Trumping the News:
A High-Frequency Analysis

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Abstract

Do mainstream media outlets actively amplify politicians' social media statements, and does this amplification influence individuals' political opinions? I first study cable news coverage of Donald J. Trump's tweets using novel high-frequency coverage measures for CNN, Fox News, and MSNBC. I show that Trump was able to set the agenda of cable news outlets through Twitter, with cable outlets covering his tweets minutes after these had been posted. I then leverage a large public opinion survey to investigate the impact of TV coverage of Trump's tweets on public opinion. I find that CNN's coverage of Donald J. Trump's tweets caused CNN viewers to decrease their approval of President Trump hours after coverage. Conversely, coverage on Fox News resulted in an increase in President Trump's approval ratings among Fox News viewers. These findings shed light on a new channel through which social media impacts individuals' political opinions.

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 issue political statements. These platforms allow for the dissemination of messages that are more sentimentally charged compared to other media. The influence of social media communications could be propagated through television news outlets if these actively cover politicians' online activities. This would allow online statements to reach a significant share of U.S. voters that are not directly exposed to social media – those that use television as their main news source (Pew, 2021).

While there exists a growing literature on the political impact of social media on their users (Allcott et al., 2020; Mosquera et al., 2020; Levy, 2021; Fujiwara et al., 2021), the indirect effects of social media through television coverage are far less understood. This paper sheds light on the amplification of social media messages by television (TV) outlets.

The paper is organized into two parts. In the first part, I study how TV news outlets cover politicians' social media activities. In the second part, I investigate how this coverage affects the political opinions of TV news' audiences. In both parts, I focus on the coverage of Donald J. Trump's tweets by the three main U.S. cable news channels – CNN, Fox News and MSNBC – both before and during his presidency.

In the first part of the paper, I study whether cable news outlets actively responded to President Trump's tweets – i.e., if the event of Trump tweeting caused cable outlets to immediately alter the subject of coverage. To do so, I take advantage of not only the text and the time of each of President Trump's tweets, but also timestamped transcripts for the universe of shows aired by CNN, Fox News and MSNBC. I leverage this information to employ a high-frequency identification strategy. More specifically, I study how the subjects covered by cable news shift in the *minutes* after the postings of Trump's tweets.

I find that cable outlets shifted their attention to the issues tweeted by in a matter of minutes. The posting of a Trump tweet about a given issue caused outlets to increase coverage of that issue by an average of 1 minute and 28 seconds. In relative terms, this means that a tweet by Trump translated almost immediately into a 4-fold increase in the amount of time, within a day, that cable outlets spent on issues addressed by President Trump's tweets. Interestingly, this pattern holds for the three main cable networks – i.e., all TV channels shifted their coverage towards issues tweeted by Donald Trump within minutes of a tweet having been posted.[1]

[1] Fox News is a predominantly conservative outlet and therefore could be expected to cover key conservative figures more intensely (see e.g., Martin and Yurukoglu, 2017; Kim et al., 2022). While, on average, Fox News spent more time on issues tweeted by President Trump compared to CNN and MSNBC, the effects for all TV channels are significant.

These findings can be interpreted as causal effects under two identifying assumptions. First, that Trump's tweets were not caused by television news. In other words, that President Trump did not regularly tweet *in response to* television news segments, eliminating concerns of reverse causality.

To test the validity of this assumption, I estimate different event-study specifications to document how cable news behaved minutes before a tweet was posted. I do not find any evidence indicative of President Trump having regularly tweeted in reaction to cable news: news coverage is consistently unrelated to President Trump's tweets, minutes before a tweet was posted. Moreover, in a robustness check, I allow cable outlets' reactions to differ according to how President Trump's tweets relate to past cable news. As before, I find that cable outlets covered Trump's tweets irrespective of how these posts relate to past TV broadcasts.[2]

Second, I assume that shifts in coverage happening close to a Trump tweet are unrelated to other events determining both cable news' broadcasts and President Trump's tweets. For example, a sports event may be followed both by a tweet from Donald J. Trump and by a news story from a cable outlet, leading to a spurious correlation (i.e. omitted variable bias).

This assumption is plausible given my high-frequency design, where I study cable news coverage minutes before and after a tweet was posted. As a robustness check, I collect an exhaustive dataset of online news to distinguish Donald J. Trump's tweets according to how these statements relate to neighboring events. Afterwards, I allow outlets to react differently to posts that were seemingly related or unrelated to "neighboring" news (i.e. proximate in time). Again, I find that outlets consistently responded to Donald Trump's tweets in a matter of minutes, irrespective of how these posts related to events that happened close to posting.

These findings support the hypothesis that Donald Trump had an agenda-setting power over cable news, insofar as his tweets caused changes in the distribution of content broadcasted by TV news channels, within a day.

I provide three additional insights. First, I show that the average tone of cable outlets became more positive when reacting to Trump's tweets. This indicates that, in the short-run, TV channels tended to report Donald Trump's tweets, instead of interpreting them. Second, I investigate the heterogeneity of coverage across time. While the estimated

[2]Note that this type of practice could have been viewed as plausible, a priori – different news reports claim that Trump cleared significant shares of his schedule, both before and throughout his presidency, in order to watch separate morning shows from alternative cable news outlets (see e.g., Axios, 2017, 2019)

effects are largest during Donald Trump's presidency, I find evidence of President Trump having already had an agenda-setting power over cable news during 2016. Third, I focus on the heterogeneity of coverage across topics and find that Donald J. Trump was able to shift the coverage of cable news outlets, irrespective of the topic he addressed in his tweets.

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 take advantage of a novel dataset featuring texts displayed on-screen by TV outlets. I first document every instance in which President Trump's tweets were explicitly covered by a cable news channel during 2020. Then, I map TV broadcasts of President Trump's tweets to a large public opinion survey. In particular, I use a unique set of survey questions to employ a high-frequency differences-in-differences strategy.

More specifically, I compare Trump's approval ratings from two different groups of news consumers in the hours before and after cable outlets broadcasted a Trump tweet. To give an example, take a situation in which a given outlet covered a Trump tweet - e.g., CNN. In this case, I compare Trump's approval ratings by CNN viewers with that of individuals that do not watch cable TV news, for the hours before and after a tweet was covered. This comparison yields a causal estimate for the effect of covering a Trump tweet on public opinion under a parallel trends assumption. I corroborate this identifying assumption by estimating different event-study regressions in which I compare the dynamics of the approval ratings of each group of interest (individuals watch a specific cable outlet vs. individuals that do not watch cable news), before the showing of a Trump tweet.

I find that a broadcast of a Trump tweet by CNN caused CNN's viewers to decrease their ratings of Donald J. Trump by 6 percent (i.e., relative to a group of individuals that do not watch cable news and that are similar to CNN viewers across different demographic characteristics). Then, I allow for heterogeneity by timing of coverage, to account for the fact that cable news audiences are larger during primetime (from 6pm to 12pm; Pew, 2021). While I do not find an average effect for Fox News and MSNBC, there appears to be an effect for coverage of Trump's tweets during primetime broadcasts. In particular: (1) the worsening of Trump's views by CNN viewers is driven by showings of Trump tweets during primetime; (2) an average primetime broadcast of a tweet by Fox News causes Fox News' viewers to significantly improve their ratings of President Trump.

Taken together, these findings suggest that the amplification of social media content by cable news outlets significantly impacts political opinions of television audiences, potentially contributing to their polarization. I interpret these results as a product of two main effects - a *priming* and a *framing* effect. The priming effect refers to how cable outlets expose their viewers to specific Trump tweets, reinforcing their audiences' priors concerning Donald Trump. A topic analysis corroborates this interpretation, showing significant differences in the distribution of tweets covered by Fox News and CNN, respectively. The framing effect refers to how channels broadcast the same issue differently, leading to divergent opinions between audiences. In line with this interpretation, a sentiment analysis shows that the coverage of Trump tweets by Fox News is significantly more positive than that of CNN's.

This paper contributes to four strands of the literature. The first is the agenda-setting power literature (started by McCombs and Shaw, 1972, 1993). In particular, it 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. congress-members, on Twitter, are more likely to follow news coverage. James et al. (2019) and Gilardi et al. (2022) instead investigate how politicians' social media posts relate to both online and offline news outlets.[3] These studies rely on correlation-based methods to study how politicians' online statements relate to news coverage. I contribute to this literature by taking a causal stance. More specifically, I leverage on a high-frequency identification strategy and a rich set of news data to present the 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 TV news on outcomes as varied as voting behavior (see e.g., DellaVigna and Kaplan, 2007; Martin and Yurukoglu, 2017; Ash et al., 2021), judicial decisions (Ash and Poyker, 2020), health behaviors (Bursztyn et al., 2020b), local government expenditure (Galletta and Ash, 2019) and, local news production (Widmer et al., 2020).[4] More specifically, the current study sheds light on a potential mechanism through which cable can persuade different actors – by the echoing of extreme content that can instead impact societal perceptions about specific matters, groups or views (à la Bursztyn et al., 2020a).

