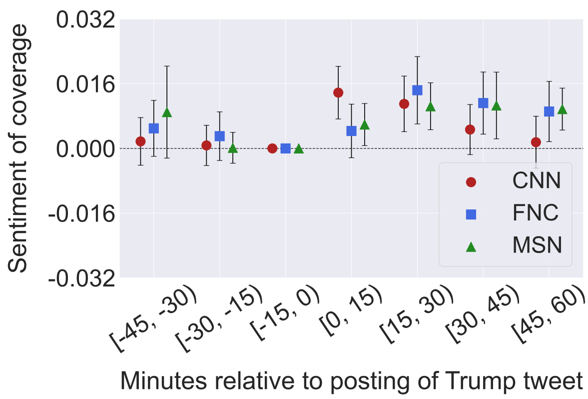


Figure 2.3.2: **Cable outlets' response to Trump tweets – sentiment of coverage**. The figure reports coefficients from an event-study regression (Eq. 1) in which the outcome is a sentiment-of-coverage measure. This measure captures the tone used by each network when covering tweet-related content, defined as the difference between positive and negative words in the textual neighborhoods surrounding matched tweet phrases. Error bars denote 95% confidence intervals based on standard errors clustered at the network × window level.

Pre-posts. Table 4.2 presents estimates from a pre-post regression focused on sentiment. As before, these estimates point to a scenario in which all three outlets tended to report on President Trump's tweets in the hours after they were posted. This reporting appears to have been similar in sentiment across outlets, regardless of which pre-post specification is used.

2.4 Robustness Checks

2.4.1 Omitted Variable Concerns

Past results could be driven by omitted variables occurring within or near an event window. In particular, changes in coverage close to a Trump tweet might be due either to

President Trump tweeting or to unobserved news events that prompted both Donald J. Trump to issue a tweet and cable outlets to air a specific news segment. In this section, I address these concerns by studying whether cable outlets reacted differently to Trump's tweets depending on how these tweets related to ongoing news events.

I construct a similarity measure that counts the number of three-word expressions in Donald J. Trump's tweets that also appear in tweets posted by national U.S. newspapers up to 6 hours before or after a tweet.[15] I then classify tweets into two groups: tweets related to recent (or upcoming) news – i.e., posts that share an abnormally large number of three-word expressions with neighboring online news – and tweets unrelated to pressing news events – i.e., posts that share either a typical or low number of expressions with contemporaneous news.[16] Finally, I extend Eq. 1 as follows:

$$\begin{aligned} y_{n,w,\tau} = & \alpha_{n,w} + \mathbb{1}\{w \in \text{Related}\} \times \Omega_{\text{related}} + \\ & (1 - \mathbb{1}\{w \in \text{Related}\}) \times \Omega_{\text{unrelated}} + \varepsilon_{n,w,\tau} \end{aligned} \tag{3}$$

$\mathbb{1}\{w \in \mathit{Related}\}$ is an indicator equal to one if and only if the tweets posted by Donald Trump during event window w share an abnormally large number of three-word expressions with neighboring online news (i.e., if tweets in window w are related to online news posted during the 6 hours preceding or following it).

$$\Omega_r = \sum_{\eta \in \{C,F,M\}} \sum_{\substack{k=-3,\\ k\neq -1}}^{3} \mathbb{1}\begin{Bmatrix} n=\eta, \\ \tau=k \end{Bmatrix} \times \text{tweets}_{w,0} \times \beta_k^{\eta,r}$$

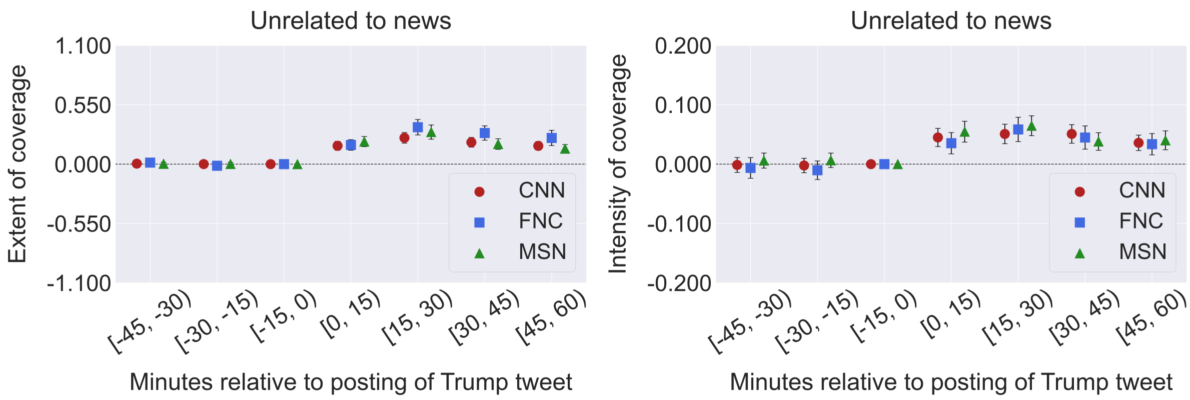
is a standard sequence of event-study coefficients, as in Eq. 1. $\beta_k^{\eta,r}$ denotes the event-study coefficient specific to how network η varied its coverage k periods before (or after) an r-related tweet (where "r-related" refers to a tweets being either related or unrelated tweets).

I find that cable news outlets shifted their coverage toward the issues raised in President Trump's tweets regardless of whether these tweets were related to current news events. In other words, Donald J. Trump was able to redirect the attention of cable news networks even when the content of his tweets was seemingly unrelated to neighboring news events (see Online Appendix Panels 2.4.1a and 2.4.1b).[17] These findings rule out residual omitted-variable concerns related to the baseline results.

[15]See Online Appendix A.3.1 for descriptive statistics.

[16]I label a tweet as related to recent or upcoming news if the similarity measure described above exceeds a given threshold—two standard deviations above its mean—in any of the 6 hours preceding or following the posting of the tweet.

[17]Note, however, that coverage shifts were larger in magnitude for tweets related to neighboring news events (see Online Appendix Panels A.3.1.2a, A.3.1.2b, and A.3.1.2c).



(a) **Extent of coverage** (b) **Intensity of coverage**

Figure 2.4.1: **Cable outlets' response to Trump tweets unrelated to news events – extent and intensity of coverage**. The panels report event-study coefficients from Eq. 3 for tweets classified as unrelated to contemporaneous news. Panel (a) uses the extent-of-coverage measure, defined as the number of shared three-word phrases (trigrams) between network transcripts and the tweets posted in the event window. Panel (b) uses the intensity-of-coverage measure, defined as the number of transcript minutes containing or adjacent to a matched trigram. Error bars show 95% confidence intervals based on standard errors clustered at the network $\times$ window level.

To complete this analysis, I examine whether these patterns also hold for tone of coverage. In contrast with the baseline results – which showed a small post-tweet increase in sentiment – I find that, for tweets unrelated to news, the tone of coverage remains indistinguishable from its pre-tweet average (see Figure 2.4.2). This stability in sentiment further supports the view that, in the minutes following a Trump tweet, cable outlets primarily reported its content in neutral language rather than providing commentary.

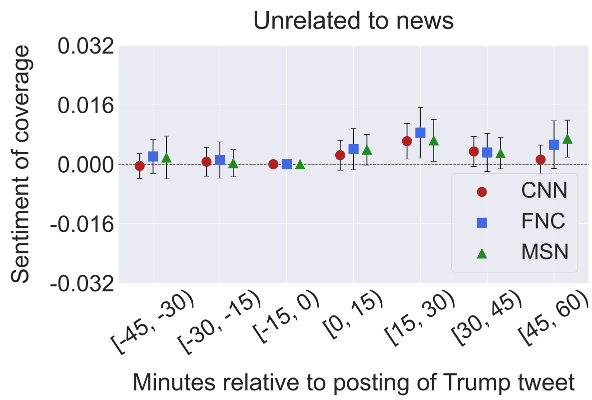


Figure 2.4.2: **Cable outlets' response to Trump tweets unrelated to news events – sentiment of coverage**. The figure reports event-study coefficients from Eq. 3 for tweets classified as unrelated to contemporaneous news. The dependent variable is a sentiment-of-coverage measure, defined as the difference between the number of positive and negative words appearing in the transcript passages surrounding a matched trigram from the tweet. Error bars show 95% confidence intervals based on standard errors clustered at the network $\times$ window level.

2.4.2 Variable and Regression Specifications

Past results focused on tweets unrelated to neighboring news events. As discussed, this class of statements is least prone to spurious correlations and therefore provides a stronger causal interpretation of how President Trump's tweets affected cable news coverage. In this subsection, I test the robustness of these estimates to alternative variable definitions and regression specifications.

News variable definitions. I test whether previous results depend on how tweets are classified as related or unrelated to news. In the baseline specification, a tweet is labeled as news-related if it shares a large number of phrases with news posted six hours before and after it. I re-estimate Eq. 3 extending the comparison window between tweets and news to up to 24 hours before and after a tweet. Results hold across all measures, irrespective of the horizon used to label tweets as related or unrelated to news (see Online Appendix Figure A.3.2.1).

Tweet sample definitions. I examine whether the baseline results depend on which Trump tweets are included. The baseline sample consists of original tweets (i.e., non-retweets) exceeding a minimum word count. I re-estimate Eq. 3 using alternative word-count thresholds, ranging from more permissive to more restrictive criteria. As shown in Online Appendix Figure A.3.2.2, post-tweet changes remain stable across all samples.

Fixed effect specifications. I test whether the baseline results are sensitive to alternative fixed-effect structures. The preferred model includes network × window fixed effects to absorb time-varying confounders at the event-window level. I re-estimate Eq. 3 using coarser fixed-effect structures. As shown in Online Appendix Figure A.3.2.3, the qualitative pattern of the results holds across all specifications.

Event-window length. I assess whether the baseline results depend on the choice of event-window length. The preferred specification uses a narrow event window for identification. I re-estimate Eq. 3 using wider windows. As shown in Online Appendix Figure A.3.2.4, results remain stable across window sizes: post-tweet increases in coverage persist for all window lengths, with effect sizes gradually declining as time progresses.

Treatment variable definitions. I test whether the results depend on the functional form of the treatment variable. The main specification treats $tweets_{w,0}$ as a continuous measure capturing the number of tweets posted in period 0. I re-estimate Eq. 3 using a binary indicator equal to one if at least one tweet was posted in that period. As shown in Online Appendix Figure A.3.2.5, results remain unchanged across all coverage measures.

Outcome variable definitions. I test whether the findings are robust to alternative measures of cable coverage. The baseline measures rely on shared three-word expressions and a LIWC-15 sentiment score. I re-estimate Eq. 3 using alternative outcome definitions: for extent and intensity, I construct measures based on shared two-word and four-word expressions; for sentiment, I use the LIWC-22 dictionary and a context-aware sentiment metric (VADER). Results hold across all measures (see Online Appendix Figure A.3.2.6).

These exercises show that the main findings are robust to alternative tweet definitions, fixed-effect structures, event-window lengths, and treatment- and outcome-variable formulations. Across all specifications, cable news outlets systematically shift their coverage toward the issues addressed in President Trump's tweets.

2.5 Additional Results

2.5.1 Coverage of Trump's Tweets Over Time

Past estimates hinge on the assumption that cable outlets' reactions to Trump's tweets were homogeneous over time. This assumption can be questioned from several angles.

A possible hypothesis is that the coverage of Trump's tweets was motivated exclusively by his role as president. If this were the case, cable outlets would have begun to cover his tweets only after 2016. This would have important implications for understanding how Trump's social media presence influenced his 2016 presidential run.

I allow cable outlets to have heterogeneous responses to Donald J. Trump's tweets over time. In particular, I extend the pre-post regression in Eq. 3 as follows:

$$y_{n,w,p} = \alpha_{n,w} + \sum_{year=2015}^{2020} \left[\sum_{\eta \in \{C,F,M\}} \mathbb{1}\left\{ \begin{matrix} w \in year, \\ n=\eta, \\ p=1 \end{matrix} \right\} \times tweets_{w} \times \beta_{post}^{\eta,\, year} \right] + \varepsilon_{n,w,p} \qquad (4)$$

where “” $w \in year$” indicates that window w occurred during year “*year*” (from 2015 to 2020). $\beta_{post}^{\eta,year}$ is a standard pre-post coefficient measuring how network η reacted to Trump's tweets in a given year.

I find two results. First, cable outlets began to follow President Trump's tweets in 2016. The posting of a Trump tweet on a given issue in 2016 caused cable outlets to increase their coverage of that issue by a magnitude comparable to the effects observed in 2019 and 2020. This pattern holds across all three dimensions of coverage (see Online Appendix Panels A.4.1.1a, A.4.1.1b, and A.4.1.1c). This suggests that Donald J. Trump exercised agenda-setting power over cable news outlets already as a presidential candidate.

Second, cable outlets did not follow Trump's tweets uniformly over time. Coverage was strongest in 2017 and then declined thereafter.[18] Two interpretations are consistent with this pattern. One possibility is that outlets gradually learned which types of Trump's statements resonated with their audiences and increasingly limited coverage to those

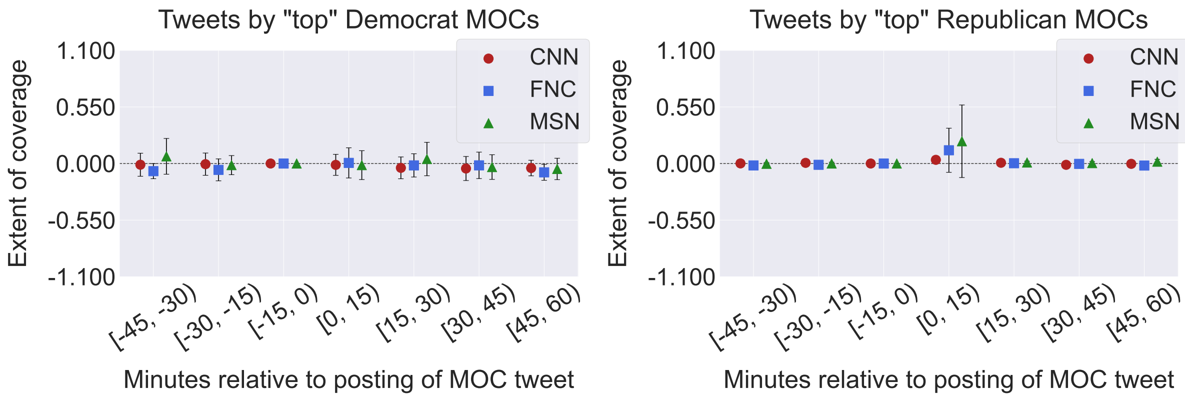
[18]The 2020 estimates may appear counterintuitive: during an election year, one might expect increased coverage of Trump's statements. This decline is consistent with evidence that COVID-19 dominated the news cycle and crowded out other political coverage (Budak et al., 2021).

tweets that attracted viewer interest. Another possibility is saturation: as Trump's tweeting became more predictable over time, tweets may become less newsworthy.

2.5.2 Coverage of Tweets by Other Politicians

Past results show that cable outlets reacted almost immediately to Trump tweets. An open question is whether this short-run response was unique to Donald Trump or whether other politicians who also use social media intensively were able to generate similar effects. If cable outlets systematically shifted their coverage towards tweets posted by social-media savy politicians other than Trump, this would suggest that the agenda-setting power documented for Trump extends to other political figures.

To examine this, I re-estimate Eq. 1 focusing on tweets posted by "prominent" members of Congress (MOCs). Using an exhaustive dataset of congressional tweets together with a dataset tracking each MOC's Twitter follower counts over time (both described in Section 2.1), I identify, for each party and each year, the five MOCs with the largest number of followers.[19] I then aggregate all tweets posted by these prominent MOCs and compare their tweets with cable transcripts in the minutes before and after each post.



(a) **Democrats** (b) **Republicans**

Figure 2.5.1: **Cable outlets' response to tweets by prominent MOCs — extent of coverage**. The figure reports event-study coefficients from Eq. 1 separately for Democrats (panel a) and Republicans (panel b). The dependent variable is an extent-of-coverage measure, defined as the number of shared three-word phrases (trigrams) between a prominent MOC's tweet and cable-news transcripts in the surrounding minutes. "Prominent" refers to the five members of each party with the largest Twitter followings in a given year. Error bars show 95% confidence intervals based on standard errors clustered at the network × window level.

[19]Democrat MOCs tweeted a total of 43,137 tweets from 2017 to 2020, summing a total of 11.5 million followers in 2017, that number increasing to 42.9 million in 2020 (see Online Appendix Panel A.4.2.1a). Republican MOCs instead tweeted 32,008 tweets from 2017 to 2020, having a total of 14.7 million followers in 2017, up to 15.9 million followers in 2020 (see Online Appendix Panel A.4.2.1b).

In contrast to the sharp, within-minutes responses observed for Trump, I find no evidence that tweets posted by widely followed Democratic or Republican MOCs produced comparable short-run changes in cable news coverage (see Panels 2.5.1a and 2.5.1b for Democrats and Republicans respectively). This suggests that the short-run agenda-setting power documented in the previous sections for Donald J. Trump does not extend to other prominent U.S. politicians.

3. Effect of TV News Coverage of Trump's Tweets on Public Opinion

In this section, I study how the coverage of President Trump's Tweets by cable news outlets affected the opinions of cable news' audiences about Donald J. Trump. In Section 3.1, I introduce a set of new data sources and I describe the variables used. Section 3.2 presents the empirical strategy. I discuss the main results in Section 3.3. Section 3.4 shows different robustness checks. Last, in Section 3.5 I review alternative heterogeneity analyses.

3.1 Data

3.1.1 Sources

Text broadcasted by cable news outlets. Text displayed on-screen by CNN, Fox News and MSNBC, from January 2020 to November 2024. This dataset has been assembled through a Google Cloud (Link) COVID research grant awarded to a partnership between the TV News Archive (Link) and GDELT (Link) – see `here`.

Public opinion concerning President Trump. Timestamped interviews, each interview having (i) news consumption questions and (ii) questions regarding Donald J. Trump, both as President and as presidential candidate. Collected from January 2020 to January 2021, by Democracy Fund + UCLA Nationscape (Link).[20]

3.1.2 Variables

Broadcasts of Trump tweets. I match the texts being shown on-screen by cable news outlets with the text of Donald J. Trump's tweets to construct two sets of complementary variables: (1) three indicator variables, each indicator being referent to

[20]The Democracy Fund + UCLA Nationscape (Link) survey was employed in weekly waves, from July 2019 until January 2021. This was a large public opinion survey that interviewed each week a representative sample of the U.S. adult population (≈ 6,250 individuals). 1,000+ individuals were interviewed each day. Interviews were conducted online, and were designed for a 15-minute span.

a specific outlet, identifying those instances within a day in which an outlet explicitly shown a Trump tweet on-screen; (2) a set of accompanying variables with information about the length in time of each of these broadcasts (measured in seconds).

In total, cable outlets showed 17+ hours of imagery featuring text from a Donald J. Trump tweet. Showings differed substantially across networks, both in terms of their duration in seconds and their timing within the day. CNN's showings of Trump tweets were on average shorter in duration than those from Fox News and MSNBC (see Online Appendix Table B.1.1.1). Fox News and MSNBC spent more time showing President Trump's tweets during primetime, relative to CNN (see Online Appendix Figure B.1.1.1).

Trump approval rating. I am able to measure how did the approval rating of Donald Trump varied within a day for a given news audience by using three different sets of Democracy Fund + UCLA Nationscape (Link) questions:

(1) When did each interview start (the date and the time in UTC timezone – this information was automatically collected at the start of each interview);

(2) An approval ratings question asking "*do you approve or disapprove of the way Donald Trump is handling his job as president?*" (allowing individuals to respond along a 1 to 5 scale where 1 stands for "*strongly disapprove*", 2 stands for "*somewhat disapprove*", 3 stands for "*not sure*", 4 stands for "*somewhat approve*" and, 5 stands for "*strongly approve*");

(3) A news consumption question – "*have you seen or head news about politics on any of the following outlets in the past week?*" – with an exhaustive set of possible answers. To be more specific, this question allowed respondents to provide information not only about their cable news viewership (i.e., which cable outlet(s) each respondent use to get their political news – if CNN, Fox News, MSNBC, a combination of these three or none) but also their social media presence (whether individuals used "*social media (e.g., Facebook, Twitter)*" as a source of political news).

Panel (a) of Online Appendix Figure B.1.2.1 shows the average Trump approval rating for four groups of news consumers. Namely, individuals that (a) only watch CNN, (b) only watch Fox News, (c) only watch MSNBC and (d) do not watch any type of cable news. Three patterns are clearly visible: (1) CNN and MSNBC viewers tended to rate Donald Trump badly; (2) individuals that do not watch cable news seem to have been neutral relative to Trump; (3) Fox News viewers rate Donald J. Trump in a particularly positive fashion.[21]

[21] Encouragingly, these patterns are aligned with each of these audiences' political leanings. In fact, CNN and MSNBC's viewers tend to be significantly more liberal than Fox News audiences (Pew, 2020). This pattern is also observable when focusing on Trump's 2020 voting intentions (see Online Appendix Figure B.1.2.2).

Trump voting intentions. In addition to approval ratings, respondents were also asked about their voting intentions for Trump – "*would you consider voting for Donald Trump in the 2020 general election?*" – with three possible responses: "*no*" (taken as 1), "*I don't know*" (taken as 2), and "*yes*" (taken as 3). This question was fielded for a shorter number of weeks than approval ratings as it was only asked prior to November 2020. As a result, analyses using this variable are based on a smaller sample and therefore have lower statistical power. For this reason, I rely on approval ratings as a primary outcome, using voting intentions as a complementary robustness check.[22]

3.2 Empirical Strategy

To examine how cable news coverage of Trump's tweets affected cable news audiences' views of President Trump, I estimate the following difference-in-differences event-study specification:

$$\begin{aligned} \text{trump\_approval}_{i,g,n,w,\tau} &= \alpha_{g,n,w} + \mathbf{X}_i + \mathbb{1}\{\text{g: "}\textit{watches n}\text{"}\} \times \\ &\times \sum_{\eta \in \{C,F,M\}} \sum_{\substack{k=-3,\\ k\neq -1}}^{3} \mathbb{1}\left\{\begin{matrix} n=\eta, \\ \tau = k \end{matrix}\right\} \times \text{broadcast}_{n,w,0} \times \beta_k^{\eta} + \varepsilon_{n,w,\tau} \end{aligned} \tag{5}$$

where $trump\_approval_{i,g,n,w,\tau}$ denotes the rating that individual i in group g gave to Donald J. Trump during relative time period τ of event window (n, w).[23] [24] $\alpha_{g,n,w}$ denotes a group × network × window fixed effect, included to control for, among other factors, time-varying macro conditions that may differentially influence how each group of news consumers rates Trump. $broadcast_{n,w,0}$ is a treatment variable measuring the amount of time network n spent displaying a Trump tweet on-screen during relative time period 0 of window w.[25] β_k^{η} represents the standard difference-in-differences event-study coefficient specific to network η and relative time period k. $\mathbf{X}_i$ is a set of individual-level controls.[26] I estimate Eq. 5 using ordinary least squares (OLS), clustering standard errors at the

[22] Panel (a) of Online Appendix Figure B.1.2.2 shows average Trump voting intentions for different news consumers.

[23] Note that g can refer either to (a) a group of individuals who watch only n and do not consume any online news (labelled "*watches n*"), or (b) a group of respondents who neither watch cable news nor consume online news.

[24] In what follows, τ corresponds to a three-hour time period. Moreover, an "*event window* (n, w)" refers to a narrow time interval centered around an instance in which network n explicitly displayed a Trump tweet on-screen.

[25] Rescaled to have a mean of 0 and a standard deviation of 1. This rescaling is performed separately for each outlet to account for differences in broadcast intensity across networks.

[26] Namely: age, race, gender, census region, education, and household income.

group × network × event-window level.

The coefficient of interest, β_k^η, captures the differential change in Trump ratings between two groups of news consumers – (a) individuals who watch outlet η and (b) individuals who do not watch cable news – from event time -1 (one period before outlet η broadcasts a Trump tweet) to event time k.[27] [28] This coefficient provides a causal estimate of how coverage of a Trump tweet by network η affects the views held by that network's audience, under a parallel-trends assumption. In other words, β_k^η can be interpreted causally if, absent the broadcast of a Trump tweet, the Trump ratings of both groups of news consumers would have evolved in parallel. To support this assumption, I estimate Eq. 5 with a set of pre-broadcast coefficients to test whether the two groups rated Trump similarly prior to the broadcast of a Trump tweet.[29]

Conditional on this assumption, including the group × network × window fixed effects allows me to control for a host of factors that could act as confounders when interpreting β_k^η. First, these fixed effects absorb any time-invariant differences in Trump ratings across audiences. For example, individuals who do not watch cable news may be consistently more moderate than cable viewers, which would lead them to rate Donald Trump more neutrally. Failing to account for such systematic differences could bias the interpretation of β_k^η. In this case, β_k^η would not only capture the effect of a Trump tweet being shown on cable news on the ratings of cable viewers, but would also partially reflect average differences in Trump evaluations between the two groups of news consumers.

Second, I rule out time-varying factors that affect both groups homogeneously. An example of such an episode is a shooting, an event likely to be covered equally across news sources and expected to induce changes in both groups' views about Trump. Third, I address concerns related to time-varying factors that affect the two groups heterogeneously. An example of this type of event would be a political scandal, which is likely to be covered asymmetrically across news sources. These asymmetries in coverage would lead each group of news consumers to update their views about Trump differently. Failing to control for these differences could result in either an under- or over-interpretation of β_k^η, depending on how both sources differed over time in their coverage of these events.

A final identification concern relates to how frequently cable outlets covered Donald

[27] To strengthen the argument that treated and control individuals were exposed and not exposed to a Trump tweet, I restrict the sample to respondents who do not use social media to gather political news. This restriction prevents cases in which respondents become aware of a Trump tweet online.

[28] Again, a broadcast of a Trump tweet in this specification corresponds to a broadcast with a duration that is normalized to an outlet-specific one-standard deviation (S.D.): for CNN, a 1 S.D. broadcast is equivalent to 14 seconds on-screen; for Fox News, 17 seconds; and for MSNBC, 18 seconds.

[29] In addition, I conduct several balance tests to show that the two groups were similarly "identical" both before and after Trump tweet showings – i.e., similar across a range of demographics relevant for explaining support for Trump, conditional on the fixed effects used to estimate Eq. 5.

Trump's tweets within a given day. In practice, TV channels explicitly showed Trump's tweets on-screen an average of three times per day. Such recurrent coverage generates event windows that partially overlap in calendar time (both within and across cable outlets).[30] This overlap across event windows prevents a clean distinction between pre- and post-broadcast periods, which can bias estimates of β_k^η.[31]

To address this issue, I proceed in two ways. As in Section 2.2, I first implement a stacked design (see Cengiz et al., 2019). In particular, I restrict attention to an event-window–specific treatment group: within each event window (n, w), I classify as treated only those individuals who report watching *only* outlet η. This restriction yields an unbiased estimate of β_k^η if and only if event windows associated with the same outlet do not partially overlap in calendar time.[32]

Second, to further address this prerequisite, I assume that only abnormally long broadcasts generate a non-zero treatment effect. I then estimate Eq. 5 using only those event windows that do not partially overlap in calendar time with other windows from the same outlet in which a Trump tweet was shown for an abnormally long period of time (2 S.D. $\approx$ 37 seconds). This sample restriction has implications for the interpretation of β_k^η. In particular, theoretically, β_k^η should be interpreted as a local coefficient specific to those broadcasts that were not closely followed in time by other long-duration showings from the same outlet. In practice, however, this class of broadcasts is representative of outlets' coverage patterns of Trump's tweets, implying that β_k^η can be interpreted as an average treatment effect.[33]

3.3 Main Results

Event-study. Panels 3.3.1a, 4.1a, and 4.1c plot the coefficients obtained from estimating Eq. 5. Panel 3.3.1a reports the coefficients specific to CNN's broadcasts, while Panels 4.1a and 4.1c present the corresponding estimates for Fox News and MSNBC, respectively.