Third, the paper provides a direct contribution to the literature that investigates the political effects of social media on, among other outcomes, protest participation (Enikolopov et al., 2020; Fergusson and Molina, 2020) , political polarization (Allcott et al., 2020; Mosquera et al., 2020; Levy, 2021), voting behavior (Rotesi, 2019; Fujiwara et al., 2021) and politicians' responsiveness to voters (Bessone et al., 2022).[5] These studies focus on

[3]James et al. (2019) find that the agenda of U.K. parties on Twitter predicts issues addressed by a subset of traditional U.K. news outlets (in television, radio and newspapers). Gilardi et al. (2022) document that the online agenda of Swiss politicians predicts and is predicted by the topics addressed on newspapers.

[4]A related literature studies the effects of television in general on voter turnout (Gentzkow, 2006), social capital (Olken, 2009), fertility decisions (La Ferrara et al., 2012), political polarization (Campante and Hojman, 2013), voting behavior (Enikolopov et al., 2011; Durante et al., 2019)

[5]See Zhuravskaya et al. (2020) for an extensive review of the literature.

measuring the political impact of social media on their active users (from voters to politicians). I provide the first causal quantification of the spillover effects of social media, onto offline audiences.

Fourth, a strand of the literature has focused on the effects of social media on other non-political outcomes.[6] This paper is in close relation with a body of work that researches the effects of social media on news production (Cagé et al., 2022; Zhuravskaya et al., 2021). More specifically, the current paper is closest to Zhuravskaya et al. (2021), which shows 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 to Zhuravskaya et al. (2021) by showing that social media events (here, political statements instead of conflict-related discussions) cause changes in cable news coverage. Relative to Zhuravskaya et al. (2021), I further measure how these editorial decisions, shaped by social media, affect public opinion.[7]

The rest of the paper is organized as follows: Section 2 shows how cable news 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 outlets 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 used. Section 2.2 outlines the empirical strategy. The main results are described in Section 2.3. Robustness checks are presented in Section 2.4. Last, Section 2.5 extends the analysis by allowing for coverage to vary along different dimensions.

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

[6]For instance, on hate-crime (Müller and Schwarz, 2021, 2018; Bursztyn et al., 2019), future earnings (Armona, 2019) and, more recently, mental health (Braghieri et al., 2022).

[7]Adding to a recent strand in the literature that studies the impact of different forms of media on public opinion outcomes collected from large opinion surveys (see e.g., Djourelova, 2020; Melnikov, 2021).

universe of shows broadcasted from January 2015 to January 2021 (not included) by each of these stations. It was kindly provided by the TV News Archive (Link).

Tweets by @realDonaldTrump. Timestamped tweets posted by Donald J. Trump's Twitter account, @realDonaldTrump (Link).[8] This dataset covers the universe of tweets posted by Donald J. Trump from January 2015 to January 2021 (not included). It was made available by the Trump Twitter Archive (Link).

Social media posts by U.S. online newspapers. Text and timestamp for the universe of Facebook (FB) posts and tweets posted by a comprehensive subset of U.S. national newspapers, from January 2015 to January 2021 (not included). FB posts were collected through CrowdTangle (Link). Tweets were collected using the Twitter API (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 20,568 tweets from 2015 to 2020. These statements accounted for 15,607 15-minute periods in which at least one Trump tweet was posted (see Table A.1.1). The number of tweets posted by President Trump increased significantly over time, in particular during his presidency – from ≈ 2,500 tweets in 2017 to ≈ 5,000 tweets in 2020 (see Figure A.1.1). Interestingly, Donald J. Trump was more likely to tweet during early mornings, between 7am and 9am (see Figure A.1.2).

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. These measures focus on short time windows, centered around Donald J. Trump's tweets – so-called event windows.[9]

[8] 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.

[9] In Appendix A.1.1.1.1, I provide a formal definition for "*event window*".

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.[10]

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 Table A.1.2). Overall, the similarity between cable news transcripts and Donald Trump's tweets was largest during 2018 (see Figure A.1.4a). In addition, cable news outlets were more likely to discuss those issues tweeted by President Trump in the early morning, when Donald Trump tweeted the most (see Figure A.1.4b)

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, the minutes before and after a Trump tweet was posted. This measure accounts both for those instances 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 main stages: a build-up, an explicit mention and, both a conclusion and a transition to another issue.[11]

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 Table A.1.3). CNN spent more time on tweet-related issues during 2017; Fox News and MSNBC instead covered these issues more intensely during 2019 (see Figure A.1.5a). Within a given day, CNN covered tweet-related issues uniformly; Fox News and MSNBC covered these issues more intensely during mornings (see Figure A.1.5b).

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). [12]

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 Table A.1.4). In addition, all cable

[10]In Appendix A.1.1.2.1, I provide a formal definition for "*extent of coverage*".

[11]In Appendix A.1.1.2.2, I provide a formal definition for "*intensity of coverage*".

[12]In Appendix A.1.1.2.3, I provide a formal definition for "*sentiment of coverage*".

news outlets seem to have covered tweet-related issues in an abnormally sentimental fashion during 2018 (see Figure A.1.6a). Third, and aligned with previous coverage measures, all networks tended to cover these types of issues more positively in the early morning (see Figure A.1.6b)

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:

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

where $y_{n,w,\tau}$ stands for an outcome variable specific to network n and relative time period τ of event window w (note: in what follows, τ stands for a 15-minute time period). $\alpha_{n,w}$ stands for a network $\times$ window fixed effect, aimed at controlling for underlying macro factors that are assumed to affect the coverage of each outlet differently.[13] $\mathbb{1}\{n = \eta,\ k = \tau\}$ stands for an indicator variable equal to one if network n is network η (where η can be CNN , Fox News or MSNBC) and relative time period τ is equal to k (where k can go from -3 to 3 and -1 is not included). $tweets_{w,0}$ stands for a treatment variable indicating how many tweets President Trump posted during relative time period 0 of event window w. β_k^{η} is a standard event-study coefficient, specific to network η and relative time period k. I estimate Eq. (1) through ordinary least squares (OLS) and I cluster standard errors at a network $\times$ event window level.

The coefficient of interest, β_k^{η}, should be interpreted differently depending on y. To start, if y rates whether a network covered issues addressed in Trump's tweets, then, β_k^{η} measures 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. After, if y refers to how did a network cover tweet-related issues, in terms of time, then, β_k^{η} measures the differential change in the amount of minutes that network η spent on issues mentioned in Trump tweets, k periods before (or after) a tweet was posted. Lastly, if y focuses on how did a network cover issues tweeted by Donald Trump, in terms of tone, then, β_k^{η} 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.

[13] This assumption is grounded on past media bias literature – Martin and Yurukoglu (2017) and more recently Kim et al. (2022) document significant differences in each of these outlets' editorial choices.

The underlying identifying assumptions necessary for β_k^η to be interpreted as a causal estimate for how President Trump's tweets affected cable news coverage are two-fold.

First, President Trump's tweets are assumed as not having been consistently caused by cable news coverage. An example of a practice that violates this assumption is Donald J. Trump having regularly tweeted in reaction to television news segments.[14] This type of action would act as a confounding factor when estimating β_k^η. More specifically, in this case, any post-tweet change in coverage could be caused either by the posting of a tweet or the continuance of a pre-tweet news piece (that led Donald J. Trump to tweet). Both causes would be indistinguishable. To test for this assumption, I estimate Eq. (1) by including a set of pre-tweet coefficients, to understand whether cable news often showed any type of abnormal dynamics prior to the posting of a Trump tweet (an indication that President Trump would have recurrently tweeted in response to cable).[15]

Second, any change in coverage that happened during an event window is assumed to be orthogonal to other omitted variables relevant at explaining both cable news' coverages and President Trump's tweets. An example of an event of this kind is a shooting – an unexpected circumstance that immediately prompts both a reaction by President Trump and a news piece by cable outlets. These types of episodes, if taken place within an event window, would act as a confounding factor when estimating β_k^η. In particular, a shift in coverage that was caused by a pressing news event could be spuriously interpreted as having been driven by the reaction of President Trump to that same event. To argue in favor of this assumption, I study cable news at an intra-hour frequency, to keep other factors relevant at explaining cable news coverage as constant as possible.[16]

A final identification concern relates to how regularly President Trump tweeted within a day. In fact, Donald J. Trump's tweets were often posted at such high frequencies that different event windows partially overlap across calendar time.[17][18] This type of

[14] A practice that could be viewed as plausible, a priori – different news reports claim that Donald J. Trump cleared significant shares of his schedule, both before and throughout his presidency, in order to watch separate morning shows from alternative cable news outlets (see e.g., Axios, 2017, 2019)

[15] To address any remaining endogeneity concerns that might be caused by reverse causality, in section 2.4 I estimate a version of Eq. (1) in which I allow cable outlets to react differently to a Trump tweet according to how that tweet related to past cable news coverage.

[16] Moreover, to tackle any additional endogeneity concerns driven by omitted variables, in section 2.4 I leverage on an exhaustive self-collected dataset of online news to estimate a version of Eq. (1) that controls for breaking news events.

[17] See Figure A.1.7 for an illustration of two partially overlapping event windows (across calendar time).

[18] President Trump tweeted a total of 20,568 tweets from 2015 to 2020. These tweets map into 15,607 event windows. 12,441 (80%) of these partially overlap across calendar time (taking event windows as time intervals with a duration of 1h45m, as in Eq. (1); note that longer event windows translate into more overlaps – e.g., windows that stretch for 3h15m map into a 90% overlapping rate).

overlap can be problematic from an identification standpoint for outcomes that are not event window specific.[19] In these instances, pre and post-tweet periods are not clearly distinguishable between each other.[20]

To address this issue, I first implement a stacked design as in Cengiz et al. (2019). More specifically, I restrict myself to studying outcomes that are defined around event window specific factors (in this case, coverage measures focused exclusively on those issues addressed on President Trump's tweets, that differ across event windows). This type of design allows for an unbiased estimation of β_k^{η} if and only if the event windows used to estimate Eq. (1) do not overlap in simultaneous across calendar time and content.[21][22]

To comply with this precondition, I estimate Eq. (1) by using only event windows that do not overlap in simultaneous across calendar time and content. In theory, this restriction implies that β_k^{η} should be interpreted as local coefficients, specific to those tweets that are not closely followed in time by statements that are similar in terms of content. In practice, this class of posts is representative of Donald J. Trump's tweets, thus, β_k^{η} may be interpreted as how an average Donald Trump tweet impacts cable news coverage.[23]

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, minutes after being posted. After, I measure the amount of time that cable outlets spent on discussing the issues addressed in these same tweets.

[19] Examples of outcomes that are not event window specific are coverage measures focused on themes that are common across calendar time – e.g., number of minutes devoted to news stories that explicitly mention "Trump".

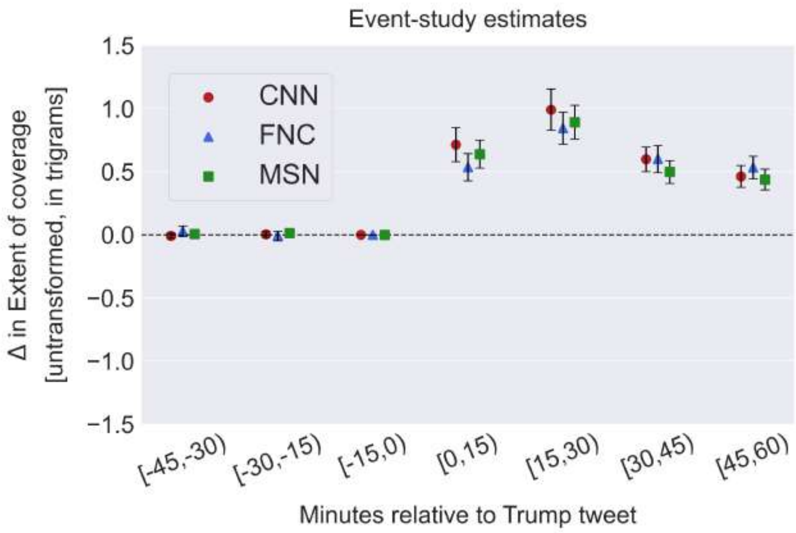
[20] In essence, for those windows that partially overlap across calendar time, a subset of pre-tweet periods from specific event windows will be mistakenly taken as post-tweet periods in other event windows. Similar to a differences-in-differences setting with staggered treatment where newly and already-treated units are erroneously compared as treated and not-treated units (see De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021; Wooldridge, 2021; Baker et al., 2022; Borusyak et al., 2022).

[21] Whereby content refers to the issues tweeted by Donald J. Trump during each event window. See Figure A.1.8 for an illustration of two partially overlapping event windows (across calendar time and content).

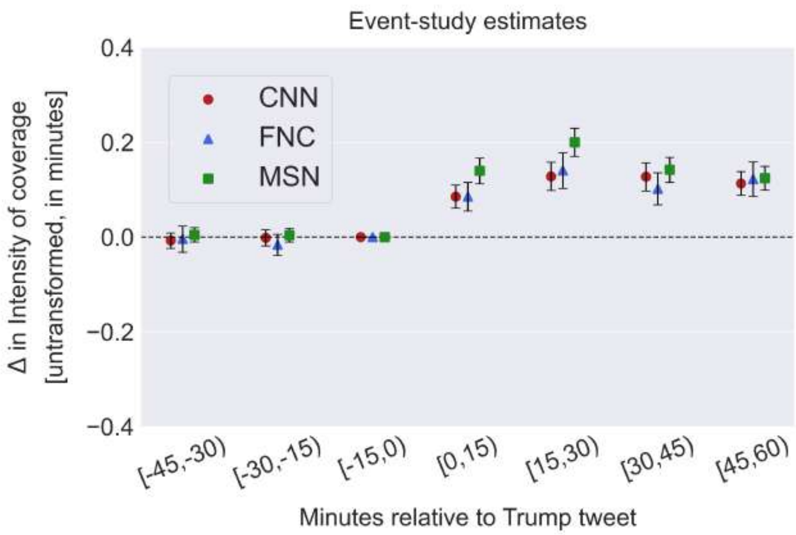
[22] 1,263 (8%) event windows partially overlap in simultaneous across calendar time and content (taking event windows as time intervals with a duration of 1h45m, as in Eq. (1); again, wider event windows imply more overlaps – windows of 3h15m generate an overlapping rate of 14%).

[23] This class of tweets accounts for more than 90% of Donald J. Trump's tweets (see Figure A.1.9) and it mimics particularly well Donald J. Trump's within-day tweeting patterns (see Figure A.1.10).

Event-studies. Panel 2.3.1a plots the coefficients for an event-study regression that has as dependent variable an extent of coverage measure (a textual similarity measure comparing the transcripts of cable news outlets with the tweets from Donald J. Trump – in trigrams). Panel 2.3.1b instead shows the coefficients for a similar regression where now the dependent variable is an intensity of coverage measure (a variable measuring how much time cable outlets spent on tweet-related issues – in minutes).



(a) **Extent of coverage**.



(b) **Intensity of coverage**.

Figure 2.3.1: **Event-study estimates – extent and intensity of coverage**. Panel (a) refers to an event-study regression, as in Equation 1, where the dependent variable is an extent of coverage measure (in trigrams; as defined in A.1.1.2.1). Panel (b) refers instead to an event-study regression, as in Equation 1, where the dependent variable is an intensity of coverage (in minutes; as defined in A.1.1.2.2). Error bars refer to 95% confidence intervals drawn from standard errors clustered at a network $\times$ window level.

Both panels suggest two sets of results. To start, the average relationship between cable news coverage and President Trump's tweets did not suffer any significant changes minutes before a tweet was posted. This result holds both from an extensive and an intensive margin. It suggests that President Trump did not tweet often in reaction to cable news broadcasts, a necessity if the post-tweet coefficients in Eq. (1) are to be taken as causal estimates for how a Trump tweet affected cable news coverage.

Second, the posting of a Trump tweet caused persistent changes in cable news coverage. In particular, those discussions being held on cable news outlets converged towards President Trump's tweets, in terms of content, within minutes after the posting of a Trump tweet. Again, this finding holds both from an extensive and an intensive margin. It suggests that President Trump was able to shift the coverage of cable outlets through his tweets, thus, having an agenda-setting power over cable news channels.

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

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

where p stands either for a *pre* (= 0) or a *post-tweet* (= 1) period (in what follows, p can stand for a 45m, 1h30m or 2h15m time period). $y_{\;n,\;\;w,\;\;p}$ stands for an aggregated coverage measure (e.g., an extent of coverage measure, as described in Section 2.1.2.2, aggregated at a 45m time frequency). $tweets_{\,w}$ stands for a treatment variable indicating how many tweets President Trump posted during event window w. β^{η}_{post} is a standard post-treatment coefficient, specific to network η.

Tables A.1.8 and A.1.9 present the coefficients from estimating Eq. (2) for the extent and the intensity of coverage measure, respectively. In both tables, column 1 refers to a specification in which I compare cable news coverage 45 minutes post vs. 45 minutes pre a Trump tweet. Columns 2 and 3 show similar comparisons, for longer time periods. More specifically, column 2 compares cable news coverage during 1h30m periods while column 3 focuses on 2h15m periods.