[30]Cable outlets broadcasted Trump's tweets 2,592 times during 2020 (CNN showed a Trump tweet on-screen 717 times, Fox News 920 times, and MSNBC 955 times). Of these broadcasts, 2,567 (99%) correspond to event windows that partially overlap in calendar time (taking event windows as 21-hour intervals, as in Eq. 5).

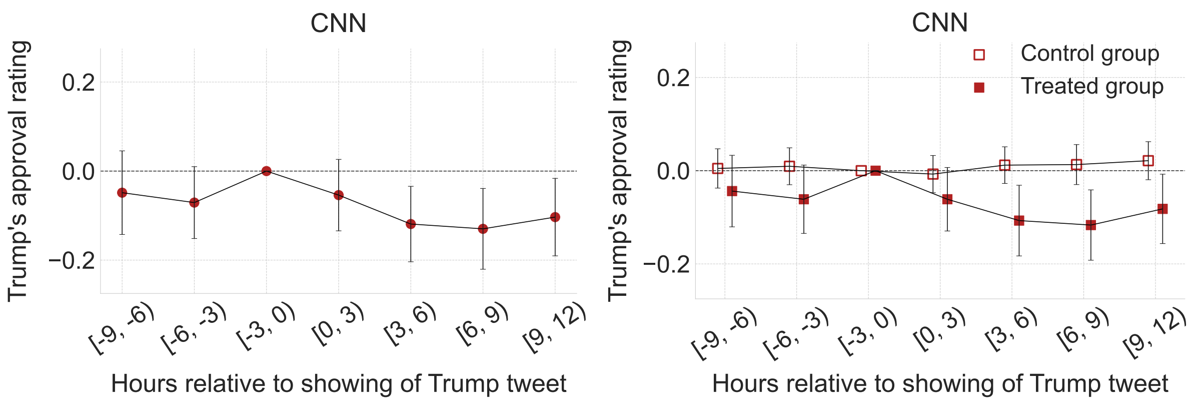
[31]As described in Section 2.2, for overlapping event windows, some pre- and post-broadcast periods from a given window will be incorrectly classified as post- and pre-broadcast periods in other windows. This issue parallels concerns in difference-in-differences (DiD) designs with staggered treatment timing (see e.g., Sun and Abraham, 2021), and more specifically resembles DiD settings with multiple treatments in which coefficients associated with a particular treatment are contaminated by other treatments (Goldsmith-Pinkham et al., 2024).

[32]When comparing event windows within outlets, 2,495 (97%) of them partially overlap in calendar time with another window from the same outlet (taking event windows as 21-hour intervals, as in Eq. 5).

[33]This class of broadcasts constitutes 83% of all tweet showings (see Online Appendix Table B.2.1.1).

CNN's broadcasts of Trump's tweets caused CNN viewers to worsen their views of the President in the hours following a broadcast. A one-standard deviation showing of a Trump tweet leads to a peak 14.3 percent decrease in Trump's approval rating among CNN viewers, relative to their pre-showing comparison with individuals who do not watch television but are otherwise similar along key demographic characteristics.[34] This peak decline occurs between 6 and 9 hours after a CNN broadcast (peak coef.: −0.129; baseline approval-rating gap between CNN viewers and respondents taken as controls: −0.899).

I do not find comparable effects for Fox News or MSNBC. This absence of results should be interpreted with caution, however. In a heterogeneity analysis presented in Section 3.5, I show that Fox News's broadcasts of Trump's tweets did produce meaningful changes in how its viewers evaluated Donald Trump's mandate as president.



(a) **Difference-in-differences** (b) **Group-specific differences**

Figure 3.3.1: **Effect of CNN broadcasts of Trump tweets on approval ratings**. The panels report coefficients from event-study regressions. Panel (a) presents the difference-in-differences event-study coefficients from Eq. 5. Panel (b) reports the group-specific coefficients from Eq. 8, which allow treated and control groups to evolve differently within each event window. The dependent variable is a five-point approval rating of Donald J. Trump (1 = "strongly disapprove"; 5 = "strongly approve"). Error bars denote 95% confidence intervals based on standard errors clustered at the network × window level.

Pre-post. I now turn to discussing the magnitude of the estimated effects for CNN. To do so, I begin by estimating the following pre-post regression:

$$\text{trump\_approval}_{i,g,n,w,\tau} = \alpha_{g,n,w} + \mathbf{X}_i + \mathbb{1}\{g\text{: ``}\textit{watches } n\text{''}\} \times \\ \times \sum_{\eta \in \{C,F,M\}} \mathbb{1}\left\{\begin{matrix} n = \eta, \\ \tau \geqslant 0 \end{matrix}\right\} \times \text{broadcast}_{n,w,0} \times \beta^{\eta}_{\text{post}} + \varepsilon_{n,w,\tau} \tag{6}$$

[34]Both groups of news consumers are indistinguishable across a set of demographic characteristics after conditioning on group × network × window fixed effects (see Online Appendix Table B.2.1.3).

where β^{η}_{post} denotes a standard difference-in-differences pre-post coefficient that measures, on average, how the Trump rating of a viewer of network η changes relative to that of an individual who does not watch cable news, comparing post-broadcast periods to the pre-broadcast period.

Table 4.3 reports the coefficients from estimating Eq. 6. On average, a one-standard deviation broadcast of a Trump tweet by CNN causes CNN viewers to revise their ratings of Trump downward by approximately 7 percent relative to their pre-showing average comparison with individuals that do not watch television nor are online (coef.: −0.061; baseline approval-rating gap between CNN viewers and respondents taken as control units: −0.925).[35]

Effect size. To benchmark this effect against previous findings in the media literature, I translate the estimated pre-post effect into a persuasion rate, following the definition in DellaVigna and Gentzkow (2010) – the "*percentage of receivers that change behavior among those who receive a message and are not already persuaded*". In this context, the persuasion rate corresponds to the fraction of CNN viewers whose approval of Trump changed after being exposed to a tweet on television, relative to the fraction of CNN viewers who could have plausibly changed their views but did not. More formally, the persuasion rate of a CNN broadcast of a Trump tweet, f_{CNN}, is given by:

$$f_{CNN} = \frac{y_T - y_C}{e_T - e_C} \frac{1}{1 - y_0} = \frac{y_T - y_C}{1 - y_0} \tag{7}$$

where y_T is the share of individuals in the treatment group (CNN viewers, assumed to be fully exposed to CNN's broadcasts of Trump's tweets) that approve of Trump, and y_C is the corresponding share among the control group (individuals who do not watch cable news and therefore were not exposed to CNN's broadcasts). Importantly, after conditioning on an exhaustive set of fixed effects, the control group is statistically indistinguishable from CNN viewers along key demographics (see Online Appendix Table B.2.1.3). e_T denotes the fraction of the treatment group exposed to the broadcast (equal to 1), while e_C denotes the fraction of the control group exposed (equal to 0). y_0 is the fraction of CNN viewers who would approve of Trump even in the absence of exposure to a CNN broadcast of a Trump tweet; in this context, it is observed directly in the baseline period. The term $(y_T - y_C)$ thus captures the effect of exposure on approval, while the factor $1/(1 - y_0)$ rescales this effect by the share of viewers who were not already persuaded.

Since Eq. 7 is defined for binary outcomes, I re-estimate both the event-study and pre-post regressions using a binarized version of the approval-rating variable. Following Chen and Yang (2019), I convert the discrete approval ratings into a binary measure,

[35] The post coefficients for Fox News and MSNBC are, in absolute value, two orders of magnitude smaller than those for CNN and are not statistically significant at the 10% level.

setting the outcome equal to 1 if it is above the median. Then, I re-estimate the pre-post regression using the binarized outcome, which provides an estimate of $y_T - y_C$. The estimated coefficient is -0.014 (standard error: 0.007), while the baseline approval rate of Trump among CNN viewers is $y_0 = 0.19$. Using these values, the persuasion rate is equal to $f_{CNN} = \frac{y_T - y_C}{1 - y_0} = \frac{-0.014}{1-0.19} \approx -0.0173 = 1.73\%$.

This negative persuasion rate suggests a small decrease in Trump approval among CNN viewers following exposure. However, the estimate may be understated for several reasons. First, it relies on the standard assumption that all CNN viewers are equally and fully exposed to each broadcast. In practice, viewer engagement varies: some individuals may be only passively watching, leading to partial or inattentive exposure, and relaxing this assumption would increase the estimated persuasion rate. Second, baseline approval ratings may be understated if CNN viewers were reluctant to express support for Trump due to social-desirability concerns or fear of judgment, which would mechanically lower the estimated persuasion rate. Third, the current persuasion rate captures only the direct effect of exposure to a CNN broadcast of a Trump tweet and does not account for potential spillover effects – for instance, individuals whose views changed after exposure may subsequently influence the political opinions of others within their social networks.

The persuasion rate estimated above is substantially smaller than those reported in prior studies on U.S. television and political persuasion. For example, DellaVigna and Kaplan (2007) find an 8% persuasion rate for Republican voting intentions following exposure to Fox News, and Martin and Yurukoglu (2017) report a much larger rate of 58% for the same context. These studies, however, examine the effects of sustained exposure to a partisan news lineup, whereas the present analysis focuses on a far narrower intervention: short and frequent broadcasts of social media posts, which are plausibly less consequential in shaping political evaluations. A closer comparison is Djourelova (2023), who studies passive exposure to shifts in media language and documents a 1.9% persuasion rate regarding immigration attitudes. The persuasion rate implied here – 1.73% – is of similar magnitude, being consistent with brief exposures to media content having a relatively modest influence on political opinions.

3.4 Robustness Checks

3.4.1 Parallel Trend Concerns

The previous results may be partially driven by individuals who do not watch cable news and are therefore unaffected by the broadcasting of Trump's tweets on cable outlets. For example, news events expected to influence how individuals evaluate Donald Trump may be covered exclusively by non-cable outlets hours after cable networks broadcast a Trump tweet. In such cases, respondents who do not watch cable news would still be expected to revise their views about Trump following a cable broadcast, even though their reactions are unrelated to the tweet shown on television.

To rule out concerns that the previous findings are driven exclusively by individuals who do not watch cable news, I extend Eq. 5 to allow the two audiences to rate Donald Trump differently within each event window:

$$\begin{aligned} \text{trump\_approval}_{\,i,\,g,\,n,\,w,\,\tau} &= \alpha_{\,g,\,n,\,w} + \mathbb{1}\,\{\,g\!:\ \text{“}\textit{no cable}\text{”}\,\} \times \\ &\times \Omega_{\,\text{“}\textit{no cable}\text{”}} + \mathbb{1}\,\{\,g\!:\ \text{“}\textit{watches n}\text{”}\,\} \times \Omega_{\,\text{“}\textit{watches n}\text{”}} + \mathbf{X}_i + \varepsilon_{\,n,w,\tau} \end{aligned} \tag{8}$$

where,

$$\Omega_{\,r} = \sum_{\eta\,\in\,\{C,F,M\}} \; \sum_{\substack{k=-3,\\ k\neq -1}}^{3} \mathbb{1}\left\{\begin{matrix} n=\eta, \\ \tau=k \end{matrix}\right\} \times \text{broadcast}_{\,n,\,w,\,0} \times \beta_k^{\eta,\,r}$$

and $\beta_k^{\eta,\,r}$ is a standard event-study coefficient measuring how group r evaluates Donald J. Trump k periods away from a one-standard deviation broadcast of a Trump tweet by outlet η.

The estimation of Eq. 8 corroborates the previous results. Specifically, the changes in Trump's approval ratings that occur in the hours following a CNN broadcast of a Trump tweet are driven exclusively by CNN viewers worsening their evaluations of the President (see Panel 3.3.1b). By contrast, the audiences of both Fox News and MSNBC exhibit no meaningful changes in their views of Trump after these outlets broadcast a Trump tweet (see Panels 4.1b and 4.1d, respectively).

3.4.2 Omitted Variable Concerns

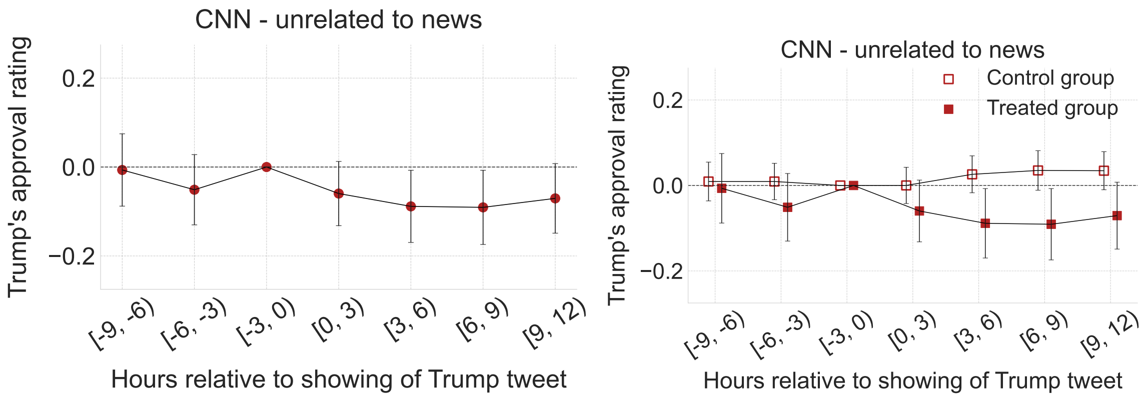
A related concern is whether viewers of specific cable outlets change their views hours after a tweet is shown solely because of that broadcast or, instead, in response to a news event covered only by certain outlets.[36] For instance, a politically salient development involving Donald Trump – such as an anti-Trump statement issued by Democratic lawmakers – could prompt an outlet to air a segment featuring a related Trump tweet, making it difficult to disentangle reactions to the tweet from reactions to the broader news event.

To address this issue, I follow the approach in Section 2.4.1. First, I construct a similarity measure comparing the text of the tweets shown on-screen in each event window with the text of online news articles posted within a 6-hour window before and after each broadcast. I then classify broadcasts according to whether their tweets are related

[36]Such an event might not affect individuals who do not watch cable news.

or unrelated to neighboring news. Finally, I estimate a version of Eq. 5 that allows individuals to react differently to broadcasts depending on their similarity to recent news.

The estimation of this equation corroborates the previous findings. A CNN broadcast of a Trump tweet leads CNN viewers to revise their opinions of Trump downward, regardless of whether the tweet shown on-screen is related or unrelated to recent news (see Panel 3.4.1a and Online Appendix Panel B.3.1.2a for unrelated and related tweets, respectively). As before, viewers of Fox News and MSNBC are, on average, insensitive to both types of broadcasts (see Figure B.3.1.1).



(a) **Difference-in-differences** (b) **Group-specific differences**

Figure 3.4.1: **Effect of CNN broadcasts of Trump tweets unrelated to news on approval ratings**. The panels report coefficients from event-study regressions for tweets classified as unrelated to contemporaneous news. Panel (a) presents difference-in-differences event-study coefficients from an extension of Eq. 5 that allows individuals to react different to broadcasts of Trump tweets related and unrelated to neighboring news. Panel (b) reports group-specific coefficients from a similar extension of Eq. 8, allowing treated and control groups to vary separately within each type of event window. The dependent variable is a five-point approval rating of Donald J. Trump (1 = "strongly disapprove"; 5 = "strongly approve"). Error bars denote 95% confidence intervals based on standard errors clustered at the network × window level.

To verify that these results are not driven solely by non-cable viewers (i.e., to rule out the concerns discussed in Section 3.4.1), I estimate an extension of Eq. 8 that allows each group of news consumers to respond differently to broadcasts featuring tweets that are related or unrelated to proximate news stories. This exercise further supports the main findings: a CNN broadcast of a tweet unrelated to recent news lowers Trump approval only among CNN viewers (see Panel 3.4.1b).

3.4.3 Placebo Analysis

I next examine whether the baseline results are affected by misreporting of media diets in the Nationscape survey. The main concern is that some respondents classified as offline (i.e., not on social media and, for controls, not watching cable) may in fact be social media users. In such cases, individuals coded as untreated could nevertheless be exposed to Trump's tweets at the time of posting, biasing treatment assignment and, consequently, the estimates discussed previously.

To test for this, I re-estimate Eq. 5 using the posting time of Trump's tweets as the treatment period, rather than the time of their broadcast on cable. I restrict the sample to tweets whose cable showing occurs at least 12 hours after posting, ensuring that any contemporaneous change in approval cannot be attributed to cable coverage. In addition, I do not distinguish between tweets that are related or unrelated to recent news, as this distinction becomes relevant only if a change in approval is observed.

The estimates show no significant change in the comparison between treated and control groups at the time of a tweet's posting (see Online Appendix Figure B.3.2.1). This finding suggests that Nationscape respondents report their media diets accurately and supports the validity of the results presented above.

3.4.4 Variable and Regression Specifications

In this subsection, I test the robustness of the results described in Section 3.4.2 – namely, the effect of tweet broadcasts unrelated to pressing news events – across alternative variable definitions and regression specifications.

News-variable definitions. I vary how I label tweet showings as related and unrelated to news events. The baseline news label compares the text of the tweet shown on-screen with the text of news posted online during the 6 hours before and after the showing. I re-estimate the regression discussed in Section 3.4.2, using measures that rely on broader news horizons (up to 24 hours before and after a showing). Across all news labels, CNN viewers reduce their approval of Trump after a broadcast, Fox News and MSNBC viewers do not (see Panels (a), (b) and (c) of Online Appendix Figure B.3.3.1).

Regression specifications. I assess whether the previous results depend on specific sets of controls or clustering choices. The baseline specification includes demographic controls, group-network-window fixed effects, and clustered standard errors. I re-estimate the extension of Eq. 5, described in Section 3.4.2, using alternative control sets and different clustering levels. The estimated effects remain stable across all specifications (see Panels (d), (e) and (f) of Online Appendix Figure B.3.3.1).

Event-window length. I vary the width of the event window used in estimating the extension of Eq. 5 described in Section 3.4.2. The baseline analysis relies on event windows with three leads and lags (9 hours before and after a showing). I re-estimate this equation using wider windows, up to 15 hours pre- and post-broadcast. Results remain stable across all window lengths. Importantly, the effect on CNN viewers' approval is not persistent over time: it becomes statistically insignificant 12 hours after a showing (see Panels (a), (b) and (c) of Online Appendix Figure B.3.3.2).

Treatment-variable definitions. I test whether the results depend on treating broadcast length as a continuous measure. In the baseline specification, the treatment variable is the standardized duration of a showing. I re-estimate the regression discussed in Section 3.4.2, using instead a binary indicator equal to one if at least one tweet was shown on-screen during a given 3-hour period. The results are stable under this alternative treatment definition (see Panels (d), (e) and (f) of Online Appendix Figure B.3.3.2).

Treated and control group definitions. Baseline results rely on strict definitions of treatment and control units: both groups are required not to use social media. This restriction minimizes treatment spillovers but limits the estimates to a relatively narrow subset of respondents. To assess external validity, I relax these definitions by allowing both treated and control units to include online individuals. I re-estimate the extension of Eq. 5, described in Section 3.4.2, using these broader groups and obtain identical results (see Panels (a), (b) and (c) of Online Appendix Figure B.3.3.3).

Outcome-variable definitions. I test whether the results hold for other outcomes. I re-estimate the main specification using voting intentions for Donald Trump in the 2020 presidential election as the dependent variable. Although this outcome is observed for fewer weeks in the Nationscape survey, being less powered, the patterns are similar: CNN broadcasts of Trump's tweets reduce voting intentions among its viewers, Fox News and MSNBC broadcasts do not (see Panels (d), (e) and (f) of Online Appendix Figure B.3.3.3).

In summary, the results described in Section 3.4.2 – the effect of tweet showings unrelated to pressing news events on public opinion – are not design driven, being robust to news-variable definition, control set, event-window length, treatment variable, sample composition and outcome measure.

3.5 Heterogeneity and Mechanisms

3.5.1 Heterogeneity by Time-Of-Day

Previous estimates implicitly assume that cable news broadcasts of Trump's tweets affect each outlet's audience homogeneously throughout the day. However, this assumption overlooks an important feature of cable viewership: TV networks attract substantially larger audiences during primetime (i.e., 8pm to 11pm; see Pew, 2021). Taking this into account, one would expect primetime broadcasts of Trump's tweets to have a broader impact on cable news audiences.

With this in mind, in this section I allow the effect of a broadcast of a Trump tweet to vary depending on when within the day it is aired. To do so, I extend Eq. 5 as follows:

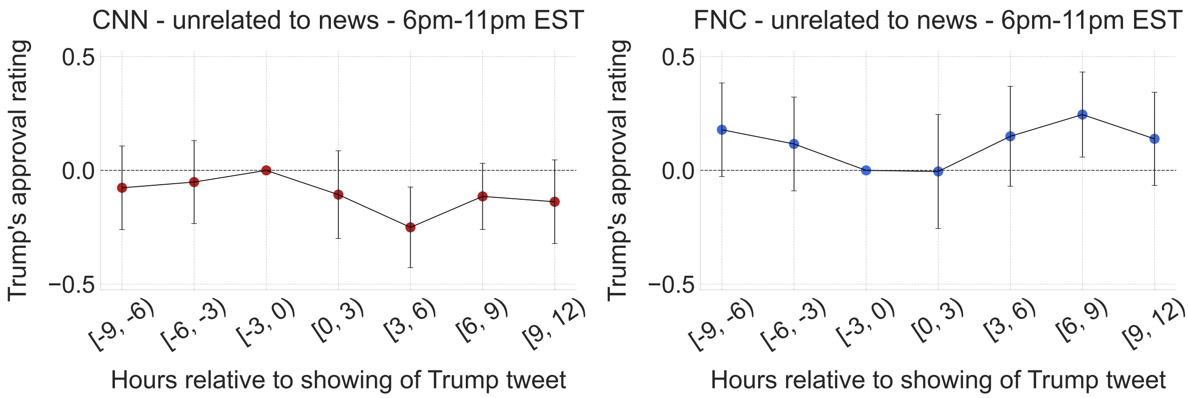
$$\text{trump\_approval}_{\mathrm{i,g,n,w,\tau}} = \alpha_{\mathrm{g,n,w}} + \mathbf{X}_{\mathrm{i}} + \sum_{\mathrm{t}=1}^{4} \mathbb{1}\left\{\begin{matrix}\text{w: ``}\textit{showing}\\ \textit{during t''}\end{matrix}\right\} \times \Omega_{\mathrm{t}} + \varepsilon_{\mathrm{n,w,\tau}} \tag{9}$$

where t indexes a time-of-day slot during which a broadcast of a Trump tweet occurs ($t \in \{1, 2, 3, 4\}$, with $1 \equiv$ dawn, 1am-6am; $2 \equiv$ morning, 7am-12pm; $3 \equiv$ afternoon, 1pm-6pm; and $4 \equiv$ primetime, 7pm-11pm),[37] and

$$\Omega_{\mathrm{t}} = \mathbb{1}\{\mathrm{g}\text{: ``}\textit{watches n}\text{''}\} \times \sum_{\eta \in \{\mathrm{C,F,M}\}} \sum_{\substack{\mathrm{k}=-3,\\ \mathrm{k}\neq -1}}^{3} \mathbb{1}\left\{\begin{matrix}\mathrm{n}=\eta,\\ \tau=\mathrm{k}\end{matrix}\right\} \times \mathrm{broadcast}_{\mathrm{n,w,0}} \times \beta_{\mathrm{k}}^{\eta,\mathrm{t}}$$

where $\beta_{\mathrm{k}}^{\eta,t}$ measures how viewers of outlet η rate Donald Trump – relative to individuals who do not watch cable – k periods away from a one-standard deviation broadcast of a Trump tweet by outlet η occurring during time-of-day slot t.

To address concerns such as those discussed in Section 3.4.2, I distinguish between tweets that are related and unrelated to news. Specifically, I extend Eq. 9 to allow news audiences to react differently within a day to each type of tweet. In what follows, I focus on changes in public opinion associated with tweets unrelated to current news.



(a) **CNN** (b) **Differences**

Figure 3.5.1: **Effect of primetime CNN and FNC broadcasts of Trump tweets unrelated to news on approval ratings**. The figure reports event-study coefficients from Eq. 9, a heterogeneity specification that allows for individuals to react differently to a broadcast of a Trump tweet depending on that broadcast's time-of-day. Both panels restrict attention to broadcasts occurring during primetime (6pm-11pm EST) and to tweets classified as unrelated to contemporaneous news. Panel (a) presents coefficients for CNN broadcasts; Panel (b) presents the corresponding coefficients for Fox News. The dependent variable is a five-category approval-rating measure of Donald J. Trump (1 = "strongly disapprove", 5 = "strongly approve"). Error bars denote 95% confidence intervals based on standard errors clustered at the network × window level.

I find two results. First, CNN viewers revise their Trump ratings downward only after primetime showings of Trump's tweets (see Panel 3.5.1a). Second, primetime showings

[37] All time-of-day slots are defined in Eastern Standard Time (EST).

on Fox News lead to a significant improvement in how Fox News viewers rate Donald J. Trump as President (see Panel 3.5.1b).[38]

3.5.2 Mechanisms

The primetime results documented in Section 3.5.1 are consistent with two complementary mechanisms: differences in audience composition and differences in how outlets select and cover Trump's tweets.

First, regarding audience composition, CNN and Fox News attract systematically different viewers, and broadcasts of Trump tweets are likely to prime these pre-existing attitudes. When an outlet shows a Trump tweet on-screen, its viewers may be reminded of their prior beliefs. This priming channel cannot be separately identified in the current setting, as it arises directly from time-invariant differences in audiences across outlets. Second, regarding coverage, I refer to this channel as a framing effect and decompose it into two components that can be tested empirically: a slanting effect, whereby Fox News and CNN discuss similar tweets in systematically different tonal terms; and a filtering effect, whereby the distribution of tweets covered on air differs across outlets.

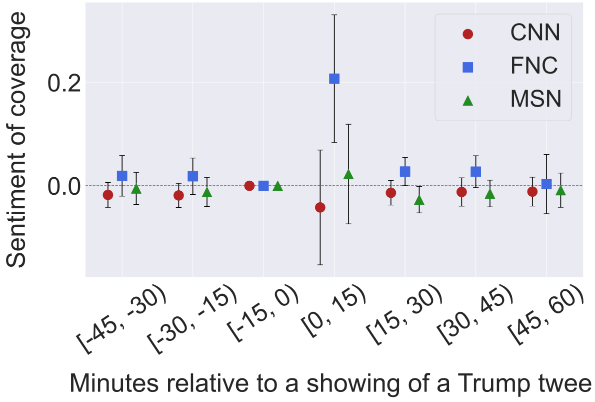
To study slanting, I extend the sentiment analysis in Section 2.3.2 and construct a sentiment-of-coverage measure for TV transcripts around each on-screen showing of a Trump tweet, using a dictionary-based score as in Part 2. I estimate a version of Eq. 1 where the outcome is the sentiment of tweet-related coverage in the minutes before and after a showing. I include showing fixed effects so that comparisons across outlets control for showing-specific factors such as the content of the tweet being shown. Estimates show that Fox News uses significantly more positive language than CNN when discussing tweets, both on average and during primetime (see Panel 3.5.2a). This is consistent with a slanting effect where tweets are framed more favourably on Fox News than on CNN.

To test for filtering, I fit a topic model to the corpus of Trump tweets posted during 2020 and use the model to assign topic probabilities to the subset of tweets that are shown on-screen by CNN and Fox News.[39] For each network, I aggregate the total on-screen time devoted to each topic and compare the implied topic distributions, with a focus on primetime. During this period, CNN allocates substantially more coverage to Trump tweets concerning the coronavirus pandemic. Fox News devotes a larger share of its Trump-tweet coverage to anti-Biden or "election integrity" claims and MAGA-themed

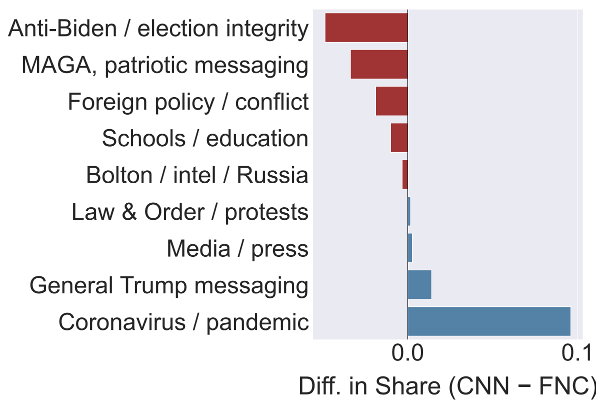
[38] I refrain from discussing the estimates for MSNBC because this network is severely underrepresented in the sample used to estimate the extension of Eq. 9, as discussed in Section 3.3.

[39] I fit a BERTopic model (Grootendorst, 2022) on all tweets posted by Donald Trump during 2020. Topic-word distributions are reported in Online Appendix Table B.4.2.1, representative tweets for each topic appear in Online Appendix Table B.4.2.2, and Online Appendix Panels B.4.2.1a and B.4.2.1b show, respectively, distribution of topics and share of on-screen time each network devotes to them.

messaging (see Panel 3.5.2b). These patterns are consistent with a filtering mechanism in which Fox News highlights Trump tweets that cater to a conservative audience.



(a) **Sentiment of TV coverage during primetime showings of Trump tweets**



(b) **Difference in distribution of topics covered during primetime (CNN - FNC)**

Figure 3.5.2: **Slanting and filtering in primetime coverage of Trump tweets.** Panel (a) plots differences in the sentiment of tweet-related coverage across networks, measured using a dictionary-based sentiment score computed from the transcript passages surrounding matched tweet phrases. Panel (b) reports differences in the distribution of topics emphasized on air during primetime showings, defined as the difference in the topic-probability distributions assigned to Trump tweets shown by CNN and Fox News (positive values indicate topics emphasized more by CNN; negative values indicate topics emphasized more by Fox News). Error bars denote 95% confidence intervals based on standard errors clustered at the network $\times$ window level.

The slanting and filtering patterns described above provide a mechanism for the heterogeneous primetime effects documented in Section 3.5.1: conditional on similar audiences being primed by Trump-related content, Fox News and CNN not only frame similar tweets differently, but also select systematically different subsets of tweets to put on air.

3.6 Additional Evidence and External Validity

In this section, I provide additional evidence on the external validity of the previous findings. I examine whether cable news outlets' amplification of online political statements extends (i) beyond Twitter and (ii) beyond Donald J. Trump.

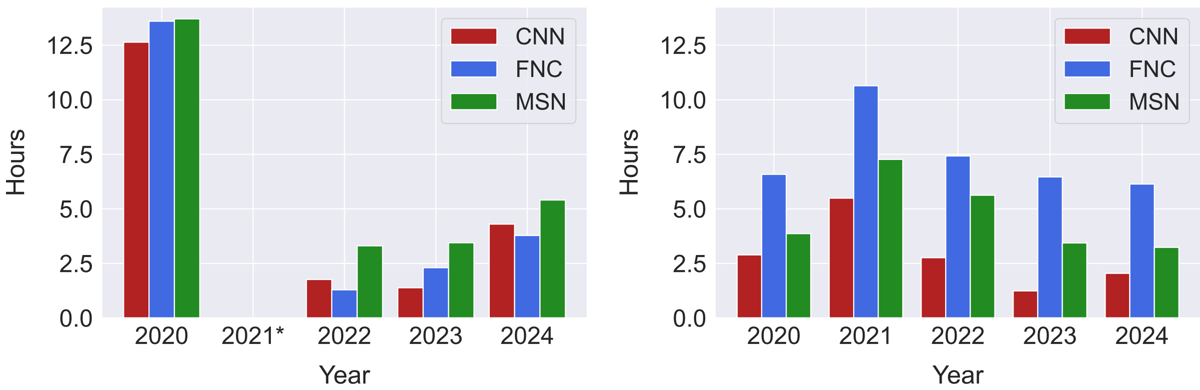
Trump's post-Twitter online activity. I map all text-on-screen segments taking place between 2020 and 2024 to the set of verified social media handles used by Donald J. Trump. Importantly, Trump was suspended from Twitter on January 8, 2021 and did not resume online activity until 2022, through his Truth Social account. Consistent with this timeline, I restrict attention to his Twitter handle during 2020 and to his Truth

Social handle from 2022 to 2024 (both handles are identical – @realDonaldTrump).[40]

For each year, I identify all moments in which Trump's social media handle appeared on screen and construct a measure of total on-screen time devoted to his online activity. As shown in Panel 3.6.1a, the practice of broadcasting Trump's online posts was not limited to his activity on Twitter. Beginning in 2022, all three cable outlets displayed his Truth Social handle, with coverage increasing over time. Between 2022 and 2024, cable outlets devoted approximately 27 hours to broadcasting President Trump's handle.

A comparison between 2020 and 2024 – both presidential election years – provides useful context. In 2020, outlets showed Trump's Twitter handle for a total of 39 hours; in 2024, these same outlets displayed his Truth Social handle for roughly 14 hours. Although coverage was lower in 2024, its magnitude – and its concentration on CNN and MSNBC – indicates that television outlets continued to amplify Trump's online statements even after his transition from Twitter to Truth Social.[41]

Taken together, these findings show that television coverage of Trump's social media activity is not platform-specific. Rather, cable outlets appear to have adopted a practice of displaying Donald Trump's online statements, regardless of whether these were issued on Twitter or Truth Social.



(a) **Number of hours showing Donald Trump's Twitter (2020) and Truth Social (2022 to 2024) handle, by network**

(b) **Number of hours showing Twitter handles from members of Congress, from 2020 to 2024, by network**

Figure 3.6.1: **Television coverage of politicians' social media handles**. Panel (a) plots the total number of hours in which cable outlets displayed Donald J. Trump's verified social media handle—Twitter in 2020 and Truth Social from 2022 to 2024—separately by network. Panel (b) reports the corresponding series for verified Twitter handles of sitting members of Congress (MOCs) between 2020 and 2024. For each year, total on-screen time is computed by summing seconds in which a handle appears on screen.

[40] I assume that any frame displaying a Trump handle is showing, or discussing, one of his posts.

[41] This analysis captures instances in which Trump's Truth Social posts were shown hours after their original posting time. As such, these results do not reflect those short-run responses examined in Section 2.

Coverage of social media posts by members of Congress. I assemble all verified Twitter handles for U.S. Members of Congress (MOCs) serving between 2020 and 2024.[42] I then match these handles to all text shown on-screen by CNN, Fox News, and MSNBC over the same period. This procedure identifies all instances in which a sitting MOC's handle appeared on screen and allows me to construct yearly measures of the total on-screen time devoted to legislators' social media activity.

Panel 3.6.1b shows that this coverage is non-trivial and, importantly, comparable in scale to that devoted to President Trump. Coverage of MOCs' social media handles peaks in 2021 at roughly 24 hours of total on-screen time and declines to about 12 hours in 2024. Fox News accounts for the majority of this coverage throughout the period.

Moreover, this type of televised amplification is highly concentrated among a small subset of legislators. I find that, although an average of roughly 300 congressional handles appear on-screen each year, approx. 50% of total coverage is concentrated among just 10 handles – those with a higher number of followers (see Online Appendix Panels B.5.1a and B.5.1b).

Overall, this evidence suggests that cable news outlets' practice of broadcasting political actors' online statements is (i) not exclusive to Trump, and (ii) not confined to Twitter. Instead, it appears to be a systematic feature of cable news programming, extending to multiple political figures and across multiple online platforms.

4. Conclusion

Social media provides politicians with a channel through which sentimentally charged statements can be disseminated rapidly and at low cost. Such statements may shape voters' opinions, attitudes and political behaviors. Past research has focused primarily on measuring these effects among social media users, abstracting from the interconnectedness of modern media ecosystems. This paper provides a first causal quantification of the spillover effects of social media through traditional news media, namely, cable television.

I first show that cable news outlets actively amplified Donald J. Trump's tweets through their coverage. Cable networks systematically shifted attention toward the issues addressed in President Trump's tweets within minutes of a post, implying that Donald Trump wielded agenda-setting power over cable news through his online statements. This constitutes the first causal evidence of a politician's ability to shape the distribution of media content through social media activity. This result also opens an important question: did President Trump use his Twitter presence strategically, redirecting cable news

[42] For each year, I include all legislators serving at any point during that calendar year. In practice, I observe verified handles for sitting MOCs from 2020 through mid-2023; the 2024 cross-section is extrapolated from 2023, as both years correspond to the 118th Congress.

attention away from topics harmful to his platform or detrimental to his executive action (à la Gratton et al., 2018)? Exploring this possibility remains an important avenue for future research.

Second, I show that cable news coverage of Trump's tweets had significant effects on how cable news audiences evaluated Donald Trump as President. CNN's broadcasts of Trump's tweets caused CNN viewers to worsen their assessments of Trump in the hours following a showing, whereas primetime broadcasts on Fox News led Fox viewers to improve approval ratings of the President. These findings offer the first causal evidence on how social media content, once amplified by television news, affects the political opinions of offline audiences. The results also carry important policy implications. For instance, content moderation policies implemented by social media platforms can influence the distribution of content discussed on other media, including television. Future assessments of these policies should account for such cross-platform spillovers.

Lastly, I provide additional evidence supportive of the external validity of the results documented in this paper. I show that cable news outlets devoted comparable levels of coverage to Donald Trump's activity on Truth Social posts in 2024 as to his tweets in 2020. I further document that widely followed members of Congress also have social media displayed on cable news, indicating that the amplification of online political statements by television outlets extends beyond Donald Trump. This broader pattern reinforces a central argument of this paper: the political impact of social media cannot be fully understood by studying social media users alone. Once online statements enter television programming, these statements shape the information environment encountered by a considerably large share of the electorate.

Appendix

Table 4.1: **Extent and intensity of coverage – pre-post regressions**

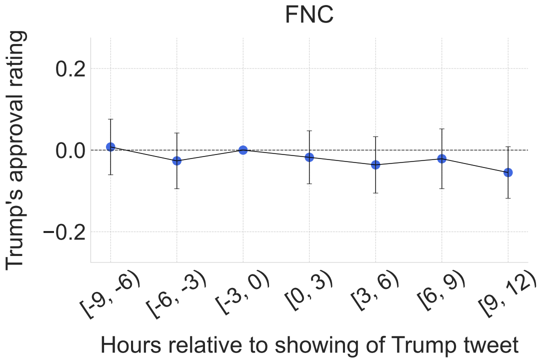
	Extent of coverage				Intensity of coverage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post × CNN	3.537	4.091	4.541	4.985	0.763	0.868	0.970	1.055
	(0.145)	(0.163)	(0.180)	(0.199)	(0.030)	(0.035)	(0.040)	(0.045)
Post × FNC	3.804	4.435	4.973	5.511	0.678	0.752	0.831	0.903
	(0.166)	(0.188)	(0.211)	(0.227)	(0.032)	(0.037)	(0.042)	(0.046)
Post × MSN	3.111	3.538	4.047	4.484	0.636	0.694	0.808	0.901
	(0.132)	(0.151)	(0.167)	(0.182)	(0.027)	(0.031)	(0.035)	(0.039)
Pre-tweet CNN avg.	0.431	0.553	0.680	0.786	0.375	0.503	0.617	0.724
Pre-tweet FNC avg.	0.761	0.981	1.230	1.424	0.549	0.728	0.897	1.070
Pre-tweet MSN avg.	0.346	0.450	0.544	0.624	0.350	0.472	0.573	0.671
Event-window size	±45m	±60m	±75m	±90m	±45m	±60m	±75m	±90m
Observations	64938	63222	61554	60162	64938	63222	61554	60162
R^2	0.543	0.544	0.557	0.558	0.667	0.674	0.687	0.695

Notes: The table reports coefficients from pre-post regressions as expressed in Eq. 2, estimating how cable-news coverage of issues featured in Trump tweets changed after a tweet was posted. Columns (1)-(4) use the extent-of-coverage measure, defined as the number of shared three-word phrases (trigrams) appearing both in a network's transcript and in tweets posted within the event window. Columns (5)-(8) use the intensity-of-coverage measure, defined as the number of transcript minutes that contain – or lie adjacent to – a matched trigram. Each coefficient compares post-tweet coverage to pre-tweet coverage: columns (1) and (5) use a ±45-minute window; columns (2) and (6) a ±60-minute window; columns (3) and (7) a ±75-minute window; and columns (4) and (8) a ±90-minute window. All regressions include network-by-window fixed effects, with standard errors clustered at the network × window level.

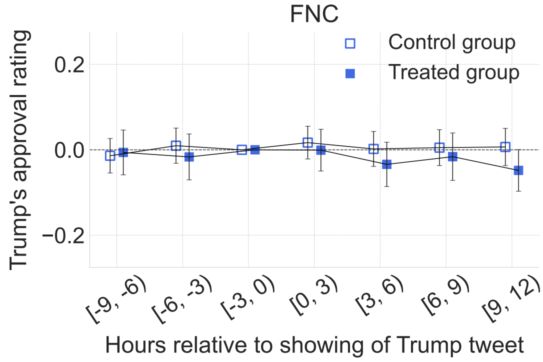
Table 4.2: **Sentiment of coverage – pre-post regressions**

	Sen. of coverage			
	(1)	(2)	(3)	(4)
Post x CNN	0.019	0.021	0.024	0.026
	(0.001)	(0.001)	(0.001)	(0.002)
Post x FNC	0.015	0.017	0.019	0.021
	(0.001)	(0.001)	(0.001)	(0.001)
Post x MSN	0.016	0.017	0.019	0.021
	(0.001)	(0.001)	(0.001)	(0.001)
Pre-tweet CNN avg.	0.010567	0.014173	0.017445	0.020398
Pre-tweet FNC avg.	0.013844	0.018338	0.022784	0.026852
Pre-tweet MSN avg.	0.008915	0.012234	0.015134	0.017750
Event-window size	±45m	±60m	±75m	±90m
Observations	64938	63222	61554	60162
R^2	0.671	0.669	0.692	0.696

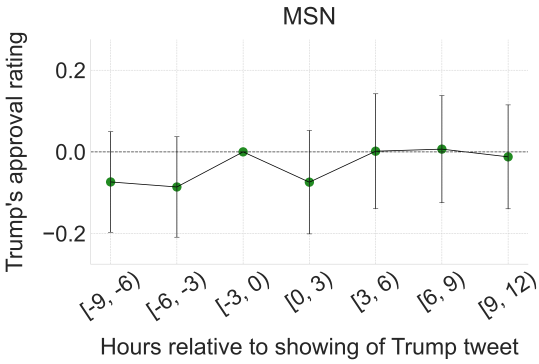
Notes: The table reports coefficients from pre-post regressions as expressed in Eq. 2, estimating how the sentiment of cable-news coverage of issues featured in Trump tweets changed after a tweet is posted. The sentiment-of-coverage measure captures the tone used by each network when covering tweet-related content, defined as the difference between positive and negative words in the textual neighborhoods surrounding matched tweet phrases. Each coefficient compares post-tweet coverage to pre-tweet coverage: column (1) uses a ±45-minute window; column (2) a ±60-minute window; column (3) a ±75-minute window; and column (4) a ±90-minute window. All regressions include network-by-window fixed effects, with standard errors clustered at the network × window level.



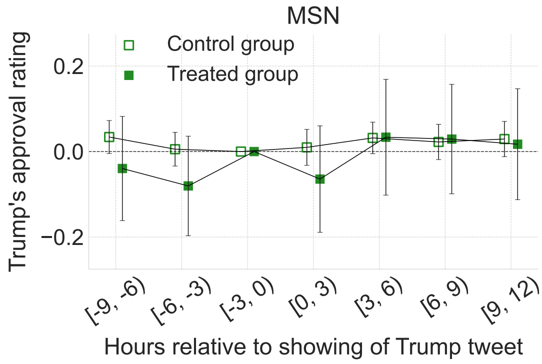
(a) **Diff.-in-diff. - FNC**



(b) **Single-diff. - FNC**



(c) **Diff.-in-diff. - MSN**



(d) **Single-diff. - MSN**

Figure 4.1: **Effect of FNC and MSN broadcasts of Trump tweets on ratings**. The panels report coefficients from event-study regressions for Fox News (Fox News) and MSNBC (MSN). Panel (a) presents the difference-in-differences event-study coefficients from Eq. 5 referent to FNC broadcasts of Trump tweets. Panel (b) reports the group-specific coefficients from Eq. 8, which allow treated and control groups to evolve differently within each event window, referent to FNC broadcasts of Trump tweets. Panel (c) presents the difference-in-differences event-study coefficients from Eq. 5 referent to MSN broadcasts of Trump tweets. Panel (d) reports the group-specific coefficients from Eq. 8, which allow treated and control groups to evolve differently within each event window, referent to MSN broadcasts of Trump tweets. The dependent variable is a five-point approval rating of Donald J. Trump (1 = "strongly disapprove"; 5 = "strongly approve"). Error bars denote 95% confidence intervals based on standard errors clustered at the network × window level.

Table 4.3: **Difference-in-differences pre-post estimates – Trump approval ratings**

	Pres. approval					
	(1)	(2)	(3)	(4)	(5)	(6)
Post x TV=1 x CNN	-0.035	-0.032	-0.032	-0.066	-0.061	-0.061
	(0.017)	(0.017)	(0.016)	(0.022)	(0.023)	(0.023)
Post x TV=1 x FNC	-0.002	0.001	0.001	-0.033	-0.026	-0.026
	(0.014)	(0.014)	(0.014)	(0.018)	(0.018)	(0.017)
Post x TV=1 x MSN	0.033	0.039	0.039	0.030	0.028	0.028
	(0.028)	(0.029)	(0.030)	(0.035)	(0.035)	(0.039)
Controls	-	x	x	-	x	x
FEs	g + w	g + w	g + w	g-w	g-w	g-w
SEs	HC1	HC1	CRV1:w	HC1	HC1	CRV1:w
Mean diff. at baseline for CNN	-0.924540	-0.924540	-0.924540	-0.924540	-0.924540	-0.924540
Mean diff. at baseline for FNC	1.464607	1.464607	1.464607	1.464607	1.464607	1.464607
Mean diff. at baseline for MSN	-0.899556	-0.899556	-0.899556	-0.899556	-0.899556	-0.899556
Observations	269339	252651	252651	269339	252651	252651
R^2	0.121	0.170	0.170	0.128	0.177	0.177
R^2 Within	0.000	0.055	0.055	0.000	0.056	0.056

Notes: The table reports coefficients from a difference-in-differences pre-post specification as in Eq. 6, which estimates how Trump approval ratings change following a broadcast of a Trump tweet by a given cable network. Dependent variable is a five-point approval measure of Donald J. Trump (1 = “strongly disapprove”; 5 = “strongly approve”). Each coefficient compares post-broadcast approval ratings to pre-broadcast ratings, contrasting viewers of a given network (treated units) with individuals who do not watch cable news (control units) within that same window. Columns (1)-(3) include group and window fixed effects; columns (4)-(6) include group × window fixed effects. Within each block of columns, regressions differ in inclusion of demographic controls and in treatment of standard errors: columns (1) and (4) include no demographic controls; columns (2) and (5) include a full vector of demographic controls X_i; columns (3) and (6) include same controls but additionally cluster standard errors at a window level. Columns (1), (2), (4), and (5) report HC1 heteroskedasticity- robust standard errors.

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Online Appendix

Online Appendix A. Effect of Trump's Tweets on TV News Coverage

Online Appendix A.1. Variables

Online Appendix A.1.1. Trump Tweets

Table A.1.1.1: **Trump tweets - descriptive statistics**

	'15-'20	'15	'16	'17	'18	'19	'20
Total tweets	37982	7530	4223	2602	3572	7835	12220
Selected tweets	19530	2881	3285	2154	2845	3878	4487
Total 15-minutes	15616	2342	2595	1868	2455	3128	3228
Min.	1	1	1	1	1	1	1
p25	1	1	1	1	1	1	1
Median	1	1	1	1	1	1	1
p75	1	1	1	1	1	1	2
Max.	18	9	14	7	5	13	18

Notes: The table summarizes descriptive statistics for @realDonaldTrump's original (non-retweet) tweets from 2015-2020. "Total tweets" counts all posts, "Selected tweets" excludes short messages by removing tweets in the bottom 10% of the yearly character-length distribution. "Total 15-minutes" and the associated percentiles describe the distribution of 15-minute intervals containing at least one tweet in each year, reporting the minimum, 25th percentile (p25), median, 75th percentile (p75), and maximum number of tweets per interval.

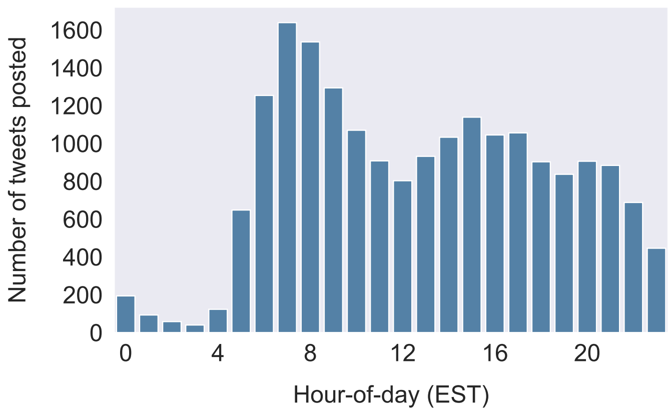


Figure A.1.1.1: **Trump tweets - tweets posted by hour-of-day**. The figure shows the number of @realDonaldTrump's original tweets posted at each hour of the day (EST), measured using 15-minute posting intervals. The plotted data correspond to the same refined sample used in Table A.1.1.1: tweets exclude retweets and omit short messages, with the latter removed by removing tweets in the bottom 10% of the yearly character-length distribution.

Online Appendix A.1.2. Extent of Coverage

Definition. The extent of coverage measure is defined as:

$$\text{extent\_of\_coverage}_{n,w,\tau} = \sum_{m \in \text{minutes}_{n,w,\tau}} \text{sim}\left(\text{trigrams}(m), \text{trigrams}(\text{tweets}_{w,0})\right) \quad (10)$$

Here, $\text{minutes}_{n,w,\tau}$ denotes the set of one-minute transcript segments broadcast on network n during relative time period τ of window w. The function *sim* is defined as the count of shared three-word phrases (trigrams) between two text documents. $\text{trigrams}(m)$ denotes the set of all 3-word phrases appearing in minute m. 3-word phrases (trigrams) are used to reduce the likelihood of incorrectly matching cable-news content to President Trump's tweets. $\text{trigrams}(\text{tweets}_{w,0})$ denotes the set of all trigrams used in the tweets posted during relative time period 0 of window w.

In summary, $\text{extent\_of\_coverage}_{n,w,\tau}$ measures the number of trigrams appearing both (a) in network n's transcripts during time period (w, τ) and (b) in President Trump's tweets during period $(w, 0)$, where transcript content is evaluated at the minute level.

Table A.1.2.1: **Extent of coverage - descriptive statistics by network**

Network	Mean	Std Dev	Min	P25	Median	P75	Max	Observations
CNN	0.61	4.96	0.00	0.00	0.00	0.00	240.00	75,761
FNC	0.74	5.91	0.00	0.00	0.00	0.00	410.00	75,761
MSN	0.53	4.70	0.00	0.00	0.00	0.00	429.00	75,761

Notes: The table summarizes descriptive statistics for the extent-of-coverage measure, computed separately for CNN, Fox News (FNC), and MSNBC (MSN). The measure counts the number of shared three-word phrases (trigrams) between (a) single-speaker interventions on a network during a given event window and (b) President Trump's tweets from that window's baseline period. The statistics use only non-overlapping event windows (13,908 in total – see Table A.2.1.1), each lasting 1 hour and 45 minutes. For each network, the table reports the mean, standard deviation, and selected quantiles (minimum, p25, median, p75, and maximum).

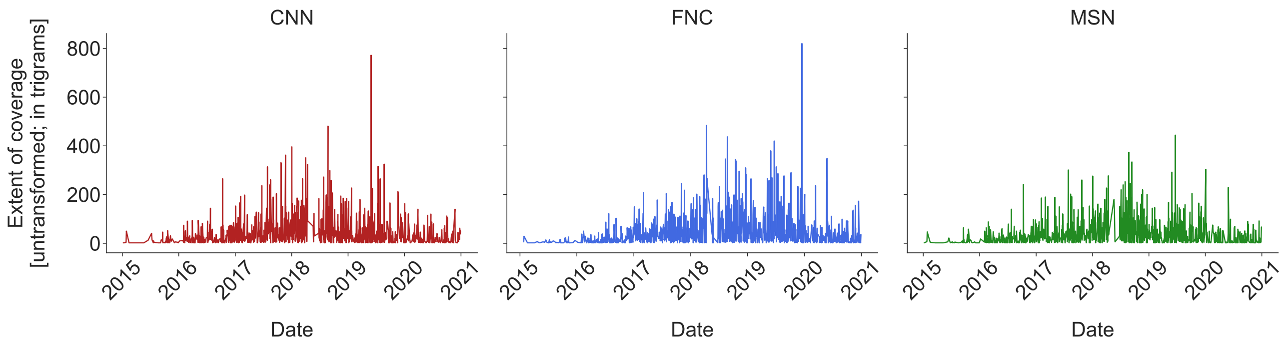


Figure A.1.2.1: **Extent of coverage - daily aggregate measure**. The figure displays the daily aggregate extent-of-coverage measure for CNN, Fox News (FNC), and MSNBC (MSN). For each network-day, the measure sums the number of shared three-word phrases (trigrams) between President Trump's tweets and single-speaker interventions aired on that network. The series is constructed using only event windows that do not overlap in timing or tweet content, yielding 13,908 windows in total (see A.2.1.1), each lasting 1 hour and 45 minutes.