As expressed in column 3 of Table A.1.9, I find that a posting of one Trump tweet about a given issue caused cable outlets to increase their coverage of that issue by, on average, 1m and 13s (during the 2h15m after the posting of a tweet). In relative terms, this added coverage meant a 4-fold increase in these outlets' tweet-related coverages (relative to their pre-tweet average). Moreover, I do not find any significant differences across outlets in terms of how each of these reacted to the posting of a Trump tweet.

2.3.2 Sentiment of Coverage

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

Event-studies. Figure 2.3.2 plots the coefficients for an event-study regression where the dependent variable is a sentiment of coverage measure (a variable measuring the tone used by each outlet to discuss the issues addressed in President Trump's tweets).

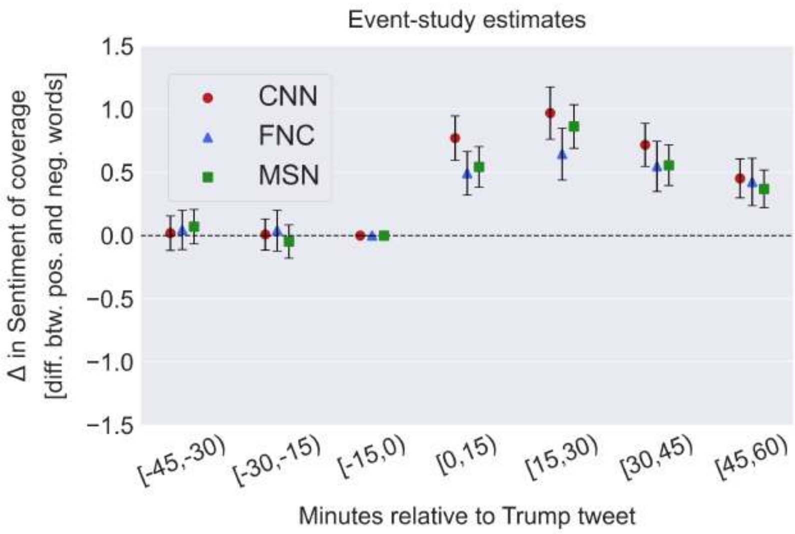


Figure 2.3.2: **Event-study estimates – sentiment of coverage**. The figure plots the coefficients for an event-study regression, as in Equation 1, with the dependent variable being a sentiment of coverage measure (based on a dictionary-based sentiment score; as defined in A.1.1.2.3). The error bars refer to 95% confidence intervals drawn from standard errors clustered at a network × window level.

As before, the figure shows two different results. First, those issues addressed in President Trump's tweets were not a target of an abnormally positive or negative coverage, minutes prior to a tweet. This finding corroborates previous results that Donald J. Trump's tweets were, on average, independent of past cable news coverage. In particular, given that Donald Trump did not tend to tweet, on average, about issues that were a target of unusually charged coverages.

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 themselves (when reacting to a Trump tweet). These findings suggest that the immediate coverage of President Trump's tweets by cable news outlets was more focused on an objective reporting of President Trump's tweets rather than a subjective, and possibly network-specific, interpretation of these statements.

Pre-posts. Table A.1.10 presents the estimates for a pre-post regression focused on the sentiment of coverage. As before, these estimates point towards a scenario in which all three outlets tended to report President Trump's tweets hours after a tweet was posted. This reporting seems to have been rather similar in sentiment across outlets (irrespective of which pre-post specification one focuses on).

2.4 Robustness Checks

2.4.1 Reverse Causality Concerns

As discussed in Section 2.2, previous estimates can be biased due to reverse causality. More specifically, changes in coverage after a Trump tweet can be either due to President Trump tweeting or to the continuation or severance of a pre-tweet news story (which instead prompted Donald Trump to tweet initially). In this section, I tackle these concerns by allowing outlets to react differently to President Trump's tweets according to how these tweets related to past cable news.

I start by identifying when were cable news transcripts most similar to President Trump's tweets. To do so, I leverage on a textual similarity measure that compares the text of cable news transcripts with the text of Donald J. Trump's tweets.[24] After, I label those event windows in which President Trump's tweets shared an abnormally large number of textual features with pre-tweet cable news transcripts as intervals in which Donald Trump was likely to have tweeted in reaction to cable.[25] Last, I extend Eq. (1) as follows:

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

where $\mathbb{1}\{w \in \mathit{Related}\}$ stands for an indicator variable equal to one if and only if the tweets posted by Donald Trump during event window w are seemingly related to past cable news coverage and,

[24] That is, the extent of coverage measure described in Section 2.1 and defined in A.1.1.2.1.

[25] Whereby "*an abnormally large number of textual features*" means the similarity measure between Donald Trump's tweets and cable news transcripts going above a given threshold. In what follows, I report results referent to a two standard deviation threshold. Note nonetheless that these results are robust to the similarity threshold chosen.

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

where $\beta_k^{\eta,r}$ stands for a standard event-study coefficient specific to how network η varied its coverage k periods before (or after) a r-related tweet (where a "*r-related tweet*" stands for a tweet that was either related or unrelated to past cable news coverage).

Estimating Eq. (3) yields two main results. First, cable news networks turned their attention away from the issues addressed by Donald J. Trump whenever President Trump seemed to tweet in reaction to cable news broadcasts (see Panel A.1.12a, Panel A.1.12b and Figure A.1.13b). This pattern is consistent with a scenario in which Donald Trump tweeted in response to a specific news story which was then severed by cable outlets, post-tweet.

Second, the findings discussed in Section 2.3 – i.e., cable outlets actively followed President Trump's tweets with their coverage – are entirely driven by the event windows in which Donald J. Trump tweeted independently of past cable broadcasts (see Panel A.1.11a, Panel A.1.11b and Figure A.1.13a). This result casts aside any remaining reverse causality concerns. Most importantly, it corroborates the previous results, that President Trump was able to shift the attention of cable news outlets by tweeting.

2.4.2 Omitted Variable Concerns

Past results can be driven by omitted variables that happened either within or close to an event window. In particular, changes in coverage close to a Trump tweet can be either due to President Trump tweeting or to unobserved news events that prompted both Donald J. Trump to issue a tweet and cable news outlets to air a specific news piece. In this section, I address these concerns by studying whether cable outlets reacted differently to Trump's tweets according to how these tweets related to ongoing news events.

To do so, I first construct a similarity measure that compares the text of Donald J. Trump's tweets with the text of the online news that were posted up to 6 hours before or after a tweet was posted.[26] Second, I leverage on this measure to distinguish across Trump's tweets according to how these tweets related to neighboring online news.[27] Third,

[26] See Section A.1.1.3 for a set of accompanying descriptive statistics.

[27] In particular, I distinguish between two types of statements: (a) tweets seemingly related to recent (or upcoming) news (i.e., statements that share an abnormally large number of textual features with neighboring online news) and (b) tweets seemingly unrelated to pressing news event (i.e., documents that share either a standard or a low number of textual features with recent or upcoming online news).

I extend Eq. (1) similarly as in (3), i.e., I allow cable outlets to react differently to Trump's tweets according to how these tweets related to current news stories.

I find that cable news outlets shifted their coverage towards those issues tweeted by President Trump irrespective of how each tweet related to current news events. In other words, Donald J. Trump was able to shift the attention of cable news networks even when the statements in his tweets were seemingly unrelated to neighboring news events (see Panels A.1.14a, A.1.14b and A.1.16a).[28] These findings rule out any residual omitted variable concerns related to past results.

2.5 Heterogeneity Analyses

2.5.1 Heterogeneity by Year

Past estimates hinge on the assumption that the reaction of cable outlets to Trump tweets was homogeneous over time. This assumption can be rebated from different angles. An interesting proposition is that the coverage of Trump tweets was exclusively motivated by Donald Trump's role as President. An implication of this would be that cable outlets only started to cover Trump tweets after 2016. This would have important ramifications in terms of how Trump's social media presence impacted his 2016 presidential run.

In this section, I allow cable outlets to have heterogeneous responses to Donald J. Trump's tweets over time. In particular, I extend the pre-post regression laid out in Eq. (2) as follows:

$$\mathrm{y}_{\,\mathrm{n,w,p}} = \alpha_{\,\mathrm{n,w}} + \sum_{\mathrm{year}=2015}^{2020} \left[\sum_{\eta \in \{\mathrm{C,F,M}\}} \mathbb{1} \begin{Bmatrix} \mathrm{w} \in \mathrm{year}, \\ \mathrm{n}=\eta, \\ \mathrm{p}=1 \end{Bmatrix} \times \mathrm{tweets}_{\,\mathrm{w}} \times \beta_{\mathrm{post}}^{\eta,\,\mathrm{year}} \right] + \varepsilon_{\,\mathrm{n,w,p}} \tag{4}$$

where "$w \in year$" stands for window w having happened during "*year*" (where "*year*" can go from 2015 to 2020). $\beta_{\mathrm{post}}^{\eta,\,\mathrm{year}}$ instead is a standard pre-post coefficient measuring how network η tended to react to Donald J. Trump's tweets during a specific year.

Two results are visible. First, cable outlets started to follow President Trump's tweets in 2016.[29] This result holds for all three dimensions of coverage (see Figures A.1.17, A.1.18

[28]Note nonetheless that these shifts were larger in magnitude when related to tweets that addressed neighboring news events (see Panels A.1.15a, A.1.15b and A.1.16b)

[29]To be more specific, the posting of a Trump tweet on a given issue (in 2016) caused cable outlets to increase their coverage of that specific subject by $\approx$ 1m (up to 2h15m post a Trump tweet). This estimate is stable across networks (i.e., all outlets, during 2016, reacted similarly to Trump's tweets).

and A.1.19). This suggests that Donald J. Trump already had an agenda-setting power over cable news outlets as a presidential candidate.

Second, cable news outlets did not follow Trump's tweets uniformly across time. In fact, these outlets' coverage was stronger in 2017. It then reduced in magnitude at a seemingly linear rate from 2017 onwards.[30] This pattern suggests an underlying process of learning about audiences' preferences regarding Trump's tweets.[31]

2.5.2 Heterogeneity by Topic

The previous results assume that the reaction of cable news outlets to Donald J. Trump's tweets was not a function of the content being addressed on each statement. Cable outlets nonetheless cater to audiences with significantly different political leanings (Pew, 2020) and are thus expected to not only devote more time of their broadcasts to those topics preferred by their viewers but also to address these topics with varying tones (see e.g., Mullainathan and Shleifer, 2005).[32]

In this section, I allow for Trump tweets to impact cable news coverage differently according to their topic. More specifically, I first draw from recent developments in the Natural Language Processing (NLP) literature to classify Donald J. Trump's tweets into an array of 10 interpretable topics.[33] After, I extend the pre-post regression laid out in Eq. (2) similarly to Eq. (4). That is, I allow cable news outlets to react differently to President Trump's tweets according to the content being addressed on each of these statements.

One result stands out – contrary to what would be expected, cable news outlets tended to cover all types of Trump tweets (from tweets related to immigration to tweets concerning foreign policy; see Figures A.1.21). Moreover, I do not find any evidence of cable outlets having followed a significantly different coverage of Trump tweets, both in terms of how

[30]Estimates for 2020 can be seen as counter-intuitive. In fact, during an electoral year, it would be expected that cable outlets would have increased their coverage of Donald J. Trump's statements instead of further decreasing it. Still, this result can be potentially explained by Covid crowding out cable and broadcast news (Budak et al., 2021).

[31]In other words, only a share of these statements is interesting to channels' audiences. News channels learn this over time, progressively narrowing down those statements that are covered, to cater to audiences' preferences.

[32]An alternative argument that can be made in favor of outlets being expected to react differently to different contents is a supply argument – i.e., the editorial bodies of each outlet being idiosyncratically biased, this bias causing each outlet to focus on different distributions of tweets (e.g., Baron, 2006).

[33]These topics span issues as different as "immigration", "news media", "economy", "foreign policy" and more. See Table A.1.11 for a description of each topic. These topics are inferred via a semi-supervised topic model (a CorEx topic model; Gallagher et al., 2017) which is estimated using a set of topic anchors that are instead inferred from a bootstrap-like routine à la Mäntylä et al. (2018). Appendix A.1.5.2 provides additional details.

much time did each outlet spend on specific topics (see Figure A.1.22) and in terms of the average tone being used to cover specific contents (see Figure A.1.23).

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 January 2021 (not included). This dataset has been assembled due to a Google Cloud (Link) Covid-19 research grant awarded to a partnership between the TV News Archive (Link) and GDELT (Link) – see `here` for more details.

Public opinion concerning President Trump. Data on timestamped interviews, each interview having (i) a set of news consumption questions and (ii) questions regarding Donald J. Trump, both as a president and as a presidential candidate. Collected as part of a large public opinion survey from January 2020 to January 2021 (not included), by Democracy Fund + UCLA Nationscape (Link).[34]

[34]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 ≈ 6,250 individuals during each week, to measure public opinion for a sample representative of the U.S. adult population. 1,000+ individuals were interviewed within each day. Interviews were conducted online, be it through a networked computer or a mobile device, and were designed to be completed in a 15-minute span.

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 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 16+ hours of imagery featuring a Donald J. Trump tweet (see Figure A.2.1). Interestingly, short-run coverages of Trump tweets (i.e., broadcasts that happened up to 3 hours after the posting of a tweet) represented only 12 percent of the total amount of time that cable networks spent covering these statements (see Figure A.2.2). Lastly, while Fox News spent more time covering President Trump's tweets, CNN was more likely to broadcast a Trump tweet during primetime (see Figure A.2.3).

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 Figure A.2.5 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.[35]

3.2 Empirical Strategy

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

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

where $\textit{trump\_approval}_{i,\,g,\,n,\,w,\,\tau}$ stands for the rating that individual i of group g gave to Donald J. Trump during relative time period τ of event window (n, w).[36][37] $\alpha_{g,\,n,\,w}$ stands for a group × network × window fixed effect aimed at controlling for, among other aspects, time-varying macro factors that are assumed to affect differently how each group of news consumers rates Trump. $\textit{broadcast}_{n,\,w,\,0}$ is a treatment variable that measures how much time network n spent showing a Trump tweet on-screen during relative time period 0 of window w.[38] β_k^{η} is a standard differences-in-differences event-study coefficients specific to network η and relative time period k. $\mathbf{X}_i$ is a set of individual-specific controls.[39] I estimate Eq. (5) through ordinary least squares (OLS) and I cluster standard errors at a group × network × event window level, accordingly.

The coefficient of interest, β_k^{η}, is estimated by comparing the ratings of Donald J. Trump as President across two different groups of news consumers: (a) individuals that watch

35 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).

36 Note that g can stand either for (a) a group of individuals that only watch n and simultaneously do not consume any online news (labelled as "*watches n*") or (b) a group of respondents that do not watch cable news nor consume any online news.

37 In what follows, τ stands for a 3-hour time period. Furthermore, an "*event window* (n, w)" refers to a narrow time interval centered around an instance in which network n explicitly showed a Trump tweet on-screen.

38 Rescaled so that it has an observed mean of 0 and a standard deviation (S.D.) equal to 1. Note that this re-scaling is done for each outlet separately, to account for differences in broadcast across networks.

39 Namely, age, race, gender, census region, education and household income.

outlet η versus (b) individuals that do not watch cable news.[40][41] This coefficient can provide a causal estimate for how the coverage of a Trump tweet by network η affects the views that the audience of that network has about President Trump, under a parallel trends assumption. In other words, β_k^η can be interpreted as causal if the Trump ratings from both groups of news consumers would have evolved in parallel had a tweet not been broadcasted by outlet η. To corroborate this assumption, I estimate Eq. (5) with a set of pre-broadcast coefficients, to test whether both groups rated Trump similarly prior to a broadcast of a Trump tweet.[42]

Conditional on this assumption, the interaction between group and network $\times$ window fixed effects allows me to control for a host of factors that could act as confounders when interpreting β_k^η. To start, I am able to control for time-invariant differences in Trump's ratings, across audiences. To give an example, individuals that do not watch cable news may have been consistently more moderate than cable viewers. This would make them rate Donald Trump more neutrally. Not controlling for this fact could then give rise to overstatements when interpreting β_k^η. In particular, in this case, β_k^η would not only measure the effect of a Trump tweet being shown on cable on cable news audiences but it would also speak to the average differences across the Trump views of both groups of news consumers.

Second, I rule out time-variant factors that affect both groups homogeneously. An example of an episode of this type is a school shooting. This is an event that is likely to be covered equally across news sources and thus, is expected to dictate similar changes in both groups' views about Trump. Third, I cast aside concerns related to time-variant factors that affect groups heterogeneously. An example of an event of this kind would be a political scandal, an event that is likely to be covered asymmetrically across news sources (i.e., cable vs. non-cable). This asymmetry in coverage would translate into each group of news consumers updating their Trump views differently. Not controlling for these differences could give rise to either an under or over interpretation of β_k^η, depending on how both sources differed over time in terms of their coverage of these matters.

[40] To better argue that those individuals taken as treated and control were respectively exposed and not exposed to a Trump tweet, I further restrict this comparison to respondents that do not use social media to gather their political news. This second restriction is put in place to avoid cases in which respondents are aware of a Trump tweet from sources other than cable, that are likely to cover Trump's activities on Twitter (in this case, online news outlets).

[41] Again, a one standard deviation (S.D.) specific to outlet η: for CNN, a 1 S.D. long broadcast translates into a showing of 14 seconds; for Fox News, a showing of 17 seconds; for MSNBC, a showing of 18 seconds.