Table A.1.2.2: Extent of coverage – CNN snippets from periods with abnormally high extent of coverage

Network	Window	Tweet (posted in Period 0 of Window...)	Period	Time (EST)	Snippets from TV Transcripts
CNN	13	general qassem **soleimani killed badly** wounded thousands americans extended period time plotting kill many caught directly indirectly responsible death millions people including recent large number **protesters killed iran** iran never able properly admit soleimani hated feared within country nearly saddened leaders outside world believe been taken many years	1	2020-01-03 09:14	last night president dining maralago club behind shoulder writing general **soleimani killed badly** wounded thousands americans extended period time plotting kill many caught [...] directly indirectly responsible death millions people including recent large number **protesters killed iran** president goes iran never able properly admit soleimani hated feared
CNN	1031	spend match better **money china longer** spending great patriot farmers agriculture small percentage total tariffs received distribute food starving people nations around world great maga **right want china** remember broke deal tried renegotiate taking tens billions dollars tariffs china buyers product make ideal nontariffed countries	1	2019-05-12 17:29	larry kudlow admitted today president claiming china paying tariffs writes **right want china** remember broke deal tried renegotiate taking tens billions dollars tariffs [...] china buyers project make ideal nontariffed countries spend match better **money china longer** spending great patriot farmers agriculture small percentage total tariffs received

Notes: The table presents illustrative examples of preprocessed Trump tweets together with neighboring preprocessed transcript snippets from CNN in which three-word phrases from the tweets were echoed. Transcript snippets originate from 15-minute aggregated minute-by-minute television transcripts. Shared trigrams between tweets and transcripts are highlighted, and ten words of surrounding context are shown. Tweets and transcripts undergo identical preprocessing. Examples were randomly sampled from the five CNN 15-minute intervals with the highest number of shared trigrams with neighboring President Trump's tweets—that is, the highest values of the extent-of-coverage measure.

Table A.1.2.3: Extent of coverage – FNC snippets from periods with abnormally high extent of coverage

Network	Window	Tweet (posted in Period 0 of Window...)	Period	Time (EST)	Snippets from TV Transcripts
FNC	1084	depleted **disaster soon stronger** ever vets finally taken care have choice courts great judges supreme court justices disastrous individual mandate protect preexisting **fake news sunday** political shows whose bias dishonesty greater ever seen country please inform viewers economy setting records people employed today time history military conditions drug **prices first time** years soon drop much right protecting amendment cuts strong foreign policy much much nobody else would able country great	1	2019-05-19 09:14	plate right tweets president trump moments twitter press trump says **fake news sunday** political shows whose bias dishonesty greater ever seen country please [...] viewers economy setting records people employed today time history military **disaster soon stronger** ever vets finally taken care have choice courts great judges [...] supreme court justices disastrous individual mandate protect preexisting conditions drug **prices first time** years soon drop much protecting second amendment strong foreign policy
FNC	2718	spoke president rterdogan **turkey told minor** sniper mortar fire quickly eliminated much wants ceasefire pause work likewise kurds want ultimate solution happen **thinking years instead** always held together weak bandaids artificial manner good sides really good chance success secured isis fighters double secured kurds turkey been **notified european nations** willing first time take isis fighters came nations good news been done captured anyway progress made	1	2019-10-18 11:59	back happening syria tweet president read wrote spoke president erdogan **turkey told minor** sniper mortar fire quickly eliminated much wants ceasefire pause work [...] likewise kurds want ultimate solution happen there second part tweet **thinking years instead** always held together weak bandaids artificial manner goodwill sides really [...] fighters double secured kurds turkey read realtime president tweeting last **notified european nations** willing first time take isis fighters came nations good news

Notes: The table presents illustrative examples of preprocessed Trump tweets together with neighboring preprocessed transcript snippets from Fox News (FNC) in which three-word phrases from the tweets were echoed. Transcript snippets originate from 15-minute aggregated minute-by-minute television transcripts. Shared trigrams between tweets and transcripts are highlighted, and ten words of surrounding context are shown. Tweets and transcripts undergo identical preprocessing. Examples were randomly sampled from the five FNC 15-minute intervals with the highest number of shared trigrams with neighboring President Trump's tweets—that is, the highest values of the extent-of-coverage measure.

Table A.1.2.4: Extent of coverage – MSN snippets from periods with abnormally high extent of coverage

Network	Window	Tweet (posted in Period 0 of Window...)	Period	Time (EST)	Snippets from TV Transcripts
MSN	1136	todays action help ensure americans learn truth **events occurred actions** taken last presidential election restore confidence public institutions presssec today **request recommendation attorney** general united states president donald trump directed intelligence community quickly fully cooperate attorney generals investigation surveillance activities presidential election attorney **general also delegated** full complete authority declassify information pertaining investigation accordance longestablished standards handling classified information	3	2019-05-23 21:14	just sort happening brand white house statement says quote todayat **request recommendation attorney** general united states president donald trump directed intelligence community quickly [...] fully cooperate attorney generals investigation surveillance activities presidential election attorney **general also delegated** full complete authority declassify information pertaining investigation accordance longestablished standards [...] handling classified information todays action help ensure americans learn truth **events occurred actions** taken last presidential election restore confidence public institutions statement tonight
MSN	1489	**cant stand back** watch happen great american city minneapolis total lack leadership either weak radical left mayor jacob frey together bring city control **send national guard** done right thugs dishonoring memory george floyd happen spoke governor walz told military difficulty assume control looting starts shooting starts thank	2	2020-05-29 01:29	escalating situation minneapolis president trump tweeted protests minutes tweetsread follows **cant stand back** watch happen great american city minneapolis total lack leadership either [...] weak radical left mayor jacob frey together bring city control **send national guard** done right thugs dishonoring memory george floyd happen spoke governor

Notes: The table presents illustrative examples of preprocessed Trump tweets together with neighboring preprocessed transcript snippets from MSNBC (MSN) in which three-word phrases from the tweets were echoed. Transcript snippets originate from 15-minute aggregated minute-by-minute television transcripts. Shared trigrams between tweets and transcripts are highlighted, and ten words of surrounding context are shown. Tweets and transcripts undergo identical preprocessing. Examples were randomly sampled from the five MSN 15-minute intervals with the highest number of shared trigrams with neighboring President Trump's tweets—that is, the highest values of the extent-of-coverage measure.

Online Appendix A.1.3. Intensity of Coverage

Definition. The intensity of coverage measure is defined as:

$$\text{intensity\_of\_coverage}_{n,w,\tau} = \sum_{m \,\in\, \text{neighborhoods}_{n,w,\tau}} 1 \tag{11}$$

where

$$\text{neighborhoods}_{n,w,\tau} = \Big\{ m \in \text{minutes}_{n,w,\tau} : \exists\, m' \in \text{matched}_{n,w,\tau} \text{ s.t. } |m - m'| \leqslant 1 \Big\}$$

$$\text{matched}_{n,w,\tau} = \Big\{ m \in \text{minutes}_{n,w,\tau} : \text{sim}(\text{trigrams}(m), \text{trigrams}(\text{tweets}_{w,0})) > 0 \Big\}$$

Here, $\text{minutes}_{n,w,\tau}$ is the set of one-minute transcript segments aired on network n during time cell (w, τ). A minute is classified as *matched* if it shares at least one 3-word phrase (trigram) with the tweets posted by President Trump in period $(w, 0)$. A *neighborhood* minute is any match minute or the minute immediately before or after it.

Thus, $\text{intensity\_of\_coverage}_{n,w,\tau}$ counts the number of minutes in (n, w, τ) linked to tweet-related content, capturing both explicit matches and their adjacent context. This definition recognizes that discussion of a tweet-related issue may extend beyond the exact minute in which a matching phrase occurs.

Table A.1.3.1: **Intensity of coverage - descriptive statistics by network**

Network	Mean	Std Dev	Min	P25	Median	P75	Max	Observations
CNN	0.21	1.12	0.00	0.00	0.00	0.00	15.00	75,761
FNC	0.24	1.22	0.00	0.00	0.00	0.00	15.00	75,761
MSN	0.19	1.05	0.00	0.00	0.00	0.00	15.00	75,761

Notes: The table summarizes descriptive statistics for the intensity-of-coverage measure, computed separately for CNN, Fox News (FNC), and MSNBC (MSN). The measure counts the number of one-minute transcript segments within an event window that either (a) share at least one three-word phrase (trigram) with President Trump's tweets from that window's baseline period, or (b) fall within one minute before or after such a match. The statistics use the same non-overlapping set of 13,908 event windows (see Table A.2.1.1), each lasting 1 hour and 45 minutes. For each network, the table reports the mean, standard deviation, and selected quantiles (minimum, p25, median, p75, and maximum).

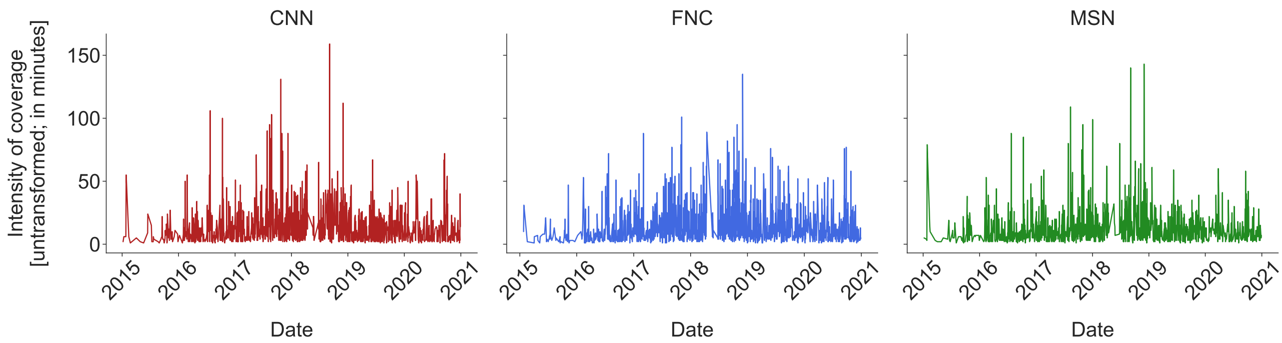


Figure A.1.3.1: **Intensity of coverage - daily aggregate measure**. The figure displays the daily aggregate intensity-of-coverage measure for CNN, Fox News (FNC), and MSNBC (MSN). For each network-day, the measure counts the number of one-minute transcript segments that either share at least one three-word phrase (trigram) with President Trump's tweets from the relevant baseline period or occur within one minute of such a match. The series is constructed using the same non-overlapping set of 13,908 event windows used in the extent-of-coverage analysis (see Table A.2.1.1), each lasting 1 hour and 45 minutes.

Online Appendix A.1.4. Sentiment of Coverage

Definition. The sentiment of coverage measure is defined as:

$$\text{sentiment\_of\_coverage}_{n,w,\tau} = \sum_{h \in \text{neighborhoods}_{n,w,\tau}} \text{sentiment}(h) \tag{12}$$

Here, $\text{neighborhoods}_{n,w,\tau}$ denotes the set of all textual neighborhoods within network n's transcripts during time cell (w, τ) that surround a matched phrase. A *matched phrase* is any 3-word expression (trigram) that appears in both President Trump's tweets posted during period $(w, 0)$ and in the transcript of (n, w, τ). For each matched phrase, a *neighborhood* h is defined as the passage consisting of the 10 words preceding the matched trigram and the 10 words following it.

Before computing sentiment, the matched trigram itself is removed from h, ensuring that the resulting score reflects only the tone of the surrounding coverage, not the sentiment embedded in the tweet phrase. The function *sentiment*(h) denotes a dictionary-based sentiment score, defined as the number of positive words minus the number of negative words in the neighborhood. A word is classified as positive or negative if it appears in the LIWC-15 sentiment lexicons (Pennebaker et al., 2015).

In summary, $\text{sentiment\_of\_coverage}_{n,w,\tau}$ measures the tone with which network n covered tweet-related issues during time cell (w, τ) by aggregating sentiment across the textual neighborhoods surrounding explicit tweet-related mentions.

Table A.1.4.1: **Sentiment of coverage - descriptive statistics by network**

Network	Mean	Std Dev	Min	P25	Median	P75	Max	Observations
CNN	0.00	0.00	-0.06	0.00	0.00	0.00	0.06	75,761
FNC	0.00	0.00	-0.08	0.00	0.00	0.00	0.07	75,761
MSN	0.00	0.00	-0.06	0.00	0.00	0.00	0.09	75,761

Notes: The table summarizes descriptive statistics for the sentiment-of-coverage measure, computed separately for CNN, Fox News (FNC), and MSNBC (MSN). The measure aggregates dictionary-based sentiment scores for the textual neighborhoods surrounding tweet-related mentions within each event window. A neighborhood consists of the ten words preceding and the ten words following any transcript trigram that also appears in President Trump's tweets from that window's baseline period; matched trigrams are removed so the measure reflects only the tone of the surrounding coverage. Sentiment scores are based on the LIWC dictionaries (Pennebaker et al., 2015). The statistics use the same non-overlapping set of 13,908 event windows (see Table A.2.1.1), each lasting 1 hour and 45 minutes.

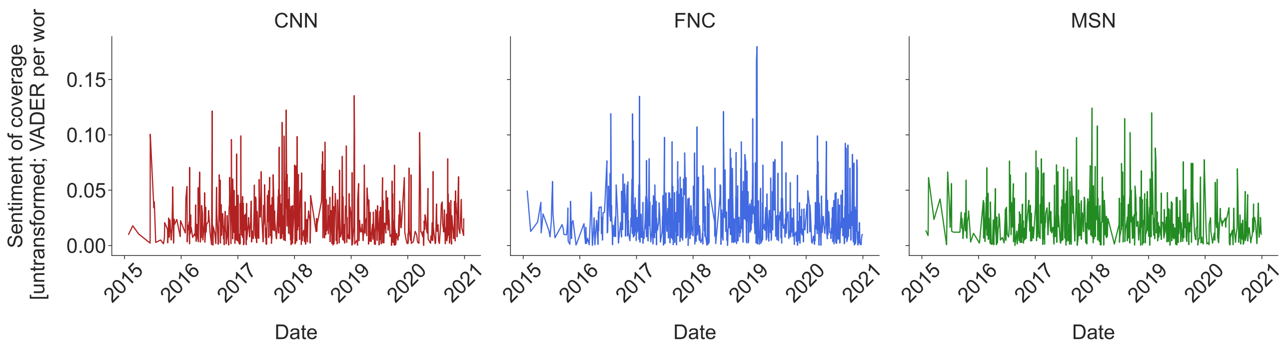


Figure A.1.4.1: **Sentiment of coverage - daily aggregate measure**. The figure displays the daily aggregate sentiment-of-coverage measure for CNN, Fox News (FNC), and MSNBC (MSN). For each network-day, the measure aggregates dictionary-based sentiment scores for the textual neighborhoods surrounding tweet-related mentions, defined as the ten words before and after any transcript trigram that also appears in President Trump's tweets from the relevant baseline period. Matched trigrams are removed so that the measure reflects only the tone of the surrounding coverage. The series is constructed using the same non-overlapping set of 13,908 event windows used in the extent- and intensity-of-coverage analyses (see Table A.2.1.1), each lasting 1 hour and 45 minutes.

Table A.1.4.2: Sentiment of coverage – CNN snippets from periods with abnormally positive/negative coverages of Trump tweets

Network	Sentiment	Window	Tweet (posted in Period 0 of Window...)	Period	Time (EST)	Snippets from TV Transcripts
CNN	Positive	275	attending white house correspondents association dinner year please wish everyone great evening	1	2017-02-25 17:14	going dinner view new yorker not planning going year member TWEET N3 GRAM since dinners since dinner moment dinner everyone gets actually toasts (...) first amendment white house war press view wouldnt appropriate president TWEET N3 GRAM din year frankly think trump everyone favor made lot easier make decision TWEET N3 GRAM purpose dinner fundraiser scholarship program extremely important one event basically make money need run TWEET N3 GRAM little bit catch talk jeff comes need dinner fund important
CNN	Negative	1763	great honor celebrate opening two extraordinary museumsthe mississippi state history museum mississippi civil rights museum pay solemn tribute heroes past dedicate building future freedom equality justice peace	-1	2017-12-09 13:14	TWEET N3 GRAM records oppression cruelty injustice inflicted africanamerican community fight end slavery

Notes: The table presents examples of preprocessed Trump tweets together with neighboring preprocessed transcript snippets from CNN drawn from periods of abnormally positive amd negative tweet coverage. Snippets originate from 15-minute aggregated minute-by-minute television transcripts and are constructed by extracting the ten words before and after the three-word phrase (trigram) that links the transcript to the tweet. Shared trigrams are removed from snippets to ensure that the sentiment-of-coverage measure reflects only the tone of the surrounding coverage rather than the sentiment of the tweet discussed. Tweets and transcripts undergo identical preprocessing. For each polarity, one example is randomly selected from among the five CNN 15-minutes transcripts with the most positive/negative sentiment-of-coverage measure.

Table A.1.4.3: Sentiment of coverage – FNC snippets from periods with abnormally positive/negative coverages of Trump tweets

Network	Sentiment	Window	Tweet (posted in Period 0 of Window...)	Period	Time (EST)	Snippets from TV Transcripts
FNC	Positive	1783	together make america great	-2	2016-08-18 20:14	protect special interests donors lobbyists time vote new american future TWEET N3 GRAM strong make america proud make america safe friends fellow citizens come november TWEET N3 GRAM greater ever thank thank god bless thank thank thank much
FNC	Negative	1520	thoughts condolences prayers victims families new york city terrorist attack god country	-3	2017-10-31 18:14	bret dances fox news alert terror hit TWEET N3 GRAM least eight people dead far attack authorities describe act terror

Notes: The table presents examples of preprocessed Trump tweets together with neighboring preprocessed transcript snippets from Fox News (FNC) drawn from periods of abnormally positive amd negative tweet coverage. Snippets originate from 15-minute aggregated minute-by-minute television transcripts and are constructed by extracting the ten words before and after the three-word phrase (trigram) that links the transcript to the tweet. Shared trigrams are removed from snippets to ensure that the sentiment-of-coverage measure reflects only the tone of the surrounding coverage rather than the sentiment of the tweet discussed. Tweets and transcripts undergo identical preprocessing. For each polarity, one example is randomly selected from among the five Fox News (FNC) 15-minutes transcripts with the most positive/negative sentiment-of-coverage measure.

Table A.1.4.4: Sentiment of coverage – MSN snippets from periods with abnormally positive/negative coverages of Trump tweets

Network	Sentiment	Window	Tweet (posted in Period 0 of Window...)	Period	Time (EST)	Snippets from TV Transcripts
MSN	Positive	1491	pleased announce chosen governor mike pence vice presidential running mate news conference tomorrow	0	2016-07-15 10:59	would vice president tweeted moments ago appeared fund raisers saying TWEET N3 GRAM decided push picture ceremony making announcement appear together chosen mike pence indiana TWEET N3 GRAM coming deadline three people alluded part people vetted chosen donald trump indiana TWEET N3 GRAM also chris christie newt gingrich mike pence needs file noon (...) going team together making sure wouldnt type collateral damage indiana TWEET N3 GRAM running reelection wasnt chosen donald trumps running mate confirmation coming (...) newt gingrich also fact someone like speaker ryan looks indiana TWEET N3 GRAM man dedicated conservative movement feels good pick nod conservative republicans
MSN	Negative	232	russian connection nonsense merely attempt coverup many mistakes made hillary clintons losing campaign	0	2017-02-15 07:14	fake news media going crazy conspiracy theories blind hatred says TWEET N3 GRAM cover TWEET N3 GRAM

Notes: The table presents examples of preprocessed Trump tweets together with neighboring preprocessed transcript snippets from MSNBC (MSN) drawn from periods of abnormally positive amd negative tweet coverage. Snippets originate from 15-minute aggregated minute-by-minute television transcripts and are constructed by extracting the ten words before and after the three-word phrase (trigram) that links the transcript to the tweet. Shared trigrams are removed from snippets to ensure that the sentiment-of-coverage measure reflects only the tone of the surrounding coverage rather than the sentiment of the tweet discussed. Tweets and transcripts undergo identical preprocessing. For each polarity, one example is randomly selected from among the five MSNBC (MSN) 15-minutes transcripts with the most positive/negative sentiment-of-coverage measure.

Online Appendix A.2. Empirical Strategy

Online Appendix A.2.1. Overlap Across Event-Windows

Table A.2.1.1: **Trump tweets - overlapping vs. non-overlapping, by year**

	'15-'20	'15	'16	'17	'18	'19	'20
Overlapping tweets	2199	197	354	112	325	462	749
Overlapping 15-minutes	1474	144	193	86	263	340	448
Overlapping Min.	1	1	1	1	1	1	1
Overlapping Max.	15	9	14	3	4	7	15
Non-overlapping tweets	17305	2680	2931	2039	2514	3403	3738
Non-overlapping 15-minutes	14120	2194	2402	1779	2187	2778	2780
Non-overlapping Min.	1	1	1	1	1	1	1
Non-overlapping Max.	18	5	6	7	5	13	18

Notes: The table summarizes yearly counts of overlapping and non-overlapping Trump tweets and their corresponding 15-minute posting intervals from 2015 to 2020. A tweet is classified as overlapping when it belongs to an event window that intersects with another window in calendar time and tweet content (overlapping trigrams); all remaining tweets are classified as non-overlapping. For each category and year, the table reports the total number of tweets, the total number of 15-minute intervals containing at least one tweet, and the minimum and maximum number of tweets observed within any 15-minute interval.

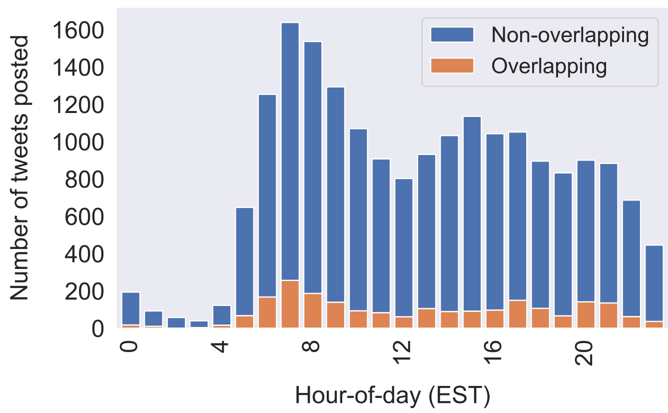


Figure A.2.1.1: **Trump tweets - non-overlapping vs. overlapping tweets by hour**. The figure displays the hourly distribution of President Trump's tweets, distinguishing between non-overlapping and overlapping tweets. A tweet is classified as overlapping when it belongs to an event window that intersects with another window in calendar time and tweet content (overlapping trigrams); all remaining tweets are labeled as non-overlapping. For each hour of the day (EST), the figure reports the total number of tweets in each category, illustrating differences in posting patterns across both groups.

Online Appendix A.3. Robustness Checks

Online Appendix A.3.1. Omitted Variable Concern

Table A.3.1.1: **Descriptive statistics on news data / news similarity measure**

Horizon (± hours)	News tweets	Mean sim.	SD sim.	Min sim.	Median sim.	Max sim.
6h	19,008,695	0.002	0.121	0.000	0.000	46.000
12h	20,344,534	0.001	0.100	0.000	0.000	46.000
24h	20,610,584	0.001	0.080	0.000	0.000	46.000

Notes: The table summarizes the online news dataset – tweets posted by a comprehensive sample of US national newspapers from 2015 to 2020, collected through Twitter API (Link) – used to construct the tweet-news similarity measures that underpin the classification of Trump tweets as related or unrelated to news. For each event-window length—±6, ±12, and ±24 hours around the posting time of a Trump tweet—the table reports: (i) the number of unique news tweets appearing within the corresponding window; and (ii) descriptive statistics of the textual similarity between Trump tweets and contemporaneous news tweets. Similarity is measured as the number of three-word phrases (trigrams) shared between a Trump tweet and a news tweet. For each window, the sample is restricted to the periods lying within the corresponding horizon (i.e., up to 24 (6h), 48 (12h), or 96 (24h) fifteen-minute intervals before or after a Trump tweet). Reported statistics include the mean, standard deviation, minimum, median, and maximum of this similarity measure across all Trump tweet–news tweet pairs in the restricted window.

Newspapers included in Twitter news corpus: (1) ABCNews; (2) ABCNewsPolitics; (3) APNews; (4) ATTNVideo; (5) Blavity; (6) BlavityIncPolitics; (7) BloombergPolitics; (8) Breitbart; (9) BuzzFeedNews; (10) BuzzFeedPol; (11) CBSNews; (12) CBSPolitics; (13) CSPAN; (14) ChristianScienceMonitor; (15) ConservativeReview; (16) DailyCaller; (17) DailyWire; (18) DetroitNews; (19) Enquirer; (20) FastCompany; (21) FoxNews; (22) FreeBeacon; (23) GuardianUs; (24) HuffPostBlackVoices; (25) HuffPostLatinoVoices; (26) HuffPostPolitics; (27) MicMedia; (28) MySA; (29) NBCNews; (30) NBCPolitics; (31) NJ.com; (32) NPR; (33) NYDailyNews; (34) NYPost; (35) NewsOneOfficial; (36) Newsweek; (37) NoticiasTelemundo; (38) NowThisNews; (39) OZY; (40) PoliticalWire; (41) PoliticsNation; (42) QuartzNewsShow; (43) RedStateBlog; (44) RenewAmericaUSA; (45) Reuters; (46) RollCall; (47) SFChronicle; (48) STLPD; (49) SanDiegoUnionTribune; (50) TheAtlantic; (51) TheBlaze; (52) TheHill; (53) TheWashingtonTimes; (54) TheYoungTurks; (55) Univision; (56) VICE; (57) Vox; (58) WSJ; (59) WSJPolitics; (60) WashingtonExaminer; (61) WesternJournal; (62) ajplusenglish; (63) aljazeera; (64) attn; (65) axiosnews; (66) azcentral; (67) baltimoresun; (68) bbcnews; (69) bloombergbusiness; (70) bostonherald; (71) businessinsider; (72) chicagotribune; (73) chroncom; (74) clevelandcom; (75) cnbc; (76) cnn; (77) cnnpolitics; (78) columbusdispatch; (79) commentarymagazine; (80) complexnews; (81) courierjournal; (82) cqrollcall;

(83) crwnmag; (84) dailykos; (85) dallasmorningnews; (86) denverpost; (87) detroitfreepress; (88) financialtimes; (89) foreign.policy.magazine; (90) frontline; (91) gettheinformation; (92) globe; (93) humaneventsmedia; (94) indianapolisstar; (95) injopolitics; (96) insideelections; (97) journalsentinel; (98) kansascitystar; (99) latimes; (100) mercurynews; (101) miamiherald; (102) motherjones; (103) msnbc; (104) newsday; (105) newshour; (106) nytimes; (107) ocregister; (108) officialbenshapiro; (109) orlandosentinel; (110) pittsburghpostgazette; (111) politico; (112) politifact; (113) quartznews; (114) realclearpolitics; (115) realratedred; (116) reviewjournal; (117) sacramentobee; (118) salon; (119) seattletimes; (120) splinternews; (121) staradvertiser; (122) startelegram; (123) startribune; (124) sunsentinel; (125) talkingpointsmemo; (126) tampabaycom; (127) theGrio; (128) theRoot; (129) thecharlotteobserver; (130) thechicagosuntimes; (131) thedailybeast; (132) theijr; (133) theoregonian; (134) time; (135) usatoday; (136) usatodayvideo; (137) usnewsandworldreport; (138) vicenews; (139) washingtonpost; (140) washingtonpostpolitics; (141) yahoonews.

Notes: List of newspapers featured in online news dataset (list collected from CrowdTangle (Link) – newspapers featured in CrowdTangle (Link)'s "US Political Media", "US General Media" and "US Top Newspapers" newspaper groups).