[42] Moreover, I perform different balance tests to argue that both groups were similarly "identical" both pre and post Trump tweets showings (i.e., "identical" along an array of demographics relevant at explaining support for Trump, conditional on those fixed effects used to estimate Eq. 5).

A last identification concern relates to how often did cable outlets cover Donald Trump's tweets within a day – in fact, TV channels tended to explicitly show Trump tweets on-screen on average 3 times a day. Such a recurrent coverage of Trump tweets gives rise to event windows that partially overlap across calendar time (both within and across cable outlets).[43] This type of overlap across event windows does not allow for a clear cut distinction between pre and post-broadcast periods, biasing β_k^η.[44]

To address this issue I proceed in two ways. As in Section 2.2, I first implement a stacked design (see e.g., Cengiz et al., 2019). In particular, I restrict myself to studying an event window specific treatment group (i.e., within an event window (n, w), I take as treated those individuals that claim to *only* watch outlet η). This restriction allows for an unbiased estimation of β_k^η if and only if those event windows that share a same outlet do not partially overlap across calendar time.[45][46]

Second, to partially address this pre-requisite, I assume that only abnormally long types of coverages have a non-zero treatment effect. Then, I estimate Eq. (5) by using only those event windows that do not partially overlap across time with event windows from a same outlet where a Trump tweet was shown during an abnormally long period of time (2 S.D. $\approx$ 37 seconds).[47] This sample restriction comes with implications for how β_k^η should be interpreted. 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 showings, from a same outlet, that took a significant amount of time. In practice, this class of broadcasts

[43] Cable outlets broadcasted Trump's tweets 3,055 times during 2020 (CNN showed a Trump tweet on-screen 864 times, Fox News 1,114 times, MSNBC 1,077 times). 2,951 (97%) of these windows partially overlap across calendar time (taking event windows as time intervals with a duration of 15h, as in Eq. 5; note that longer event windows translate into more overlaps – e.g., windows that stretch for 33h map into a 100% overlapping rate).

[44] As described in Section 2.2, for those windows that partially overlap across calendar time, a subset of pre and post-broadcast periods from specific event windows will be wrongly taken as post and pre-broadcast periods in other event windows, respectively. Again, similar to a differences-in-differences (DiD) setting with staggered treatment (see De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021; Wooldridge, 2021; Baker et al., 2022; Borusyak et al., 2022). Or, more specifically, comparable to a DiD setting with multiple treatments where coefficients referent to a specific treatment are contaminated with information from different treatments (Goldsmith-Pinkham et al., 2022).

[45] Moreover, I restrict control units to never-treated types of individuals. First, by taking individuals that do not watch *any* type of cable news. Second, by further restricting myself to studying a subset of these individuals that are not on social media, thus, being significantly less likely to be aware of a Trump tweet (i.e., being treated) from other sources.

[46] Within outlets, 1,509 (49%) event windows partially overlap across calendar time (taking event windows as time intervals with a duration of 15h, as in Eq. (5); again, wider event windows imply more overlaps – windows of 33h generate an overlapping rate of 94%).

[47] I corroborate this assumption by estimating an extension of Eq. (5) in which I allow for cable news audiences to react differently to a showing of a Trump tweet according to a duration of a showing (in particular, if below or above median).

appers to be representative of cable outlets' showings of Trump tweets, meaning that, β_k^η can be interpreted as an average treatment effect.[48]

3.3 Main Results

Event-studies. Panels 3.4.1a, A.2.8a and A.2.8b plot the coefficients from estimating Eq. (5). Panel 3.4.1a refers to the coefficients that are specific to CNN showings. Panels A.2.8a and A.2.8b show similar estimates for Fox News and MSNBC, respectively.

Two results stand out. First, CNN's broadcasts of Trump tweets caused CNN viewers to worsen their views about Trump hours after a broadcast. More specifically, a 1 standard deviation (S.D.) long showing of a Trump tweet caused an average 6 percent decrease in CNN viewers' ratings of Trump (in between 3 to 9 hours post a CNN broadcast; relative to individuals that do not watch cable news and are similar to CNN viewers across different demographic characteristics).[49]

Second, I do not find any such results for Fox News and MSNBC. This second set of results should be interpreted with caution, nonetheless. In an heterogeneity analysis to be discussed in Section 3.4, I show that the broadcast of Trump tweets by Fox News caused real changes in how Fox News viewers rated Donald Trump. Alternatively, the estimates referent to MSNBC are likely to be underpowered due to a severe under-representation of MSNBC viewers on the estimation sample of Eq. (5).[50]

Pre-posts. The previous trends in public opinion were not persistent over time. In particular, CNN viewers seem to have consistently reverted back to their pre-broadcast priors 12 hours after a 1 standard deviation long showing of a tweet. To rate then whether this temporary shift in opinions translated into a significant post-broadcast development in how cable news viewers evaluated Donald Trump, I estimate the following pre-post regression:

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

[48] In particular, this class of showings represents 87% of all broadcasts made by cable outlets (see Figure A.2.6). Moreover, it follows well cable outlets' within-day broadcast patterns of Trump's tweets (see Figure A.2.7).

[49] Both groups of news consumers are indiscernible along a wide array of demographic controls (age, race, gender, income and education) after controlling for group × network × window fixed effects (see Table A.2.3 for more details).

[50] Both in absolute terms and relative to CNN and Fox News – see Table (A.2.1).

where β^{η}_{post} stands for a standard differences-in-differences post coefficient that measures on average how a viewer of network η compared with an individual that did not watch cable news (i.e., in terms of how both individuals rated Donald Trump, post a showing).

Table A.2.4 shows the coefficients from estimating Eq. (6). On average, a 1 standard deviation long CNN showing of a Trump tweet caused CNN viewers to revise their Trump ratings negatively by 2 percent (p-value 0.196). This result reinforces previous estimates – an average broadcast of a Trump tweet on CNN caused this outlet's viewers to revise their views about Donald J. Trump downwardly; these same updates in how CNN viewers rated Donald Trump as President were nonetheless short-lived.[51]

3.4 Robustness Checks

3.4.1 Parallel Trend Concerns

The past results can be driven by individuals that do not watch cable news thus, being likely unrelated to the broadcasting of Trump tweets by cable outlets. To give an example, news events that would be expected to influence how individuals rate Donald Trump could be exclusively covered by non-cable outlets hours after cable networks broadcasted Trump's tweets. In this case, respondents that do not watch cable news would be expected to revise their views about Trump after a cable news broadcast of a Trump tweet.

To rule out then concerns that the previous findings were exclusively driven by individuals that do not watch cable news, I extend Eq. (5) to allow both audiences to rate Donald Trump differently along each event-window:

$$\begin{aligned} \text{trump\_approval}_{i,g,n,w,\tau} &= \alpha_{g,n,w} + \mathbb{1}\{g\text{: ``}\textit{no cable}\text{''}\} \times \\ &\times \Omega_{\text{``}\textit{no cable}\text{''}} + \mathbb{1}\{g\text{: ``}\textit{watches n}\text{''}\} \times \Omega_{\text{``}\textit{watches n}\text{''}} + \mathbf{X}_i + \varepsilon_{n,w,\tau} \end{aligned} \tag{7}$$

where,

$$\Omega_r = \sum_{\eta \in \{C,F,M\}} \sum_{\substack{k=-3,\\ k\neq -1}}^{3} \mathbb{1}\left\{\substack{n=\eta,\\ \tau=k}\right\} \times \text{broadcast}_{n,w,0} \times \beta^{\eta,r}_{k}$$

[51]The post coefficients referent to Fox News and MSNBC are in absolute terms two orders of magnitude smaller than those from CNN (with p-values of 0.394 and 0.732, respectively).

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

Encouragingly, the estimation of Eq. (7) corroborates previous results. Namely, those changes in Trump's approval ratings taking place hours after a CNN showing of a Trump tweet are exclusively driven by CNN viewers worsening their opinions concerning President Trump (see Panel 3.4.1b). Alternatively, the audiences from both Fox News and MSNBC do not change their views about Trump hours after a showing of a tweet by these outlets (see Panels A.2.9a and A.2.9b respectively).

3.4.2 Omitted Variable Concerns

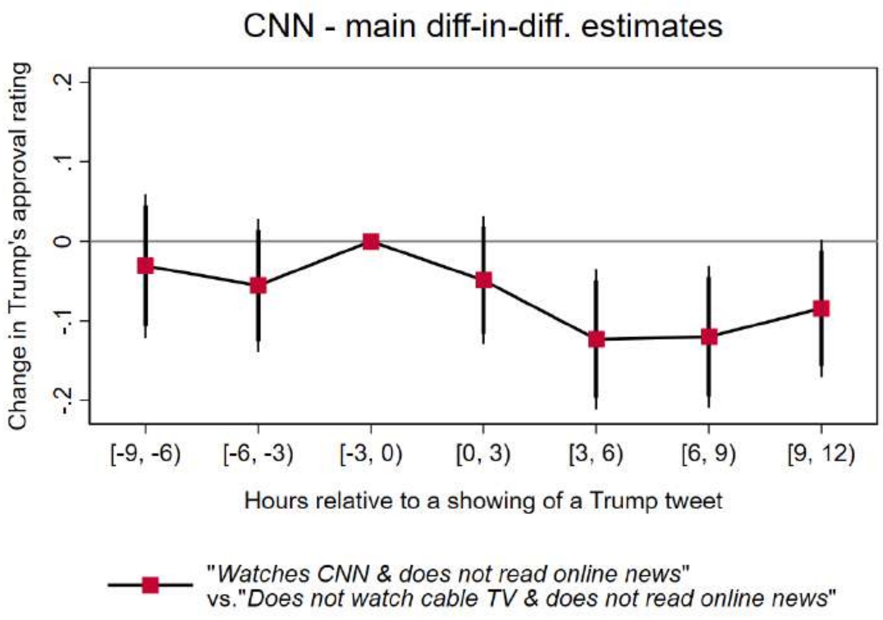
A similar concern relates to whether the individuals that watch specific cable outlets changed their views hours after a showing of a tweet only because of that showing or, alternatively, also due to a news event that was only covered by specific news outlets.[52] An example where this could happen would be a pressing event related to Donald Trump – e.g., an anti-Trump statement by Democrat congress-members – that would prompt specific outlets to air a story where a tweet related to that same issue would be shown.

To address this issue, I proceed as in Section 2.4.2. I first construct a similarity measure that compares the text of the tweets broadcasted on-screen at each event window with the text of the news posted online up to 18 hours before and after each showing. After, I distinguish broadcasts according to how the tweets covered in each showing related to neighboring news. Last, I estimate a version of Eq. (5) in which I allow individuals to react differently to broadcasts that are related and unrelated with recent news.

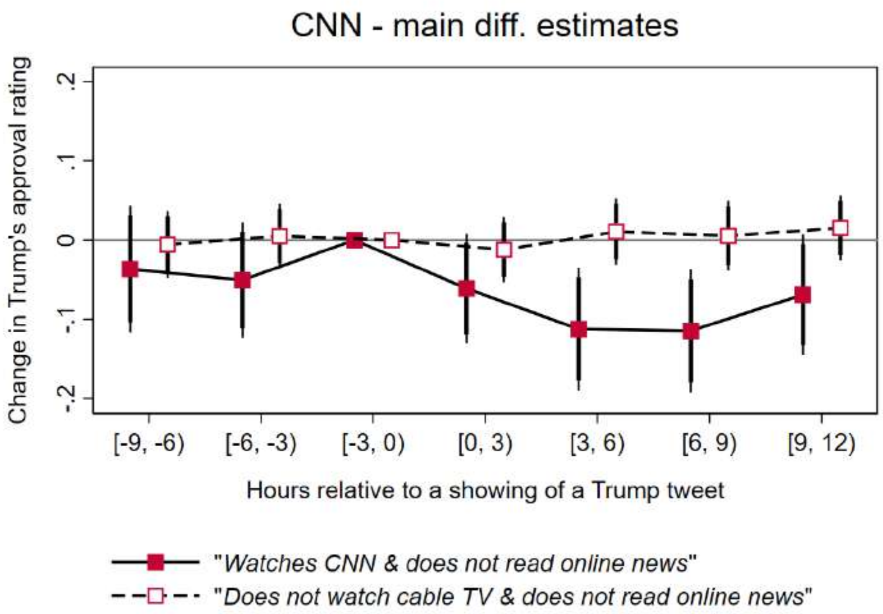
The estimation of this extended equation authenticates previous findings. In particular, a showing of a tweet by CNN caused CNN viewers to revise their opinions about Trump downwardly, independently of how the tweet being shown on-screen related to recent news (see Panels A.2.10a and A.2.10a for tweets seemingly unrelated and related to neighboring events, respectively). As before, Fox News and MSNBC viewers were on average insensitive to both types of showings (see Figures A.2.12 and Figures A.2.14).[53]

[52] Thus, possibly not affecting individuals that do not watch cable.

[53] In addition, to understand whether these findings were exclusively driven by cable news viewers (i.e., to rule out those concerns tackled in Section 3.4.1), I estimate an extension of Eq. (7) where I allow each group of news consumers to rate Donald Trump differently along two different types of cable broadcasts: showings of tweets that were seemingly related and unrelated to neighboring news stories, accordingly. This exercise further corroborates previous conclusions: a CNN showing of a tweet unrelated to recent news caused a deterioration of Trump's approval ratings only for CNN viewers (see Panel A.2.10b.)



(a) **Differences-in-differences**



(b) **Differences**

Figure 3.4.1: **Event-study estimates – CNN**. The figure plots CNN coefficients from different event-study regressions. Panel (a) shows CNN coefficients from a diff.-in-diff. event-study regression as in Equation 5. Panel (b) instead shows CNN coefficients referent to an event-study regression as in Equation 7. The dependent variable is an approval ratings measure of Trump taking five values: (1) "*strong disapprove*", (2) "*somewhat disapprove*", (3) "*not sure*", (4) "*somewhat approve*" and (5) "*strongly approve*". The error bars refer to 95% confidence intervals drawn from standard errors clustered at a network $\times$ window level.

3.5 Heterogeneity Analyses

3.5.1 Heterogeneity by Time-Of-Day

Previous estimates implicitly assume that the broadcast of Trump tweets by cable news outlets affects these outlets' audiences homogeneously within the day. This assumption nonetheless abstracts from a key fact related to cable news viewership – TV networks tend to have significantly more viewers during primetime (i.e., from 8pm to 11pm; see Pew, 2021). Having this fact into account, it is then expectable that primetime coverages of Trump tweets have a wider impact on cable news audiences.

With this in mind, in this section I allow for a broadcast of a Trump tweet to have different effects over cable news audiences according to when is this broadcast aired within a day. To do so, I extend Eq. (5) as follows:

$$\text{trump\_approval}_{\,i,\,g,\,n,\,w,\,\tau} = \alpha_{\,g,\,n,\,w} + \mathbf{X}_i + \sum_{t=1}^{4} \mathbb{1}\left\{\begin{matrix}\text{w: “\textit{showing}} \\ \textit{during t”}\end{matrix}\right\} \times \Omega_{\,t} + \varepsilon_{\,n,w,\tau} \qquad (8)$$

where t stands for a time-of-day slot in which a broadcast of a Trump tweet can take place (t takes four values: $1 \equiv$ dawn, from 1am to 6am; $2 \equiv$ morning, from 7am to 12am; $3 \equiv$ afternoon, from 1pm to 6pm; $4 \equiv$ primetime, from 7pm to 11pm)[54] and,

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

where $\beta_k^{\eta,\,t}$ measures how differently were outlet η's viewers rating Donald Trump, relative to a group of individuals that do not watch cable, k periods away from a one standard deviation long showing of a Trump tweet (by outlet η, during time-of-day t).

To address identification concerns such as those discussed in Section 3.4.2, I further distinguish between tweets that are and are not related to neighboring news events. In particular, I extend Eq. (8) to allow for news audiences to react differently within a day to each type of tweet. To avoid spurious conclusions, I only discuss those changes in public opinion that are associated to tweets seemingly unrelated to current news. I find two results. First, CNN viewers revised their Trump ratings downwardly only after

[54]Each time-of-day slot is defined in Eastern Standard Time (EST).

primetime showings of Trump tweets (see Figure A.2.16). Second, those showings that happened at Fox News during primetime translated into a significant improvement in how Fox News viewers rated Donald J. Trump as President (see Figure A.2.17).[55]

Altogether, these findings show that television broadcasts of social media content causally affects audiences' political opinions.

4. Conclusion

Social media provides politicians with a tool through which sentimentally charged statements can be released more easily. These statements can shape voters' opinions, attitudes and voting behaviors. Past literature has focused exclusively on measuring these effects over social media users. While doing so, it has abstracted from the interconnectedness of modern media platforms. This paper provides a first causal quantification of the spillover effects of social media through traditional news media, namely, television news.

I first show that cable news outlets actively amplified Donald J. Trump's tweets through their coverage. So far so that President Trump had an agenda-setting power over cable news outlets through his tweets (i.e., he was able to *cause* cable outlets to change their focus of coverage simply by tweeting). This finding represents a first causal account of a politician's agenda-setting power over media content. Furthermore, it opens up an important question – did Donald J. Trump use his Twitter presence strategically, shifting cable news attention away from topics harmful to his platform support (similar to Gratton et al., 2018) or detrimental to his executive action (à la Djourelova and Durante, 2021)? I leave this question, together with other analyses, for future research.