Table A.3.1.2: **Trump tweets (non-overlap) - related vs. unrelated to news**

	'15-'20	'15	'16	'17	'18	'19	'20
Related tweets	2812	321	294	386	546	654	611
Related 15-minutes	2132	239	207	315	458	499	414
Related Min.	1	1	1	1	1	1	1
Related Max.	11	4	6	7	5	5	11
Unrelated tweets	14219	2359	2637	1570	1863	2673	3117
Unrelated 15-minutes	11776	1955	2195	1398	1648	2221	2359
Unrelated Min.	1	1	1	1	1	1	1
Unrelated Max.	18	5	6	6	4	13	18

Notes: The table summarizes yearly counts of non-overlapping Trump tweets classified as either related or unrelated to online news from 2015 to 2020. A tweet is defined as related when, within a six-hour window before or after its posting time, the textual similarity between the tweet and an exhaustive sample of U.S. national newspaper tweets becomes abnormally high; similarity is measured as the count of shared three-word phrases (trigrams), and "abnormally high" corresponds to values exceeding two standard deviations above the mean. All other tweets are classified as unrelated. For each category and year, the table reports the total number of tweets, the total number of 15-minute intervals containing at least one tweet, and the minimum and maximum number of tweets observed within any 15-minute interval

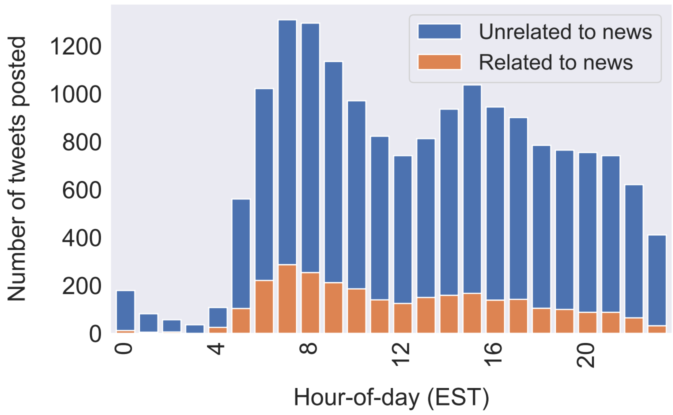
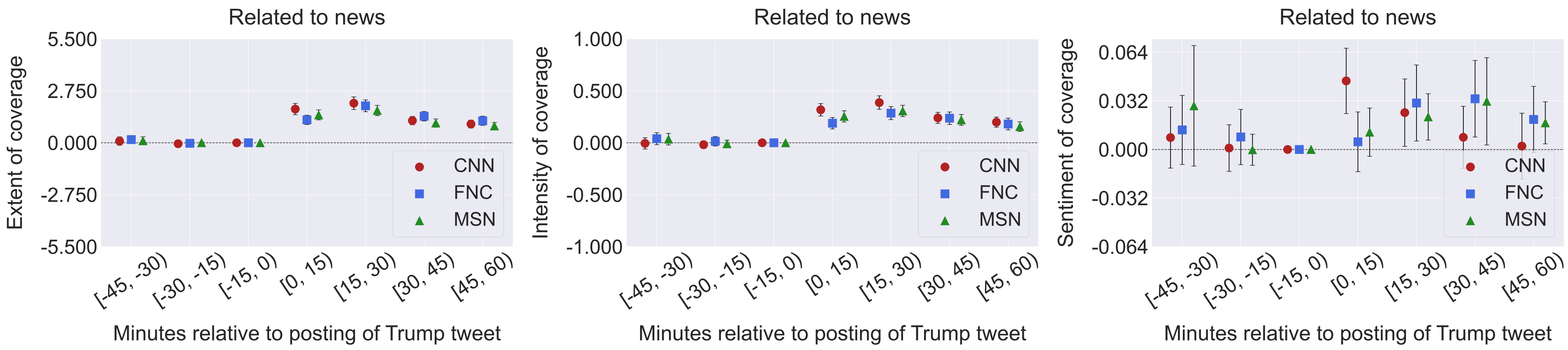


Figure A.3.1.1: **Trump tweets (non-overlap) - related vs. unrelated to news by hour**. The figure displays the hourly distribution of non-overlapping Trump tweets, distinguishing between those classified as related and unrelated to online news. A tweet is defined as related when, within a six-hour window before or after its posting time, the similarity between its text and contemporaneous articles from a comprehensive set of U.S. national newspapers becomes abnormally high; similarity is measured by the number of shared three-word phrases (trigrams), and abnormally high values are those exceeding two standard deviations above the mean. All other tweets are classified as unrelated. For each hour of the day (EST), the figure reports the total number of tweets in each category, illustrating differences in posting patterns across both groups.

Table A.3.1.3: Trump tweets - examples of tweets related to online news

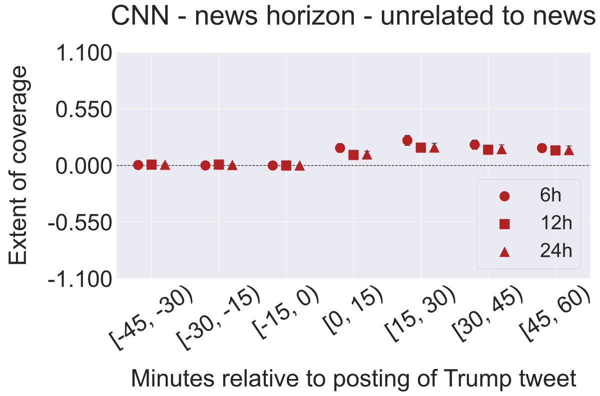
Type	Tweet Time	Tweet Text	News Time	News Text
Related to news	2020-09-19 02:34:33	Statement from the President on the Passing of Supreme Court (...)	2020-09-18 23:52:48	#BREAKING U.S. Supreme Court Associate Justice Ruth Bader Ginsburg has died at (...)
			2020-09-19 00:15:01	Supreme Court Associate Justice Ruth Bader Ginsburg, a legal pioneer for gender equality who (...)
			2020-09-19 01:11:26	RT : Supreme Court Associate Justice Ruth Bader Ginsburg leaves behind an enormous (...)
Related to news	2018-11-07 19:44:11	We are pleased to announce that Matthew G. Whitaker, Chief (...)	2018-11-07 19:47:49	MORE: Pres. Trump: ”We are pleased to announce that Matthew G. Whitaker, Chief (...)
			2018-11-07 19:56:31	President Trump: ”We are pleased to announce that Matthew G. Whitaker, (...)
			2018-11-07 20:03:59	President Trump tweets that Matthew G. Whitaker, chief of staff to Attorney General Jeff (...)



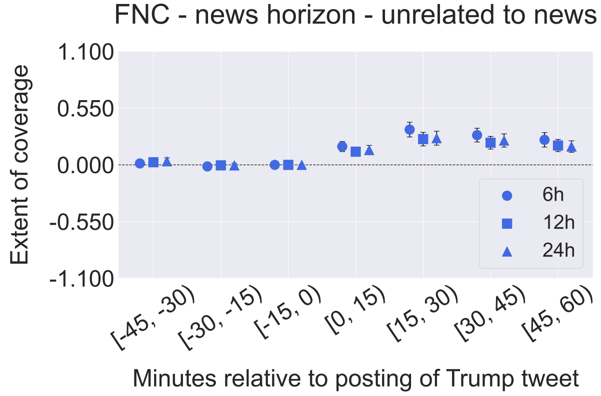
(a) **Extent of coverage** (b) **Intensity of coverage** (c) **Sentiment of coverage**

Figure A.3.1.2: **Cable outlets' response to Trump tweets related to news events – extent, intensity and sentiment of coverage**. Panel (a), (b) and (c) plot event-study coefficients related to tweets related to neighboring news events, retrieved from estimating Equation 3 of Section 2.4. Panel (a) uses the extent-of-coverage measure, defined as the number of shared three-word phrases (trigrams) between network transcripts and the tweets posted in the event window. Panel (b) uses the intensity-of-coverage measure, defined as the number of transcript minutes containing or adjacent to a matched trigram. Panel (c) uses the sentiment-of-coverage measure, defined as the difference between the number of positive and negative words appearing in the transcript passages surrounding a matched trigram from the tweet. The analysis uses all original (non-retweeted) Trump tweets with a minimum word count posted between 2015 and 2020. Error bars refer to 95% confidence intervals drawn from standard errors clustered at a network-window level.

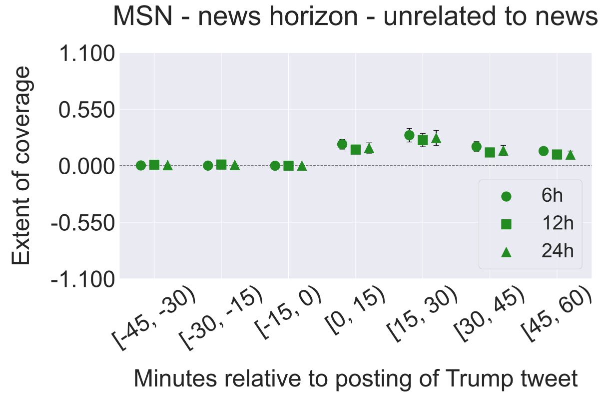
Online Appendix A.3.2. Variable and Regression Specification



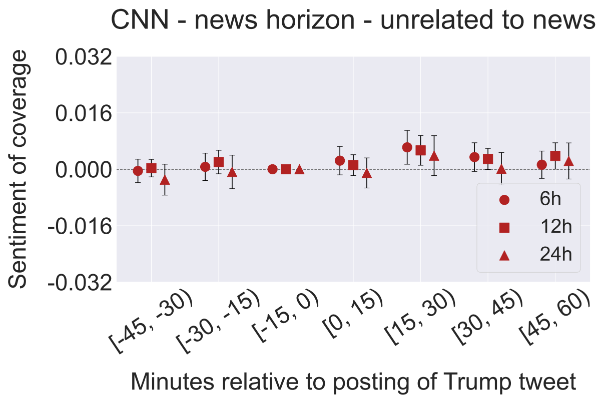
(a) **Extent/ CNN**



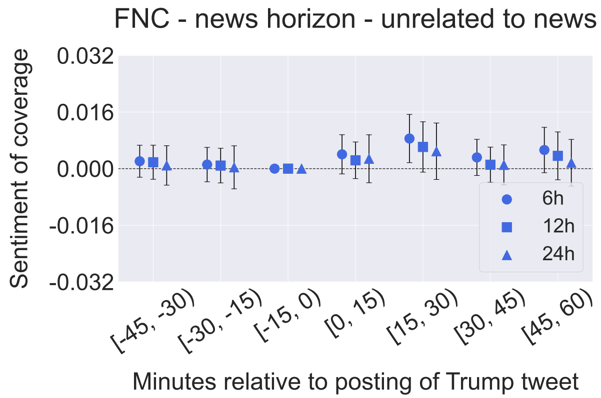
(b) **Extent/ FNC**



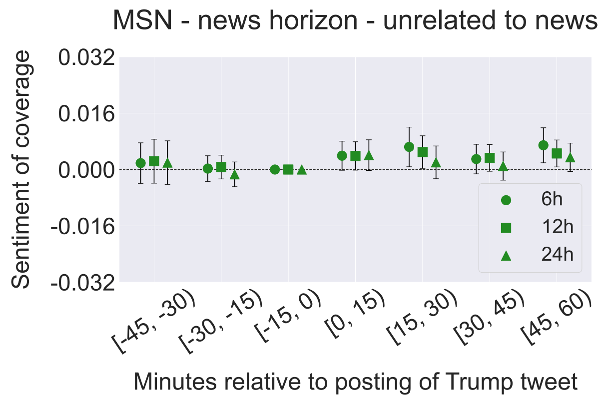
(c) **Extent/ MSN**



(d) **Sentiment/ CNN**

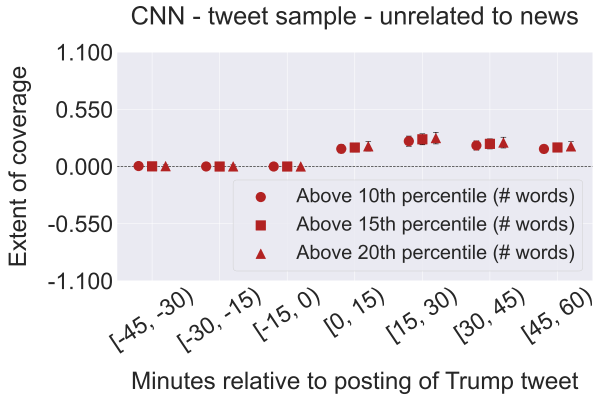


(e) **Sentiment/ FNC**

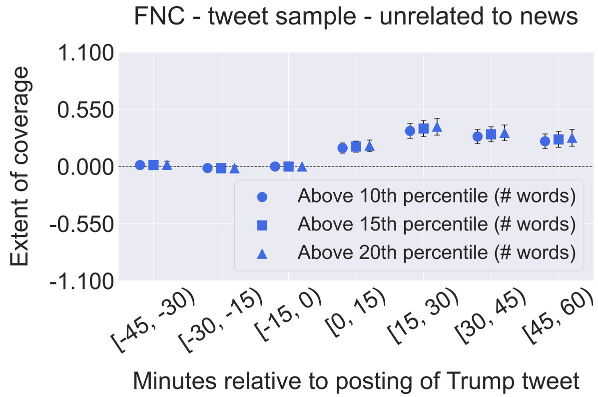


(f) **Sentiment/ MSN**

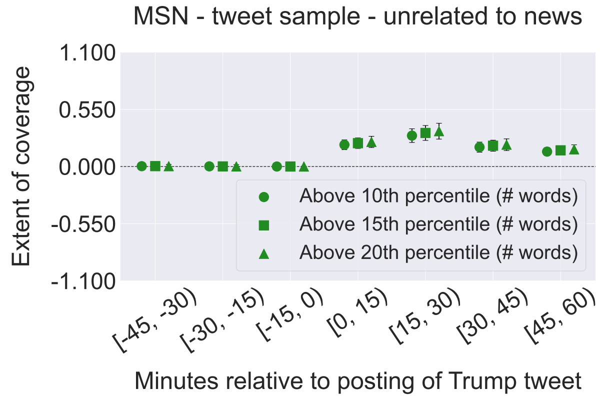
Figure A.3.2.1: **Cable outlets' response to Trump tweets unrelated to news events – robustness on news-variable definition**. The figure reports estimates from Eq. 3 of Section 2.4 when expanding the news horizon used to classify Trump tweets as unrelated to contemporaneous news. The baseline relies on matching tweet text to articles from U.S. national newspapers within ±6 hours; this exercise extends the horizon to ±12 and ±24 hours. Panels (a)-(c) plot coefficients from regressions using an extent-of-coverage measure for CNN, FNC and MSN, respectively. Panels (d)-(f) plot coefficients for a sentiment-of-coverage measure. Intensity-of-coverage estimates are omitted because these closely mirror the extent-of-coverage results. The sample includes all original Trump tweets with a minimum word count posted between 2015 and 2020. Error bars report 95% confidence intervals with standard errors clustered at the network × window level.



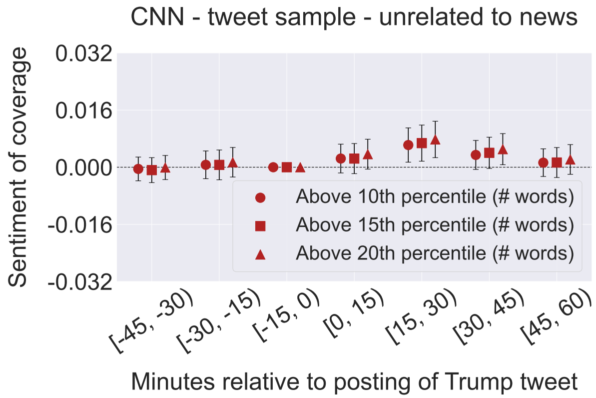
(a) **Extent/ CNN**



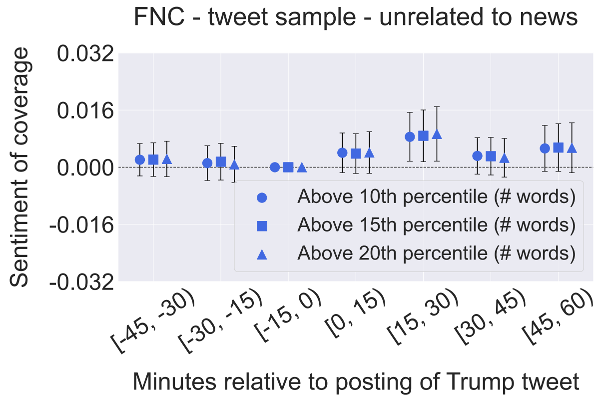
(b) **Extent/ FNC**



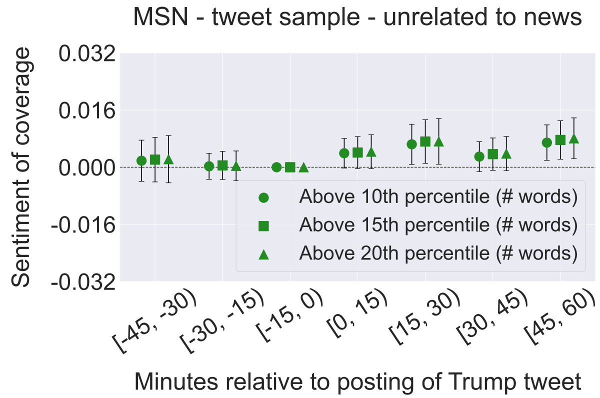
(c) **Extent/ MSN**



(d) **Sentiment/ CNN**

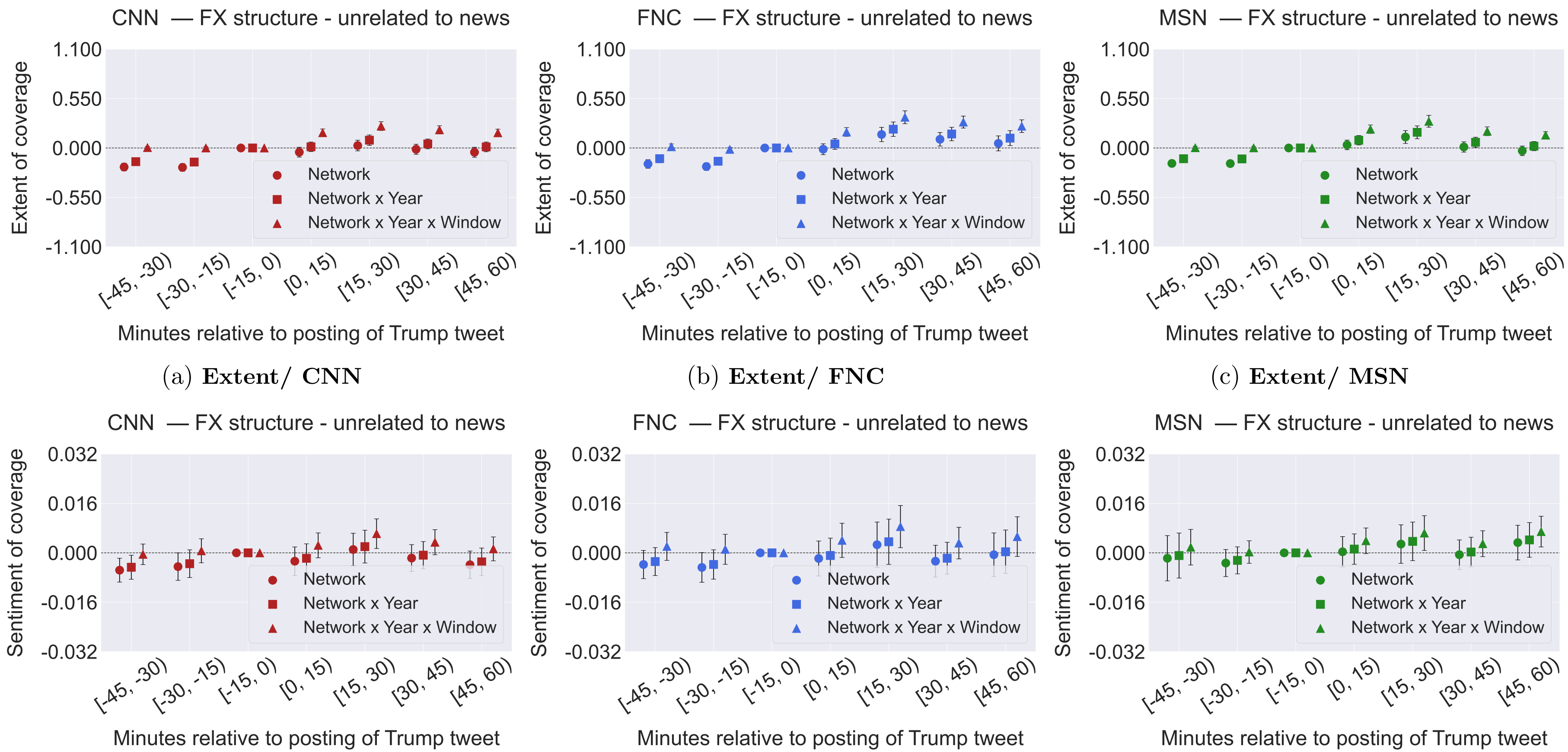


(e) **Sentiment/ FNC**



(f) **Sentiment/ MSN**

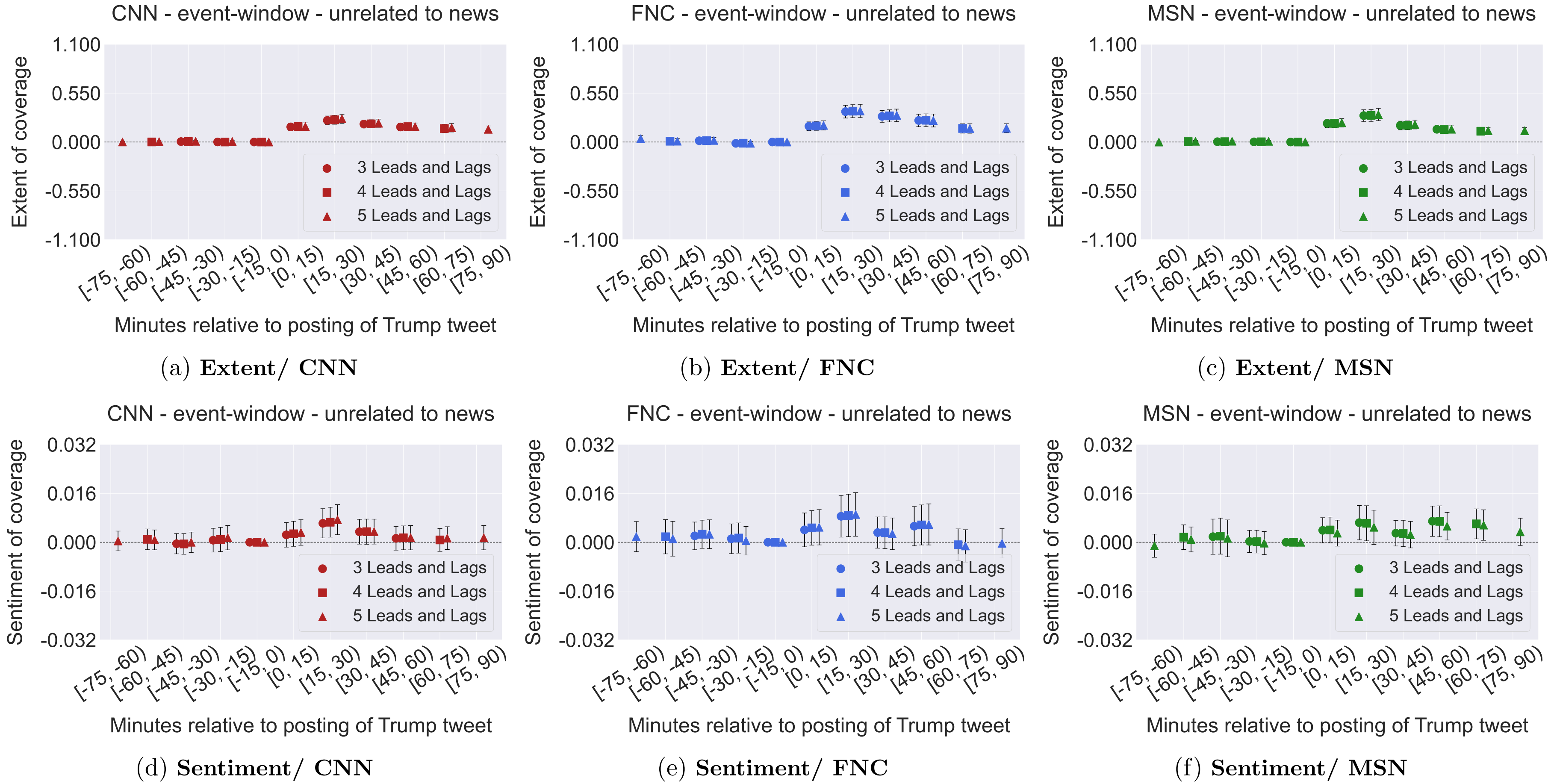
Figure A.3.2.2: **Cable outlets' response to Trump tweets unrelated to news events – robustness on tweet sample definition.** The figure reports estimates from Eq. 3 of Section 2.4 when using alternative samples of original Trump tweets. The baseline excludes retweets and removes posts in the bottom 10% of the tweet-length distribution after standard preprocessing. This robustness exercise re-estimates the event studies after excluding tweets in the bottom 15% and 20% of the distribution. Panels (a)-(c) plot coefficients for the extent-of-coverage measure for CNN, FNC and MSN, respectively. Panels (d)-(f) report coefficients for the sentiment-of-coverage measure. Intensity-of-coverage estimates are omitted because these closely mirror the extent results. The sample covers all original Trump tweets posted between 2015 and 2020. Error bars show 95% confidence intervals with standard errors clustered at the network × window level.



(a) **Extent/ CNN** (b) **Extent/ FNC** (c) **Extent/ MSN**

(d) **Sentiment/ CNN** (e) **Sentiment/ FNC** (f) **Sentiment/ MSN**

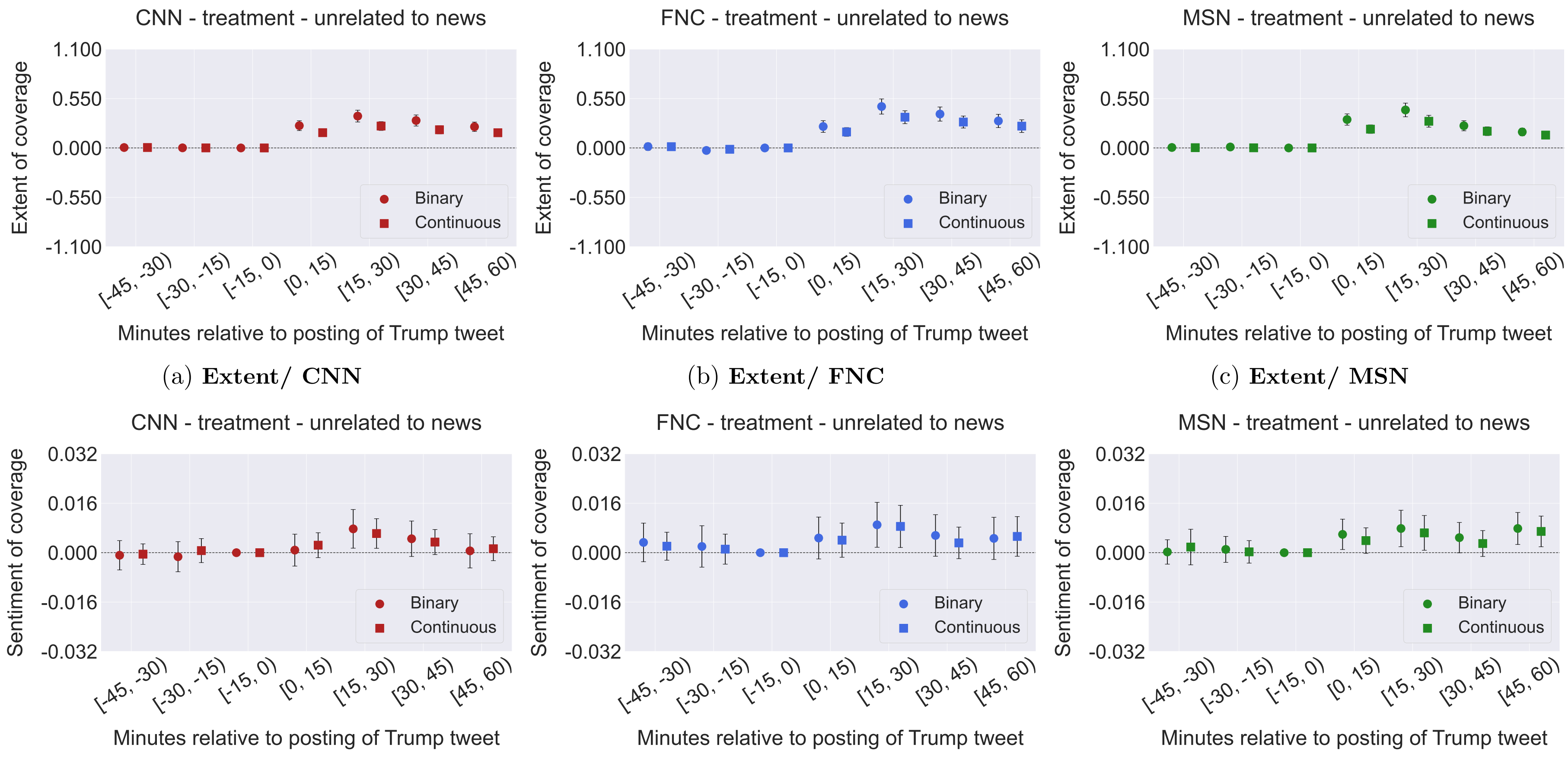
Figure A.3.2.3: **Cable outlets' response to Trump tweets unrelated to news events – robustness on fixed effect specification**. The figure reports estimates from Eq. 3 of Section 2.4 when using alternative sets of fixed effects. The baseline relies on a demanding specification with network-by-window fixed effects. This robustness exercise re-estimates the event studies with coarser structures, including specifications with separate network and window fixed effects, and specifications with network fixed effects only. Panels (a)-(c) plot coefficients for the extent-of-coverage measure for CNN, FNC and MSN, respectively. Panels (d)-(f) report coefficients for the sentiment-of-coverage measure. Intensity-of-coverage estimates are omitted because these closely mirror the extent results. Error bars show 95% confidence intervals with standard errors clustered at the network $\times$ window level.



(a) **Extent/ CNN** (b) **Extent/ FNC** (c) **Extent/ MSN**

(d) **Sentiment/ CNN** (e) **Sentiment/ FNC** (f) **Sentiment/ MSN**

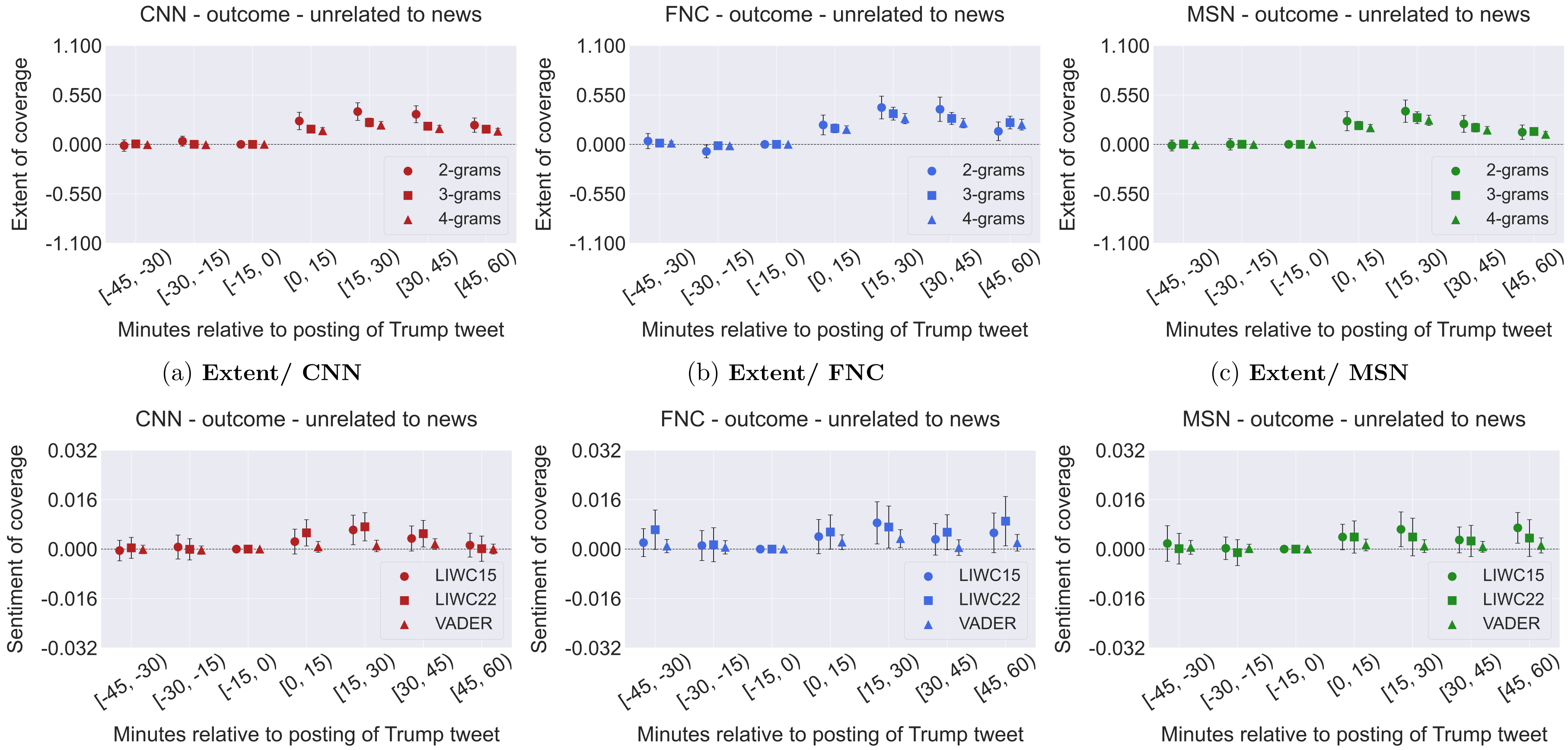
Figure A.3.2.4: **Cable outlets' response to Trump tweets unrelated to news events – robustness on event-window length.** The figure reports estimates from Eq. 3 of Section 2.4 when expanding the event-study window. The baseline relies on a narrow window of three leads and three lags (45 minutes before and after a tweet). This robustness exercise re-estimates the event studies using four and five leads and lags, corresponding to windows of one hour and one hour and fifteen minutes, respectively. Panels (a)-(c) plot coefficients for the extent-of-coverage measure for CNN, FNC and MSN, respectively. Panels (d)-(f) report coefficients for the sentiment-of-coverage measure. Intensity-of-coverage estimates are omitted because these closely mirror the extent results. Error bars show 95% confidence intervals with standard errors clustered at the network $\times$ window level.



(a) **Extent/ CNN** (b) **Extent/ FNC** (c) **Extent/ MSN**

(d) **Sentiment/ CNN** (e) **Sentiment/ FNC** (f) **Sentiment/ MSN**

Figure A.3.2.5: **Cable outlets' response to Trump tweets unrelated to news events – robustness on treatment variable defintion**. The figure reports estimates from Eq. 3 of Section 2.4 when using an alternative definition of the treatment. The baseline relies on a continuous measure equal to the number of Trump tweets posted at relative time 0 of the event window. This robustness exercise re-estimates the event studies with a binary treatment that equals one whenever at least one Trump tweet is posted at relative time 0. Panels (a)-(c) plot coefficients for the extent-of-coverage measure for CNN, FNC and MSN, respectively. Panels (d)-(f) report coefficients for the sentiment-of-coverage measure. Intensity-of-coverage estimates are omitted because these closely mirror the extent results. Error bars show 95% confidence intervals with standard errors clustered at the network × window level.



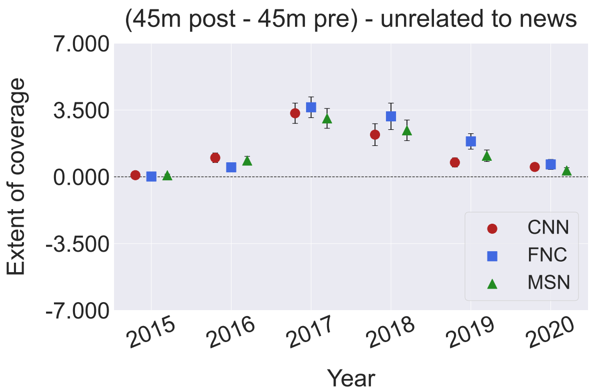
(a) **Extent/ CNN** (b) **Extent/ FNC** (c) **Extent/ MSN**

(d) **Sentiment/ CNN** (e) **Sentiment/ FNC** (f) **Sentiment/ MSN**

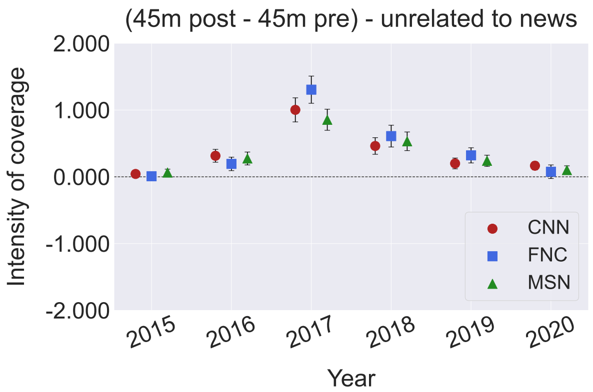
Figure A.3.2.6: **Cable outlets' response to Trump tweets unrelated to news events – robustness on outcome variable definition**. The figure reports estimates from Eq. 3 of Section 2.4 when using alternative definitions of the coverage measures. The baseline extent and intensity measures rely on the intersection of trigrams between Trump tweets and cable transcripts. This robustness exercise redefines these outcomes using coarser bigram matches and stricter quadgram matches. For sentiment, the baseline relies on a dictionary-based measure using LIWC-15, computed from positive and negative words in the neighborhood of a matched tweet trigram. The exercise expands this outcome using the updated LIWC-22 dictionary and a context-aware sentiment score based on VADER. Panels (a)-(c) plot coefficients for the extent-of-coverage measure for CNN, FNC and MSN, respectively. Panels (d)-(f) report coefficients for the sentiment measure. Intensity-of-coverage estimates are omitted because these closely mirror the extent results. Error bars show 95% confidence intervals with standard errors clustered at the network × window level.

Online Appendix A.4. Additional Results

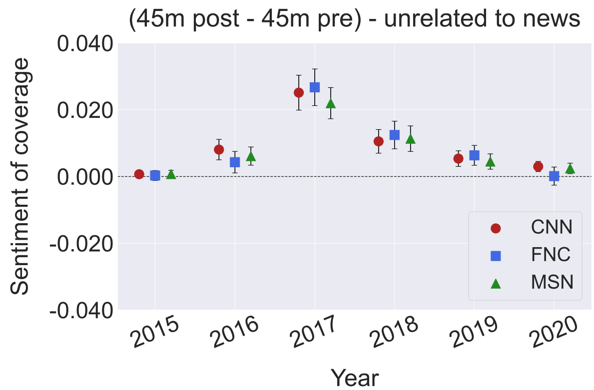
Online Appendix A.4.1. Coverage of Trump's Tweets Over Time



(a) **Extent of coverage**



(b) **Intensity of coverage**



(c) **Sentiment of coverage**

Figure A.4.1.1: **Cable outlets' response to Trump tweets unrelated to news events – pre–post coefficients by network and year**. The figure reports coefficients from the pre-post regression described in Eq. 4 of Section 2.5, estimating how cable-news coverage of issues featured in Trump's tweets changed after a tweet was posted. The coefficients compare post-tweet coverage to pre-tweet coverage for each network and each year from 2015 to 2020. Panel (a) presents estimates for the extent-of-coverage measure, defined as the number of shared three-word phrases (trigrams) between a network's transcript and the tweets in the window. Panel (b) reports estimates for the intensity-of-coverage measure, defined as the number of transcript minutes that contain—or lie adjacent to—a matched trigram. Panel (c) reports estimates for the sentiment-of-coverage measure, defined as the dictionary-based tone (positive minus negative words) in the textual neighborhoods surrounding matched tweet phrases. All regressions include network-by-window fixed effects, with standard errors clustered at the network × window level.

Online Appendix A.4.2. Coverage of Tweets by Other Politicians

Table A.4.2.1: **Top MOCs - handles, followers, number of tweets**

(a) **Democrats**

	2017	2018	2019	2020
Rank 1	senwarren (3.9M followers) ((618 tweets))	senwarren (4.7M followers) ((1077 tweets))	aoc (6.0M followers) ((3229 tweets))	kamalaharris (13.6M followers) ((2687 tweets))
Rank 2	corybooker (3.7M followers) ((1966 tweets))	corybooker (4.2M followers) ((3326 tweets))	senwarren (5.5M followers) ((1078 tweets))	aoc (11.1M followers) ((2499 tweets))
Rank 3	nancypelosi (1.4M followers) ((1090 tweets))	ewarren (2.2M followers) ((7 tweets))	corybooker (4.4M followers) ((5220 tweets))	senwarren (6.6M followers) ((2381 tweets))
Rank 4	senschumer (1.3M followers) ((1273 tweets))	kamalaharris (2.0M followers) ((2557 tweets))	speakerpelosi (3.6M followers) ((1612 tweets))	speakerpelosi (6.2M followers) ((1301 tweets))
Rank 5	kamalaharris (1.2M followers) ((1376 tweets))	nancypelosi (1.8M followers) ((1486 tweets))	ewarren (3.6M followers) ((4823 tweets))	ewarren (5.4M followers) ((3531 tweets))
Top 5 tweets	6323	8453	15962	12399
Top 5 followers (M)	11.5	14.8	23.2	42.9

(b) **Republicans**

	2017	2018	2019	2020
Rank 1	marcorubio (3.4M followers) ((814 tweets))	marcorubio (3.7M followers) ((2255 tweets))	marcorubio (4.0M followers) ((2711 tweets))	tedcruz (4.3M followers) ((4863 tweets))
Rank 2	speakerryan (3.2M followers) ((1467 tweets))	speakerryan (3.7M followers) ((1575 tweets))	tedcruz (3.5M followers) ((2474 tweets))	marcorubio (4.3M followers) ((2141 tweets))
Rank 3	tedcruz (3.1M followers) ((1296 tweets))	senjohnmccain (3.4M followers) ((401 tweets))	randpaul (2.6M followers) ((812 tweets))	randpaul (3.1M followers) ((984 tweets))
Rank 4	senjohnmccain (3.1M followers) ((1024 tweets))	tedcruz (3.3M followers) ((3156 tweets))	mittromney (2.0M followers) ((107 tweets))	mittromney (2.1M followers) ((102 tweets))
Rank 5	randpaul (1.9M followers) ((590 tweets))	randpaul (2.4M followers) ((1028 tweets))	sentedcruz (1.4M followers) ((2690 tweets))	lindseygrahamsc (2.1M followers) ((1518 tweets))
Top 5 tweets	5191	8415	8794	9608
Top 5 followers (M)	14.7	16.5	13.5	15.9

Online Appendix B. Effect of TV News Coverage of Trump's Tweets on Public Opinion

Online Appendix B.1. Variables

Online Appendix B.1.1. Trump Showings

Table B.1.1.1: **Trump showings - descriptive statistics**

	Total showings			Total 3-hours			3-hours populated w/ data		
	CNN	FNC	MSN	CNN	FNC	MSN	CNN	FNC	MSN
Number of showings	1585	2055	2264	877	1119	1162	717	920	955
Avg. duration (in secs)	8.7	11.3	11.1	15.6	20.7	21.6	15.7	20.0	21.8
Min. duration (in secs)	1	1	1	1.0	1.0	1.0	1.0	1.0	1.0
Max. duration (in secs)	59	52	95	196.0	200.0	212.0	196.0	161.0	212.0

Notes: The table summarizes descriptive statistics for cable-news broadcasts displaying text of President Trump's tweets, computed separately for CNN, Fox News (FNC), and MSNBC (MSN). "Total of showings" refers to all on-screen displays of a Trump tweet. "Total 3-hours" refers to three-hour periods in which a given network displayed at least one tweet. "3-hours populated w/ data" restricts attention to those same three-hour periods that contain interview data from the Nationscape survey and can therefore be used in public-opinion regressions. For each network and sample definition, the table reports the average, minimum, and maximum duration of showings (in seconds).

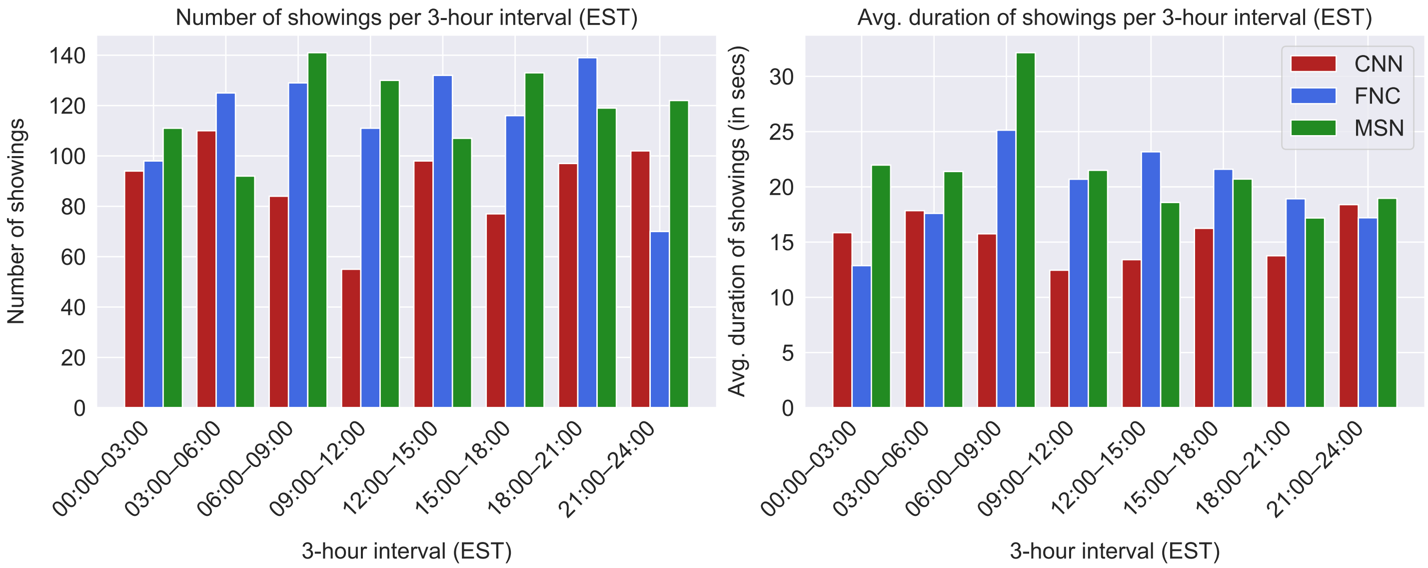


Figure B.1.1.1: **Trump showings - descriptive statistics**. The figure displays descriptive statistics for cable-news broadcasts of President Trump's tweets, separately for CNN, Fox News (FNC), and MSNBC (MSN). The left panel reports, for each three-hour interval of the day (EST), the number of intervals in which a given network displayed at least one Trump tweet. The right panel reports the corresponding average duration of showings (in seconds) within each interval.

Online Appendix B.1.2. Trump Approval Rating and Voting Intention

Table B.1.2.1: **Nationscape sample - "offline" and "online or not" sample**

Sample	"Offline"			"Online or not"		
Station	CNN	FNC	MSN	CNN	FNC	MSN
Windows	717	920	955	717	920	955
Control	73,433	93,377	96,131	219,743	279,514	276,862
Treated	15,092	36,409	7,085	60,216	110,753	24,339

Notes: The table summarizes the composition of the Nationscape estimation samples, reported separately for CNN, Fox News (FNC), and MSNBC (MSN). "Windows" counts the number of event windows for which a given network displayed at least one Trump tweet. "Control" and "Treated" report the number of Nationscape respondents classified, respectively, as control units (individuals who do not watch any cable news) and treated units (individuals who watch only the corresponding network). The "Offline" sample restricts respondents to those who do not use social media to obtain political news, while the "Online or not" sample includes all respondents regardless of their online-news consumption.

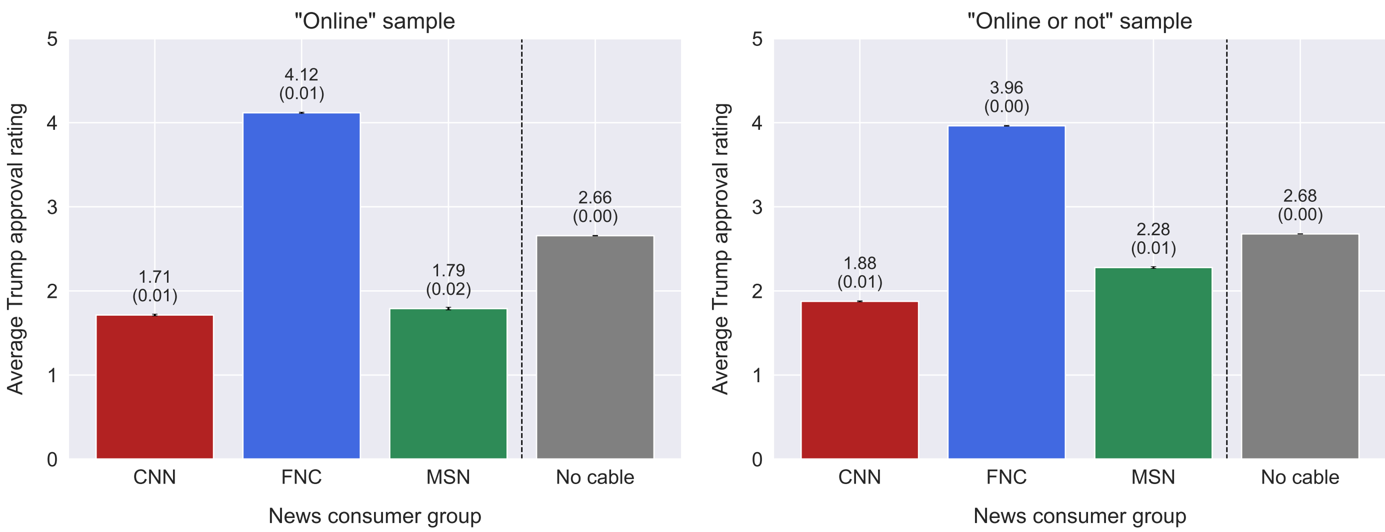


Figure B.1.2.1: **Trump approval rating - "offline" and "online or not" sample**. The figure displays average Trump approval ratings for groups of news consumers in the Nationscape survey, separately for CNN viewers, Fox News (FNC) viewers, MSNBC (MSN) viewers, and individuals who do not watch cable news. The left panel uses an "offline" sample, which restricts respondents to those who do not use social media to obtain political news. The right panel uses a broader "online or not" sample, which includes all respondents regardless of their online news consumption. Approval ratings range from 1 ("strongly disapprove") to 5 ("strongly approve").

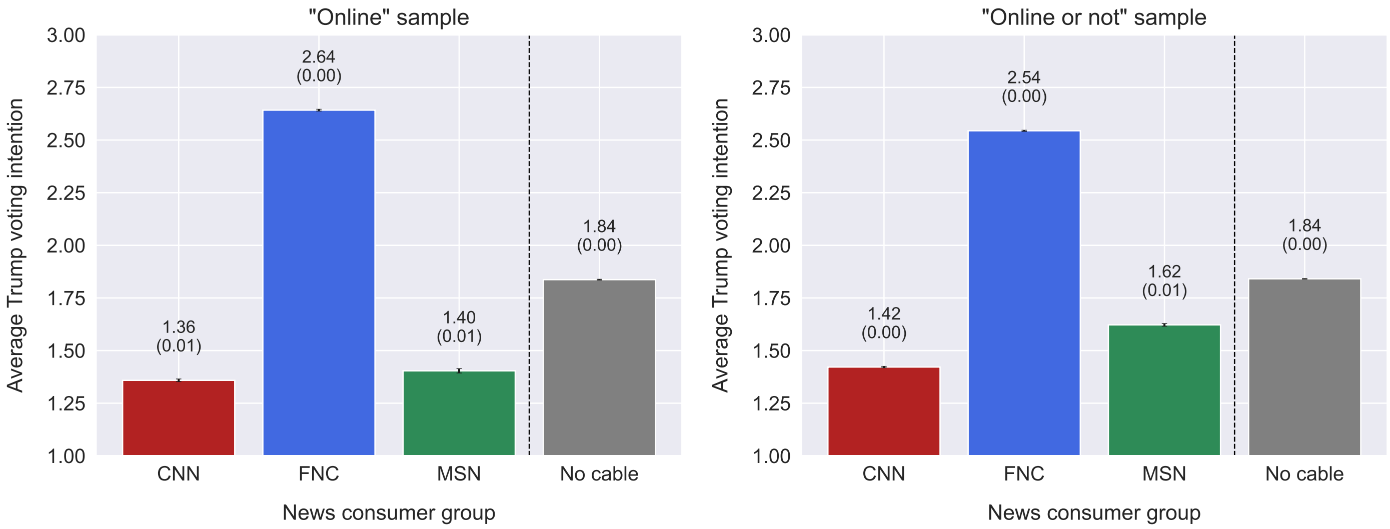


Figure B.1.2.2: **Trump voting intention - "offline" and "online or not" sample**. The figure displays average Trump voting intentions for groups of news consumers in the Nationscape survey, separately for CNN viewers, Fox News (FNC) viewers, MSNBC (MSN) viewers, and individuals who do not watch cable news. The left panel uses an "offline" sample, which restricts respondents to those who do not use social media to obtain political news. The right panel uses a broader "online or not" sample, which includes all respondents regardless of their online news consumption. Voting intentions take three values – 1 ("no"), 2 ("I don't know") and 3 ("yes").

Online Appendix B.2. Empirical Strategy

Online Appendix B.2.1. Overlap Across Network-Specific Event-Windows

Table B.2.1.1: **Trump showings - descriptive statistics, total vs. non-overlap**

	Total windows			Non-overlapping windows		
	CNN	FNC	MSN	CNN	FNC	MSN
Number of windows	717	920	955	654	756	742
Avg. duration (in secs)	15.7	20.0	21.8	13.7	16.1	16.9
Min. duration (in secs)	1.0	1.0	1.0	1.0	1.0	1.0
Max. duration (in secs)	196.0	161.0	212.0	70.0	76.0	108.0

Notes: The table summarizes descriptive statistics for cable-news broadcasts displaying President Trump's tweets, reported separately for CNN, Fox News (FNC), and MSNBC (MSN). "Total windows" includes all event windows in which a network displayed at least one Trump tweet and for which Nationscape data are available. "Non-overlapping windows" restricts to those windows that do not partially overlap in calendar time and with any abnormally long window from the same network. For each network-window, the table reports the average, minimum, and maximum duration of showings (in seconds).

Table B.2.1.2: **Nationscape sample - total vs. non-overlapping respondents**

Sample	Total "Offline"			Non-overlapping "Offline"		
Station	CNN	FNC	MSN	CNN	FNC	MSN
Windows	717	920	955	654	756	742
Control	73,433	93,377	96,131	68,473	76,920	75,031
Treated	15,092	36,409	7,085	14,057	29,791	5,635

Notes: The table summarizes the composition of the Nationscape estimation samples by network. "Total Offline" includes all event windows containing respondents who do not use social media to obtain political news, distinguishing treated units (individuals who watch only the corresponding network) from control units (individuals who do not watch cable news). "Non-overlapping Offline" restricts to the same offline respondents observed in event windows that do not partially overlap in calendar time and with any abnormally long window from the same network. For each network-sample, the table reports the number of usable windows and the associated counts of treated and control respondents.

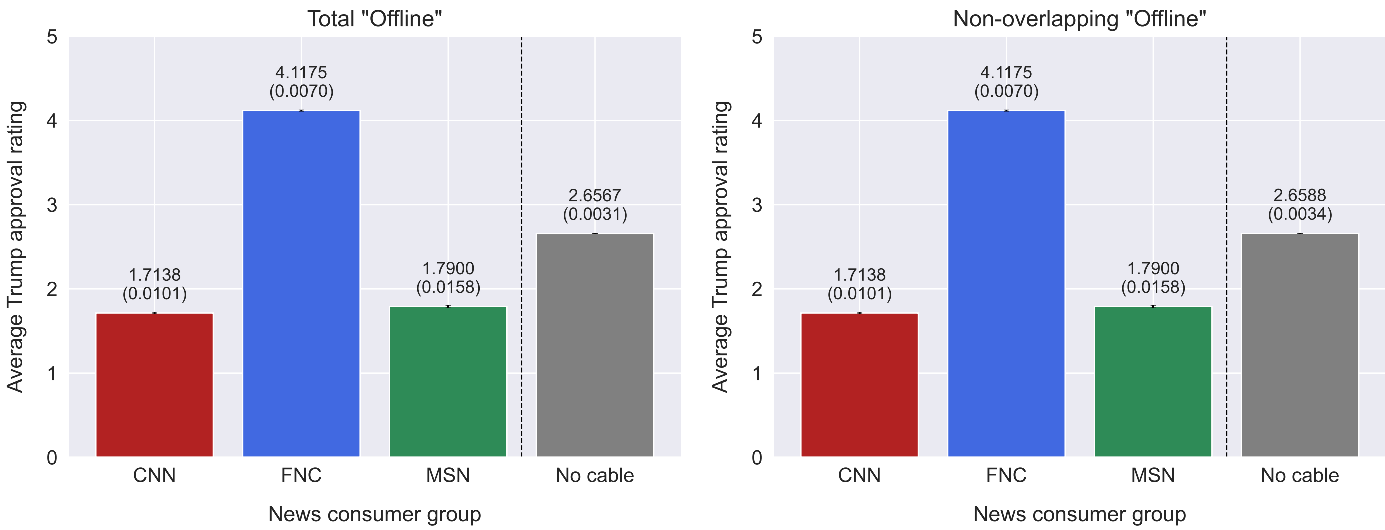


Figure B.2.1.1: **Trump approval rating - total and non-overlapping respondents**. Notes: The figure displays average Trump approval ratings for respondents in the Nationscape "offline" sample—individuals who do not use social media to obtain political news—reported separately for viewers of CNN, Fox News (FNC), MSNBC (MSN), and for respondents who do not watch cable news. The left panel uses all event windows containing offline respondents ("Total Offline"), while the right panel restricts to offline respondents observed in event windows that do not overlap in calendar time with other windows of the same network and that do not overlap with any abnormally long window ("Non-overlapping Offline"). Bars report mean approval ratings for each news-consumer group, with standard errors in parentheses.

Table B.2.1.3: **Pre-post estimates – balance tables**

(a) **CNN**

	Pre	Post	Diff
Age	0.290	0.287	0.288
Gender	0.773	0.780	0.776
Race	0.297	0.299	0.297
Income	0.866	0.863	0.865
Education	0.886	0.885	0.885
Obs.	34,711	47,819	82,530
Clusters	654	654	654

(b) **FNC**

	Pre	Post	Diff
Age	0.224	0.223	0.224
Gender	0.528	0.529	0.529
Race	0.921	0.921	0.921
Income	0.311	0.314	0.311
Education	0.255	0.255	0.255
Obs.	45,561	61,150	106,711
Clusters	756	756	756

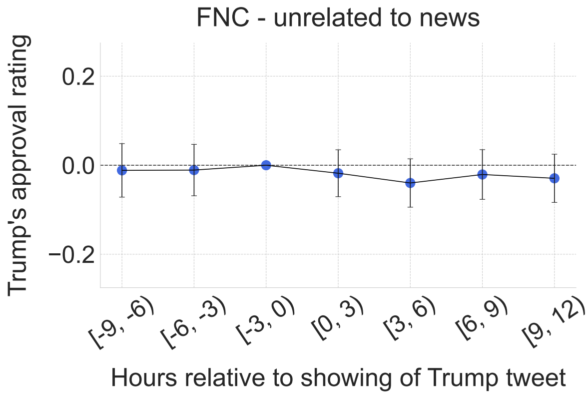
(c) **MSN**

	Pre	Post	Diff
Age	0.959	0.972	0.965
Gender	0.441	0.454	0.447
Race	0.149	0.152	0.150
Income	0.274	0.283	0.276
Education	0.746	0.743	0.744
Obs.	35,271	45,395	80,666
Clusters	742	742	742

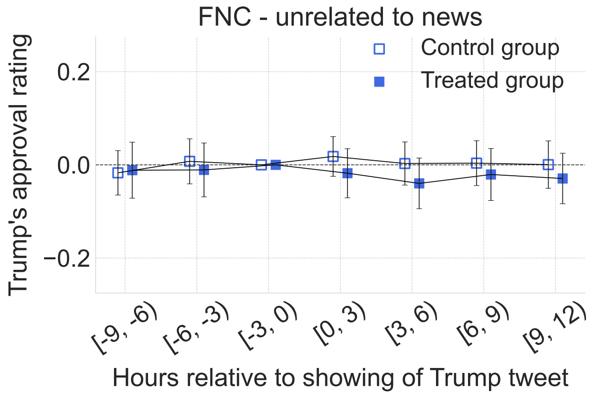
Notes: The tables show p-values for different balance-check regressions. Each demographic is first residualized according to those fixed effects used to estimate Eq. 5 and 6 of Section 3.2 and 3.3 respectively. Afterwards, I compare each demographic separately across treated and control groups via a standard balance-check regression. Column (Pre) refers to regressions restricted to pre-broadcast periods (to rate how both groups compare in terms of e.g., age, pre-treatment). Column (Post) refers to regressions restricted to post-broadcast periods (to rate how both groups compare in terms of e.g., education, post-treatment). Column (Difference) refers to a pre-post balance-check regression (aimed at understanding whether those differences across groups are on average constant along an event window).

Online Appendix B.3. Robustness Checks

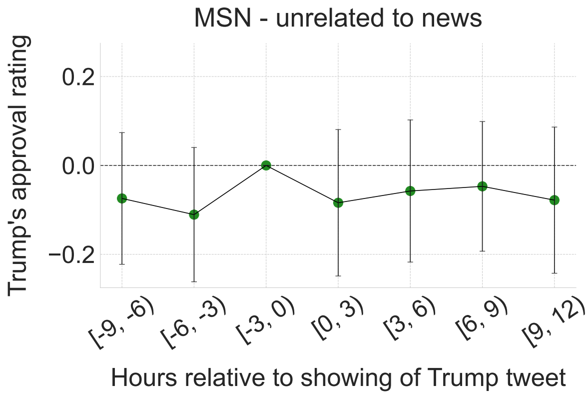
Online Appendix B.3.1. Omitted Variable Concerns



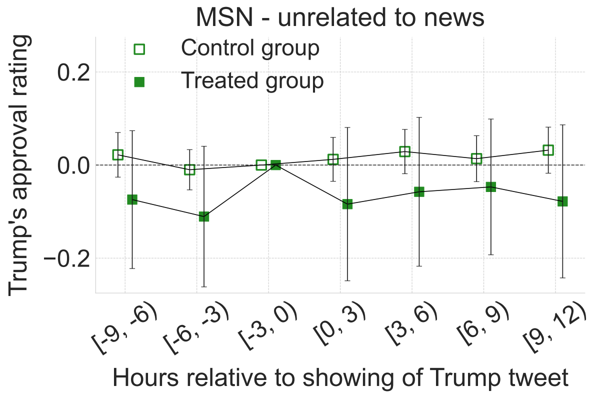
(a) **FNC – diff.-in-diff.**



(b) **FNC – group-specific diff.**

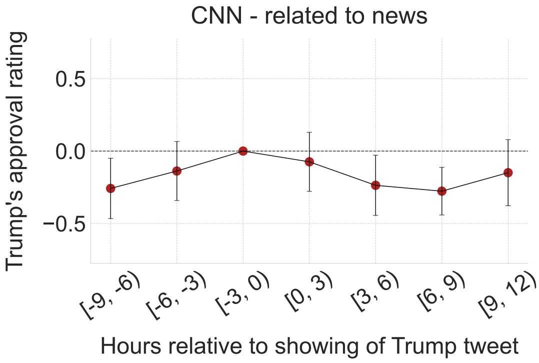


(c) **MSN – diff.-in-diff.**

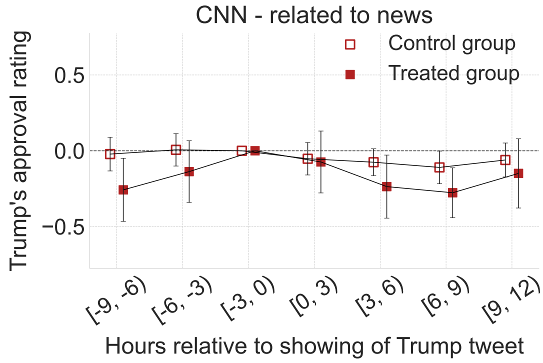


(d) **MSN – group-specific diff.**

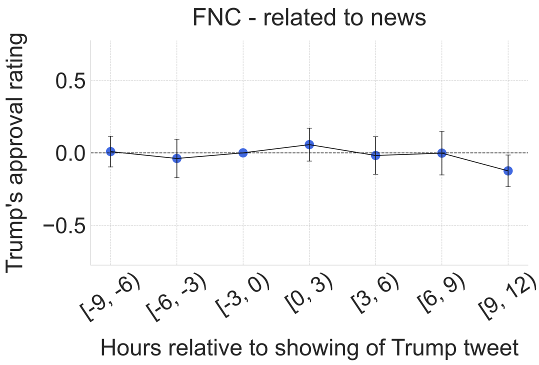
Figure B.3.1.1: **Effect of FNC and MSNBC broadcasts of Trump tweets unrelated to news on approval ratings**. The panels report coefficients from event-study regressions for tweets classified as unrelated to contemporaneous news. For each network, Panel (a) presents difference-in-differences event-study coefficients from an extension of Eq. 5 (in Section 3.2) that allows individuals to react differently to broadcasts of Trump tweets that are related or unrelated to neighboring news. Panel (b) reports group-specific coefficients from a corresponding extension of Eq. 8 (in Section 3.4), allowing treated and control groups to evolve separately within each type of event window. The dependent variable is a five-point approval rating of Donald J. Trump (1 = "strongly disapprove"; 5 = "strongly approve"). Error bars denote 95% confidence intervals based on standard errors clustered at the network × window level.



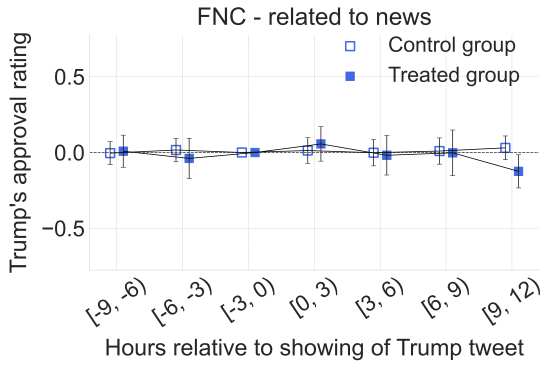
(a) **CNN – diff.-in-diff.**



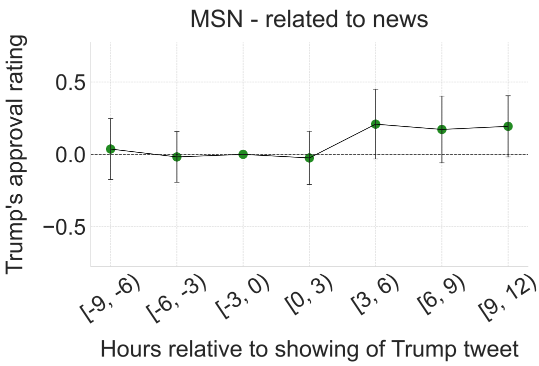
(b) **CNN – group-specific diff.**



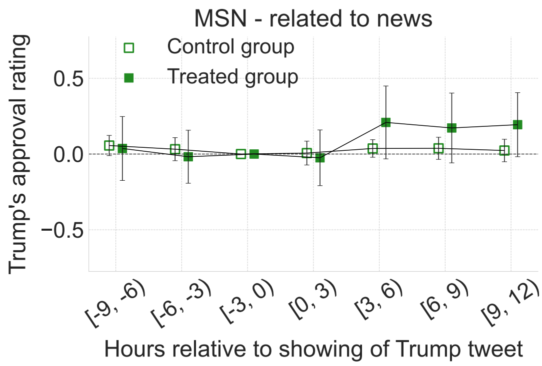
(c) **FNC – diff.-in-diff.**



(d) **FNC – group-specific diff.**



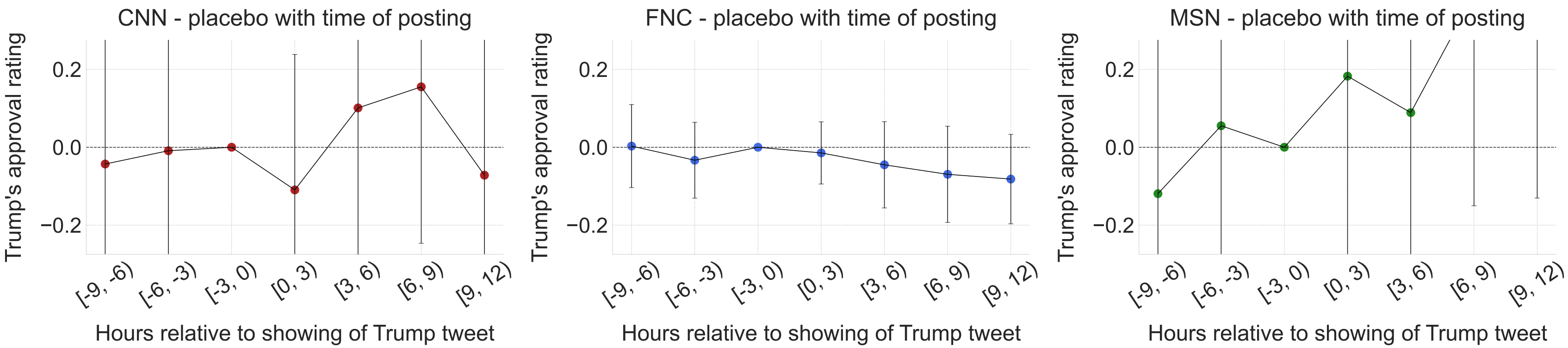
(e) **MSN – diff.-in-diff.**



(f) **MSN – group-specific diff.**

Figure B.3.1.2: **Effect of CNN, FNC, and MSNBC broadcasts of Trump tweets related to news on approval ratings**. The panels report coefficients from event-study regressions for tweets classified as related to contemporaneous news. For each network, Panel (a) presents difference-in-differences event-study coefficients from an extension of Eq. 5 (in Section 3.2) that allows individuals to react differently to broadcasts of Trump tweets that are related or unrelated to neighboring news. Panel (b) reports group-specific coefficients from a corresponding extension of Eq. 8 (in Section 3.4), allowing treated and control groups to evolve separately within each type of event window. The dependent variable is a five-point approval-rating measure of Donald J. Trump (1 = "strongly disapprove"; 5 = "strongly approve"). Error bars denote 95% confidence intervals based on standard errors clustered at the network × window level.

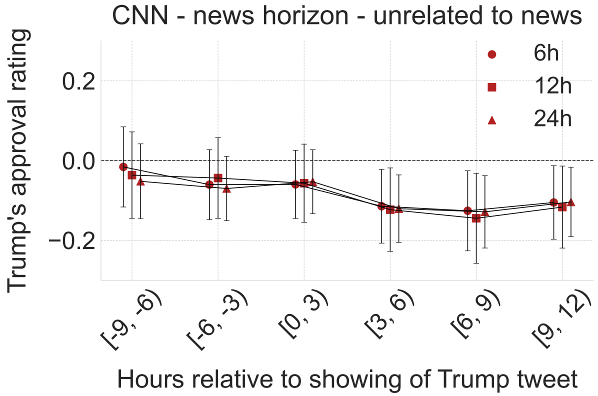
Online Appendix B.3.2. Placebo Analysis



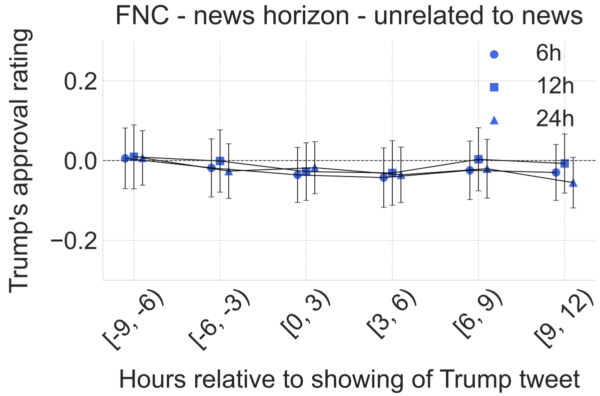
(a) **CNN – placebo analysis** (b) **FNC – placebo analysis** (c) **MSN – placebo analysis**

Figure B.3.2.1: **Effect of posting of Trump tweets on CNN, FNC, and MSNBC viewers' Trump approval ratings**. The figure reports coefficients from event-study regressions that replace the time of a cable broadcast with the time a Trump tweet was posted as the treatment period. For each network (CNN, Fox News (FNC), and MSNBC (MSN)), the coefficients compare changes in approval ratings between treated individuals (viewers of the corresponding network) and control individuals (who do not watch cable news), restricting the sample to tweets whose on-air showing occurred at least 12 hours after posting. This ensures that any contemporaneous change in approval cannot be attributed to cable coverage. Tweets are not classified by their news relatedness, as this distinction is irrelevant when no change is observed. Across all networks, no systematic differences appear at the posting time, supporting the accuracy of respondents' reported media diets. Error bars denote 95% confidence intervals based on standard errors clustered at the network × window level.

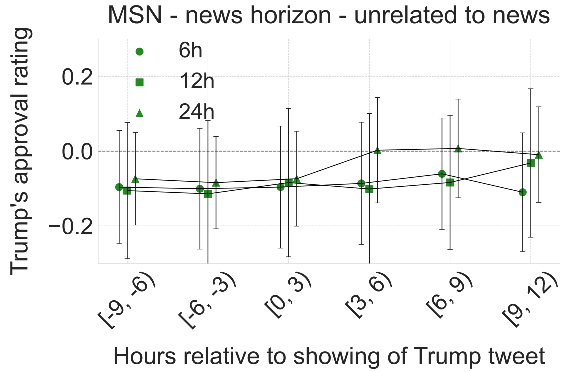
Online Appendix B.3.3. Variable and Regression Specifications



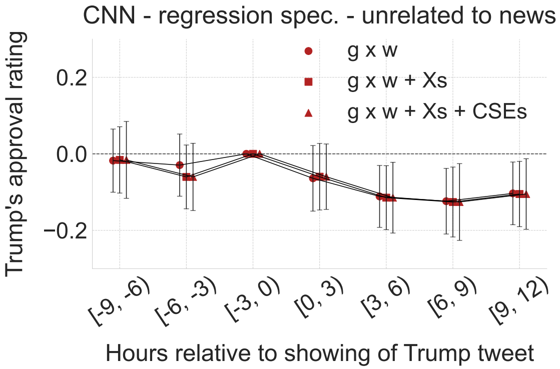
(a) **CNN – varying news**



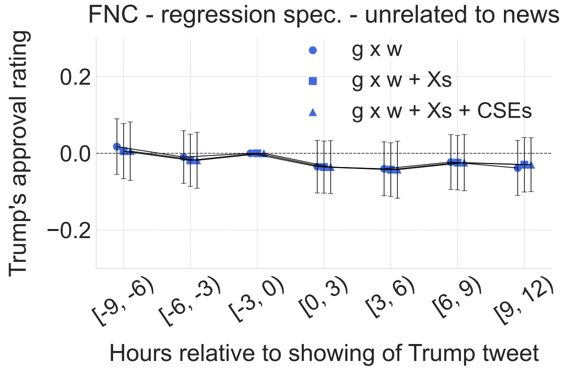
(b) **FNC – varying news**



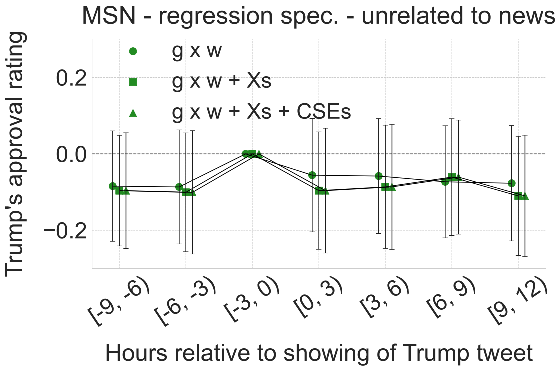
(c) **MSN – varying news**



(d) **CNN – varying specification**

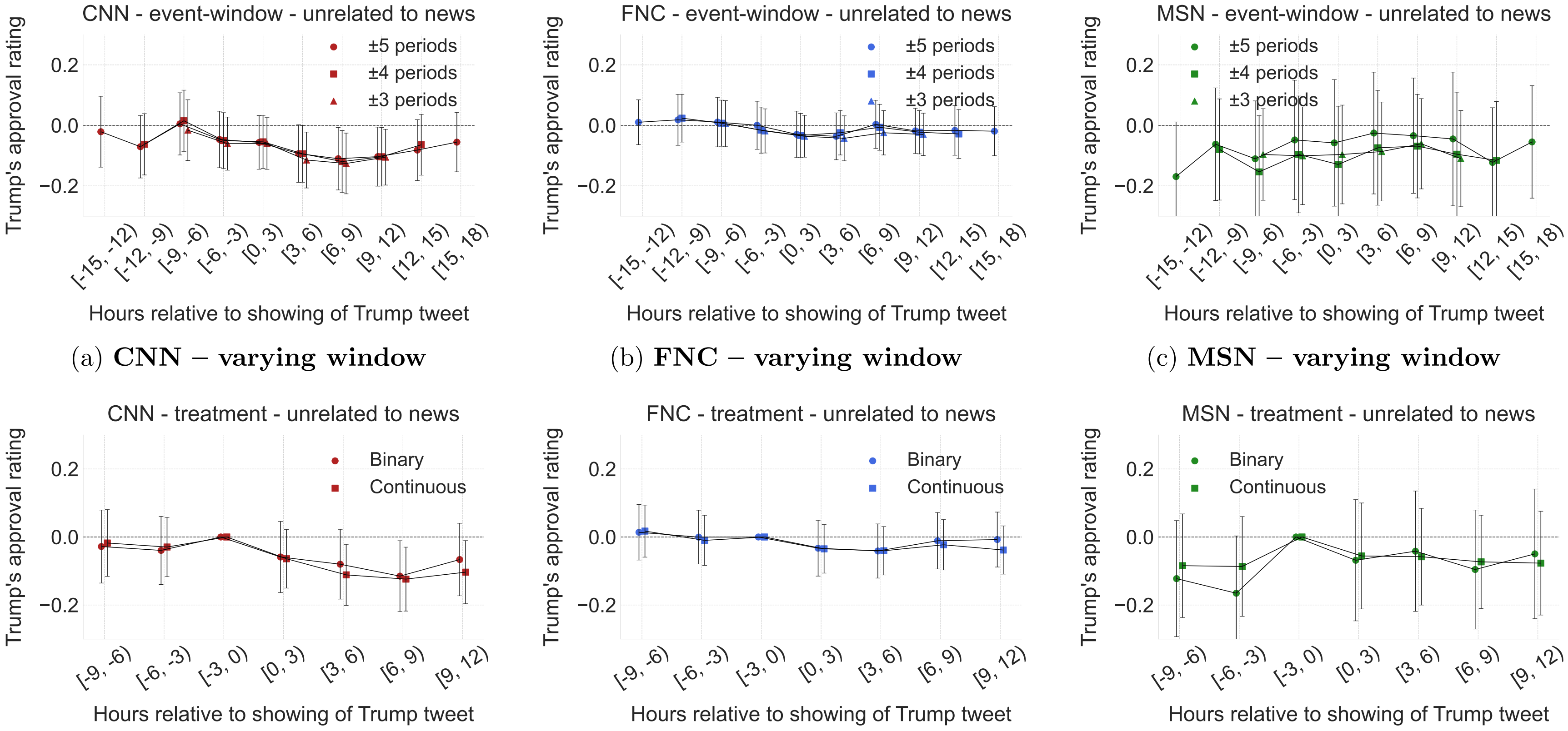


(e) **CNN – varying specification**



(f) **CNN – varying specification**

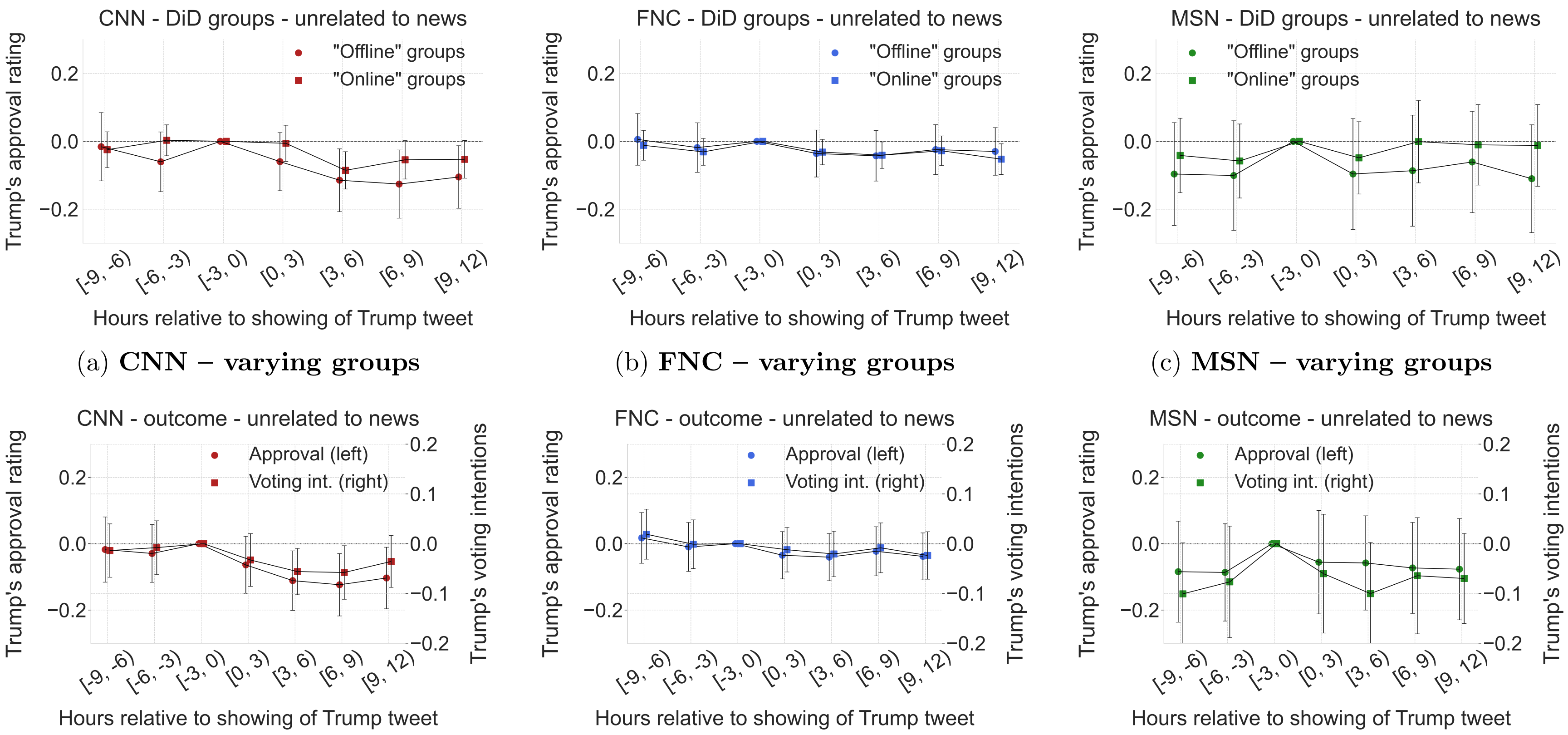
Figure B.3.3.1: **Effect of cable-news broadcasts of Trump tweets unrelated to news on approval ratings – news-variable definition and regression specification robustness checks**. The figure reports event-study coefficients from difference-in-differences regressions. Panels (a)-(c) vary the definition used to classify tweets as unrelated to news by expanding the pool of news with which each tweet is matched (news posted 6, 12 and 24 hours pre and post broadcast). Panels (d)-(f) re-estimate the event studies using alternative regression specifications in place of the baseline network-by-window fixed effects with controls. Each panel corresponds to a separate network (CNN, Fox News (FNC), and MSNBC (MSN)). The dependent variable is a five-point approval rating of Donald J. Trump (1 = "strongly disapprove"; 5 = "strongly approve"). Error bars show 95% confidence intervals based on standard errors clustered at the network × window level.



(a) **CNN – varying window** (b) **FNC – varying window** (c) **MSN – varying window**

(d) **CNN – varying treatment** (e) **CNN – varying treatment** (f) **CNN – varying treatment**

Figure B.3.3.2: **Effect of cable-news broadcasts of Trump tweets unrelated to news on approval ratings – event-window length and treatment variable definition robustness checks**. The figure reports event-study coefficients from difference-in-differences regressions examining the effect of cable-news broadcasts of Trump tweets unrelated to contemporaneous news on approval ratings. Panels (a)-(c) re-estimate the baseline specification using alternative event-window lengths, expanding the number of leads and lags around the broadcast time (baseline: 3 leads and lagds, extended to up to 5). Panels (d)-(f) re-estimate the event studies using an alternative treatment definition that replaces the baseline continuous measure (number of tweets shown at relative time 0) with a binary indicator equal to one when at least one Trump tweet is broadcast at relative time 0. Each panel corresponds to a separate network (CNN, Fox News (FNC), and MSNBC (MSN)). The dependent variable is a five-point approval rating of Donald J. Trump (1 = "strongly disapprove"; 5 = "strongly approve"). Error bars denote 95% confidence intervals based on standard errors clustered at the network × window level.



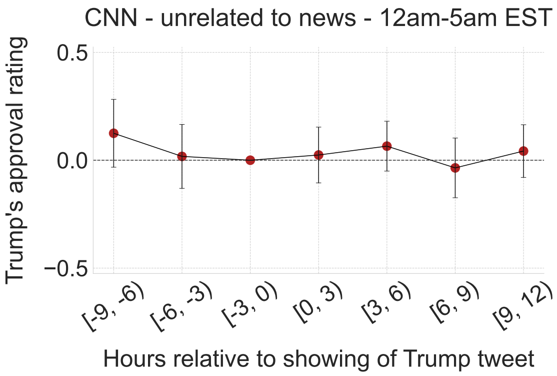
(a) **CNN – varying groups** (b) **FNC – varying groups** (c) **MSN – varying groups**

(d) **CNN – varying outcome** (e) **FNC – varying outcome** (f) **CNN – varying outcome**

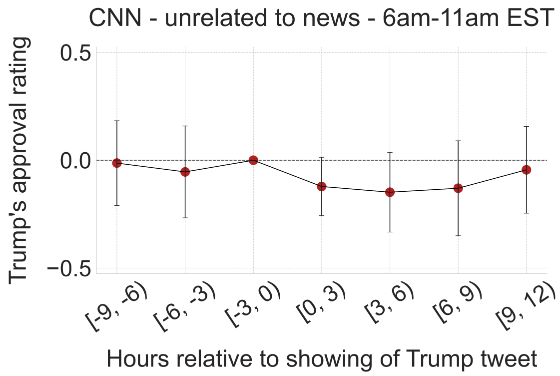
Figure B.3.3.3: **Effect of cable-news broadcasts of Trump tweets unrelated to news on approval ratings – treated and control group definition and outcome variable definition robustness checks**. The figure reports event-study coefficients from difference-in-differences regressions examining the effect of cable-news broadcasts of Trump tweets unrelated to contemporaneous news on public opinion. Panels (a)-(c) re-estimate the baseline specification using broader definitions of the treated and control groups, relaxing the restriction that both groups consist solely of respondents who do not use social media for political news. Panels (d)-(f) re-estimate the event studies using an alternative outcome measure – Trump's 2020 presidential vote intention, measured from 1 to 3 (1 = "No", 2 = "I do not know", 3 = "Yes") – in place of the five-point approval rating used in the baseline analysis. Each panel corresponds to a separate network (CNN, Fox News (FNC), and MSNBC (MSN)). Error bars denote 95% confidence intervals based on standard errors clustered at the network × window level.

Online Appendix B.4. Heterogeneity and Mechanisms

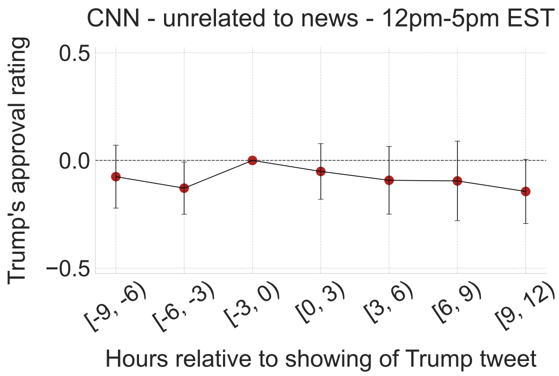
Online Appendix B.4.1. Heterogeneity by Time-of-Day



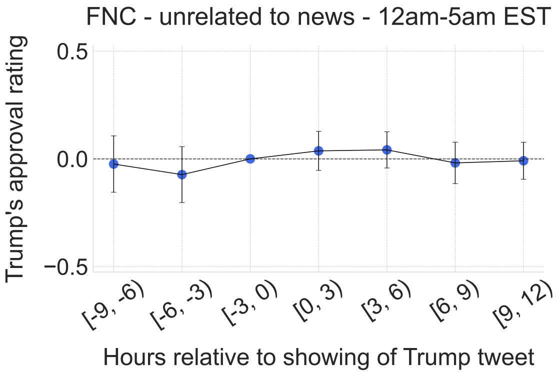
(a) **CNN, 12am to 5am EST**



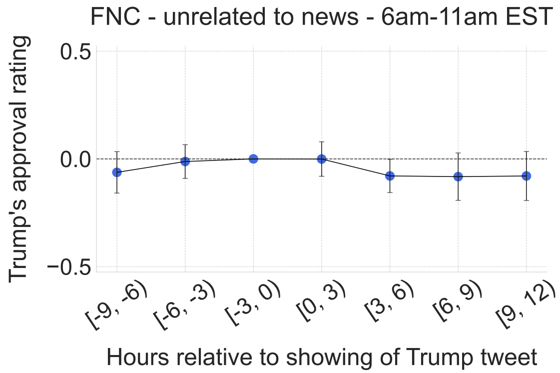
(b) **CNN, 6am to 11am EST**



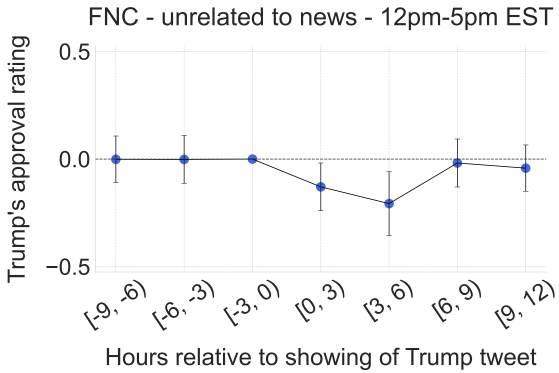
(c) **CNN, 12pm to 5pm EST**



(d) **FNC, 12am to 5am EST**

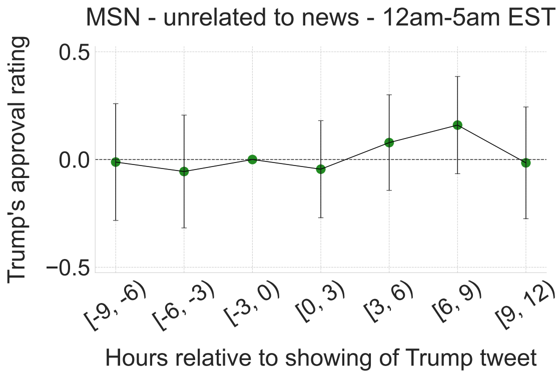


(e) **FNC, 6am to 11am EST**

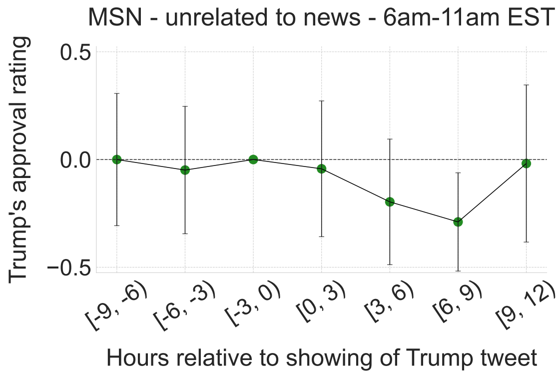


(f) **FNC, 12pm to 5pm EST**

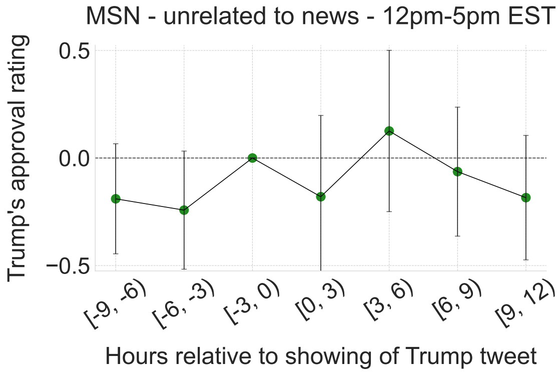
Figure B.4.1.1: **Effect of CNN and FNC broadcasts of Trump tweets unrelated to news on approval ratings, by time of day**. The figure reports event-study coefficients from Eq. 9 in Section 3.5, a heterogeneity specification that allows for individuals to react differently to a broadcast of a Trump tweet depending on that broadcast's time-of-day. All panels restrict attention to tweets classified as unrelated to contemporaneous news. Panels (a)-(c) present coefficients for CNN broadcasts occurring between 12am-5am, 6am-11am, and 12pm-5pm (EST), respectively; Panels (d)-(f) present the corresponding coefficients for Fox News. The dependent variable is a five-category approval rating of Donald J. Trump (1 = "strongly disapprove"; 5 = "strongly approve"). Error bars denote 95% confidence intervals based on standard errors clustered at the network × window level.



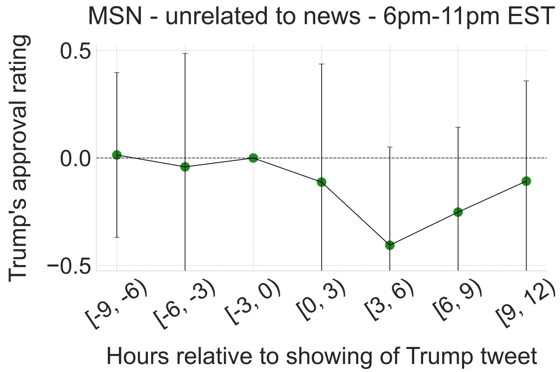
(a) **MSN, 12am to 5am EST**



(b) **MSN, 6am to 11am EST**



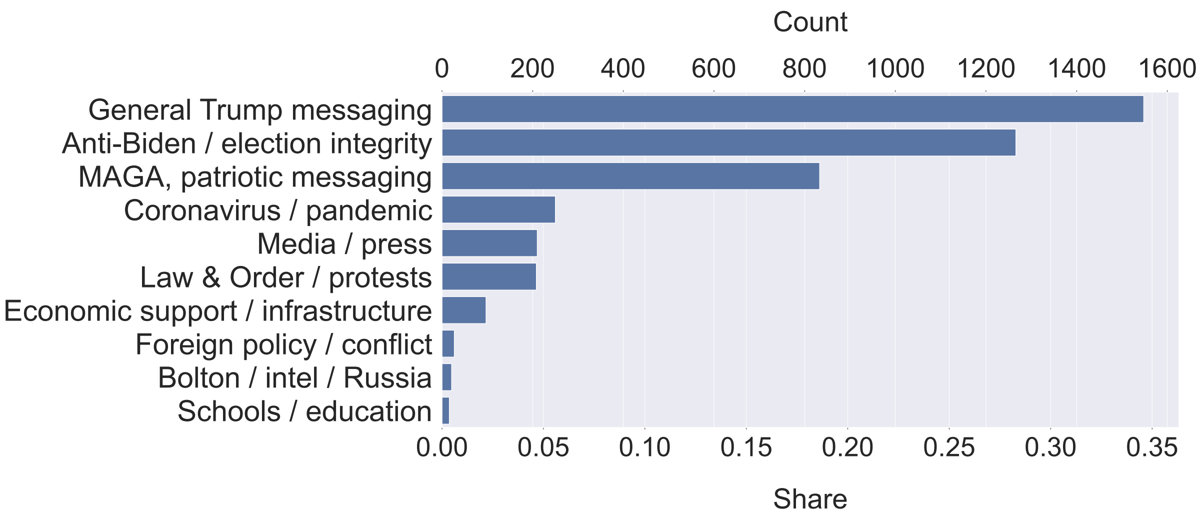
(c) **MSN, 12pm to 5pm EST**



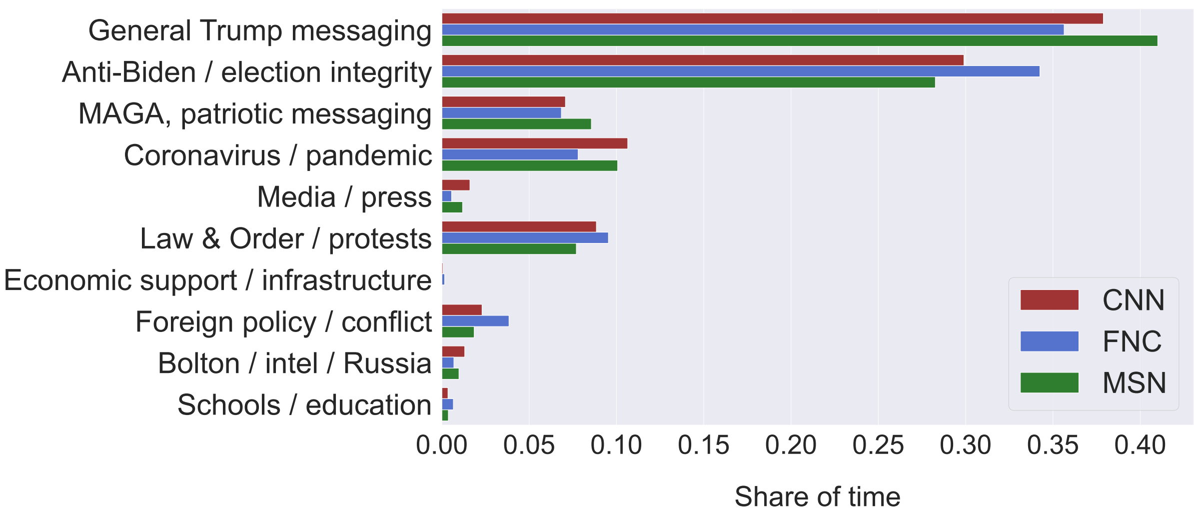
(d) **MSN, 6pm to 11pm EST**

Figure B.4.1.2: **Effect of MSNBC broadcasts of Trump tweets unrelated to news on approval ratings, by time of day**. The figure reports event-study coefficients from Eq. 9, a heterogeneity specification that allows for individuals to react differently to a broadcast of a Trump tweet depending on that broadcast's time-of-day. All panels restrict attention to tweets classified as unrelated to contemporaneous news. Panels (a)-(d) present coefficients for MSNBC broadcasts occurring, respectively, between 12am-5am, 6am-11am, 12pm-5pm, and 6pm-11pm (EST). The dependent variable is a five-category approval rating of Donald J. Trump (1 = "strongly disapprove"; 5 = "strongly approve"). Error bars denote 95% confidence intervals based on standard errors clustered at the network $\times$ window level.

Online Appendix B.4.2. Mechanisms



(a) **Topic distribution for (2020) Trump tweets**



(b) **Coverage of (2020) Trump tweets by topic / network**

Figure B.4.2.1: **Topic distribution for Trump tweets**. Panel (a) plots the distribution of topics assigned to all Trump tweets posted in 2020 using a BERTopic model, which embeds tweets and clusters them into ten coherent semantic themes. Panel (b) reports the share of on-screen time that CNN, Fox News (FNC), and MSNBC devoted to each of these topics when broadcasting Trump's tweets during 2020.

Table B.4.2.1: **Topic-word distribution for (2020) Trump tweets**

Topic	Theme	Top Words
0	General political messaging / broad Trump rhetoric	great, people, election, trump, fake, biden, country, vote, president, joe, news, just, big, thank, years, fake news, democrats, like, states, media
1	Anti-Biden, anti-China, fake news, "election integrity"	biden, joe, vote, election, fake, joe biden, news, big, fake news, just, democrats, people, republican, party, president, history, trump, georgia, country, sleepy
2	Endorsements / MAGA / patriotic messaging	complete, great, total, thank, second amendment, amendment, second, strong, maga, congressman, military, state, incredible, america, carolina, border, america great, big, north, tremendous
3	Coronavirus / China / pandemic	coronavirus, china, news, virus, world, fake news, doing, fake, covid, great, just, job, deaths, far, people, good, 000, states, president, country
4	Media appearances / press conferences	conference, 00, book, white house, white, house, foxnews, today, great, 30, tonight, news, new, press, thank, great new, having, trump, foxandfriends, 10
5	Law & Order, protests, governors, Democrat-run cities	guard, national, federal, law, city, left, new york, york, governor, radical left, radical, government, federal government, new, job, democrat, run, want, night, people
6	Funding, recovery, infrastructure, economic support	wall, funding, service, support, moving, economic, people, federal, border, proud, important, recovery, state, million, help, receive, built, great, announce, big
7	Foreign policy / Iran / military conflict	united, united states, killed, attack, states, world, people, american, leaders, years, killing, americans, war, leader, death, let, watching, wants, attacks, equipment
8	John Bolton / intelligence agencies / Russia claims	john, wacko, information, book, war, ve, korea, said, statements, like, law, met, stories, approved, gave, just, guy, true, stupidly, people
9	Schools reopening / education funding	school, open, school choice, choice, funding, democrats, closed, safely, send, families, want, looking, think, november, money, dems, help, continues, issue, fauci

Notes: The table reports, for each topic generated by a BERTopic model fitted to all Trump tweets posted in 2020, the most representative words defining that topic together with a short thematic label (assigned using ChatGPT 5.1).

Table B.4.2.2: **Representative Trump tweet by topic**

Topic	Theme	Representative Tweet
0	General political messaging / broad Trump rhetoric	Just In: Chinese State Media and Leaders of CHINA want Biden to win "the U.S. Election". If this happened (which it won't), China would own our Country, and our Record Setting Stock Markets would (...)
1	Anti-Biden, anti-China, fake news, "election integrity"	Joe Biden is a corrupt politician. He wants to send YOUR jobs to China, while his family rakes in millions from the Chinese Communist Party. If Biden wins, China will OWN the USA. When we win, YOU (...)
2	Endorsements / MAGA / patriotic messaging	Utah Attorney General Sean Reyes (@SeanReyesUT) is a fighter and hard worker for the Great State of Utah. He is a big supporter of our #MAGA Agenda – Strong on Crime, the Second Amendment, and (...)
3	Coronavirus / China / pandemic	Just received a briefing on the Coronavirus in China from all of our GREAT agencies, who are also working closely with China. We will continue to monitor the ongoing developments. We have (...)
4	Media appearances / press conferences	White House news conference at 5:00 P.M. Eastern. Thank you! (...)
5	Law & Order, protests, governors, Democrat-run cities	"Chaos, lawlessness, and destruction take over New York." @FoxNews When will Governor Cuomo call the Federal Government for help? (...)
6	Funding, recovery, infrastructure, economic support	Relief is on the way to Utah! I'm proud to send $187.18M in CARES Act funding to @RideUTA. This money will keep people moving and support a swift and smooth economic recovery for the GREAT people of (...)
7	Foreign policy / Iran / military conflict	Iran is talking very boldly about targeting certain USA assets as revenge for our ridding the world of their terrorist leader who had just killed an American, badly wounded many others, not to mention all of the (...)
8	John Bolton / intelligence agencies / Russia claims	John Bolton, one of the dumbest people I've met in government and sadly, I've met plenty, states often that I respected, and even trusted, Vladimir Putin of Russia more than those in our Intelligence (...)
9	Schools reopening / education funding	Now that we have witnessed it on a large scale basis, and firsthand, Virtual Learning has proven to be TERRIBLE compared to In School, or On Campus, Learning. Not even close! Schools must be open in (...)

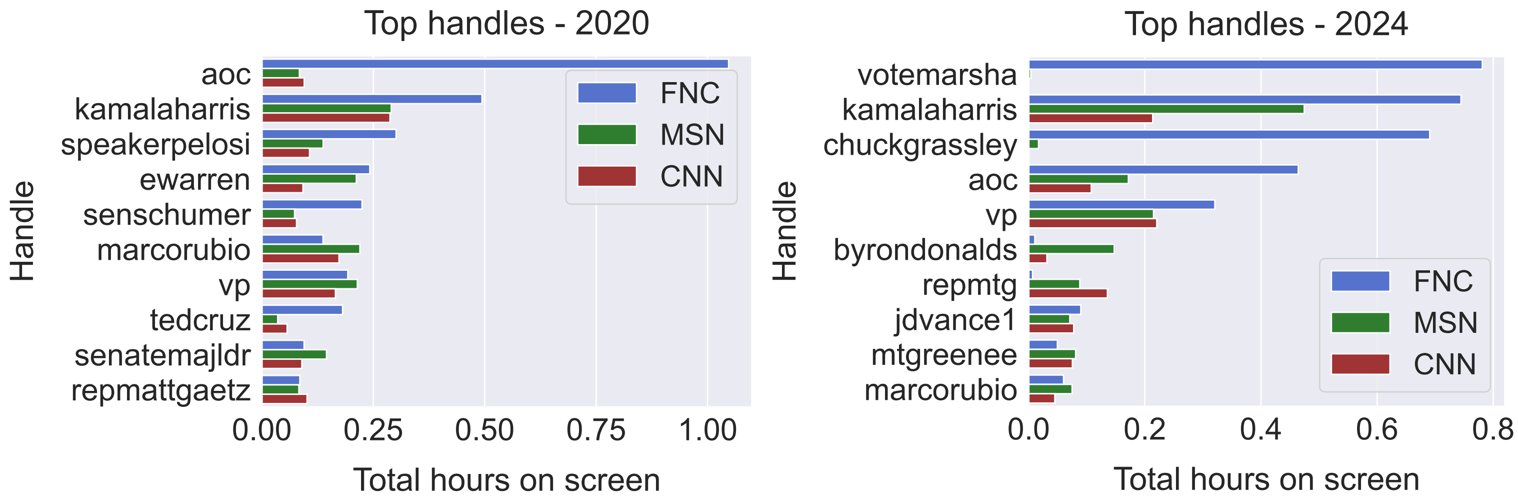
Notes: The table presents one representative Trump tweet for each BERTopic cluster.

Online Appendix B.5. Additional Evidence and External Validity

Table B.5.1: **Members of Congress and Twitter account coverage, 2020–2024**

year	MOC members	Handles	Dem. MOC members	Dem. Handles	Rep. MOC members	Rep. Handles
2020	605	1,147	297	564	259	495
2021	643	1,211	310	589	284	528
2022	603	1,147	286	545	270	510
2023	552	1,126	260	471	249	440
2024	552	1,126	260	471	249	440

The table reports the number of unique Members of Congress (MOCs) and the number of unique Twitter handles appearing in the congressional tweets dataset from 2020 to 2024. Counts are shown separately for all MOCs, as well as by party. Note that the congressional tweets dataset used to compile all statistics does not include tweets from 2024; therefore, counts reported for 2023 are extrapolated to 2024, as both years correspond to the 118th U.S. Congress.



(a) **Top handles shown by network, 2020**

(b) **Top handles shown by network, 2024**

Figure B.5.1: **Top congressional Twitter handles shown on cable news, 2020 and 2024**. Panels (a) and (b) report the ten most frequently displayed congressional Twitter handles in 2020 and 2024, respectively, together with the total number of on-screen hours each network devoted to those handles. For each year, the figure aggregates all instances in which a sitting member of Congress's verified handle appeared on screen and sums the corresponding on-screen duration by network (CNN, Fox News (FNC), and MSNBC).