Second, I find that coverages of Trump's tweets by cable news outlets caused significant changes in how cable news audiences' rated Donald Trump as President. Namely, CNN's showings caused this outlet's viewers to worsen their opinions about Trump hours after a showing. Fox News' broadcasts translated instead into significant improvements in Trump's approval ratings. These findings shed a first light on how social media can affect offline audiences and come with important policy implications. To give an example, in light of this paper, content moderation policies in social media can have an impact on the distribution of content being discussed in other media platforms. Future assessments of these policies should take these effects into account.

[55] I refrain from discussing the results referent to MSNBC as this network is severely under-represented in the sample used to estimate the extension of Eq. (8) – as discussed in Section 3.3.

References

Allcott, H., Braghieri, L., Eichmeyer, S., and Gentzkow, M. (2020). The Welfare Effects of Social Media. *American Economic Review*, 110(3):629–76. [URL].

Armona, L. (2019). Online Social Network Effects in Labor Markets: Evidence From Facebook's Entry into College Campuses. *SSRN Research Paper Series*. SSRN 3381938 [URL].

Ash, E., Galletta, S., Pinna, M., and Warshaw, C. (2021). The Effect of Fox News Channel on U.S. Elections: 2000-2020. *SSRN Research Paper Series*. SSRN 3837457 [URL].

Ash, E. and Poyker, M. (2020). Conservative News Media and Criminal Justice: Evidence from Exposure to Fox News Channel. *SSRN Research Paper Series*. [URL].

Axios (2017). Trump 101: What He Reads and Watches. Written by Jim VandeHei and Mike Allen on Jan. 24, 2017 [URL].

Axios (2019). Scoop: Insider Leaks Trump's "Executive Time"-filled Private Schedules. Written by Alexi McCammond and Jonathan Swan on Feb. 3, 2019 [URL].

Baker, A., Larcker, D. F., and Wang, C. C. Y. (2022). How Much Should We Trust Staggered Difference-In-Differences Estimates? *Journal of Financial Economics*, 144(2):370–395. [URL].

Barberá, P., Casas, A., Nagler, J., Egan, P. J., Bonneau, R., Jost, J. T., and Tucker, J. A. (2019). Who Leads? Who Follows? Measuring Issue Attention and Agenda Setting by Legislators and the Mass Public using Social Media Data. *American Political Science Review*, 113(4):883–901. [URL].

Baron, D. P. (2006). Persistent Media Bias. *Journal of Public Economics*, 90(1-2):1–36. [URL].

Bessone, P., Campante, F., Ferraz, C., and C.L. Souza, P. (2022). Internet, Social Media, and the Behavior of Politicians: Evidence from Facebook in Brazil. *NBER Working Paper Series*. W30306 [URL].

Borusyak, K., Jaravel, X., and Spiess, J. (2022). Revisiting Event Study Designs: Robust and Efficient Estimation. *SSRN Research Paper Series*. SSRN 4121430 [URL].

Braghieri, L., Levy, R., and Makarin, A. (2022). Social media and mental health. *American Economic Review*, 112(11):3660–93. [URL].

Budak, C., Muddiman, A., Kim, Y., Murray, C. C., and Stroud, N. J. (2021). COVID-19 Coverage By Cable and Broadcast Networks. In *ICWSM*, pages 952–960. [URL].

Bursztyn, L., Egorov, G., Enikolopov, R., and M., P. (2019). Social Media and Xenophobia: Evidence from Russia. *NBER Working Paper Series*. W26567 [URL].

Bursztyn, L., Egorov, G., and Fiorin, S. (2020a). From Extreme to Mainstream: The Erosion of Social Norms. *American Economic Review*, 110(11):3522–48. [URL].

Bursztyn, L., Rao, A., Roth, C., and Yanagizawa-Drott, D. (2020b). Misinformation During a Pandemic. *NBER Working Paper Series*. W26669 [URL].

Cagé, J., Hervé, N., and Mazoyer, B. (2022). Social media and newsroom production decisions. *CEPR Discussion Paper Series*. CEPR DP17358 [URL].

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-Differences with Multiple Time Periods. *Journal of Econometrics*, 225(2):200–230. [URL].

Campante, F. R. and Hojman, D. A. (2013). Media and Polarization: Evidence from the Introduction of Broadcast TV in the United States. *Journal of Public Economics*, 100:79–92. [URL].

Cengiz, D., Dube, A., Lindner, A., and Zipperer, B. (2019). The Effect of Minimum Wages on Low-Wage Jobs. *The Quarterly Journal of Economics*, 134(3):1405–1454. [URL].

CrowdTangle (Link). https://www.crowdtangle.com/ [URL].

De Chaisemartin, C. and d'Haultfoeuille, X. (2020). Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. *American Economic Review*, 110(9):2964–96. [URL].

DellaVigna, S. and Kaplan, E. (2007). The Fox News Effect: Media Bias and Voting. *The Quarterly Journal of Economics*, 122(3):1187–1234. [URL].

Democracy Fund + UCLA Nationscape (Link). https://www.voterstudygroup.org/nationscape [URL].

Djourelova, M. (2020). Media Persuasion through Slanted Language: Evidence from the

Coverage of Immigration. *BSE Working Paper*. WP1177 [URL].

Djourelova, M. and Durante, R. (2021). Media Attention and Strategic Timing in Politics: Evidence from U.S. Presidential Executive Orders. *American Journal of Political Science*, 66(4):813–834. [URL].

Durante, R., Pinotti, P., and Tesei, A. (2019). The Political Legacy of Entertainment TV. *American Economic Review*, 109(7):2497–2530. [URL].

Enikolopov, R., Makarin, A., and Petrova, M. (2020). Social Media and Protest Participation: Evidence from Russia. *Econometrica*, 88(4):1479–1514. [URL].

Enikolopov, R., Petrova, M., and Zhuravskaya, E. (2011). Media and Political Persuasion: Evidence from Russia. *American Economic Review*, 101(7):3253–85. [URL].

Fergusson, L. and Molina, C. (2020). Facebook Causes Protests. *SSRN Research Paper Series*. SSRN 3553514 [URL].

Fujiwara, T., Müller, K., and Schwarz, C. (2021). The Effect of Social Media on Elections: Evidence from the United States. *NBER Working Paper Series*. WP28849 [URL].

Gallagher, R. J., Reing, K., Kale, D., and Ver Steeg, G. (2017). Anchored Correlation Explanation: Topic Modeling with Minimal Domain Knowledge. *Transactions of the Association for Computational Linguistics*, 5:529–542. [URL].

Galletta, S. and Ash, E. (2019). How Cable News Reshaped Local Government. *SSRN Research Paper Series*. SSRN 3082972 [URL].

GDELT (Link). https://www.gdeltproject.org/ [URL].

Gentzkow, M. (2006). Television and voter turnout. *The Quarterly Journal of Economics*, 121(3):931–972. [URL].

Gilardi, F., Gessler, T., Kubli, M., and Müller, S. (2022). Social Media and Political Agenda Setting. *Political Communication*, 39(1):39–60. [URL].

Goldsmith-Pinkham, P., Hull, P., and Kolesár, M. (2022). Contamination Bias in Linear Regressions. *NBER Working Paper Series*. W30108 [URL].

Goodman-Bacon, A. (2021). Difference-in-Differences with Variation in Treatment Timing. *Journal of Econometrics*, 225(2):254–277. [URL].

Google Cloud (Link). https://cloud.google.com/ [URL].

Gratton, G., Holden, R., and Kolotilin, A. (2018). When to Drop a Bombshell. *The Review of Economic Studies*, 85(4):2139—2172. [URL].

James, C., Banducci, S., Cioroianu, I., Coan, T., Katz, G., and Stevens, D. P. (2019). Flows of Information in Election Campaigns: Who Influences Whom? *SSRN Research Paper Series*. SSRN 3722044 [URL].

Kim, E., Lelkes, Y., and McCrain, J. (2022). Measuring Dynamic Media Bias. *Proceedings of the National Academy of Sciences*, 119(32):e2202197119. [URL].

La Ferrara, E., Chong, A., and Duryea, S. (2012). Soap Operas and Fertility: Evidence from Brazil. *American Economic Journal: Applied Economics*, 4(4):1–31. [URL].

Levy, R. (2021). Social Media, News Consumption, and Polarization: Evidenve from a Field Experiment. *American Economic Review*, 111(3):831–870. [URL].

Martin, G. J. and Yurukoglu, A. (2017). Bias in Cable News: Persuasion and Polarization. *American Economic Review*, 107(9):2565–99. [URL].

McCombs, M. E. and Shaw, D. L. (1972). The Agenda-Setting Function of Mass Media. *Public Opinion Quarterly*, 36(2):176–187. [URL].

McCombs, M. E. and Shaw, D. L. (1993). The Evolution of Agenda-Setting Research: Twenty-five Years in the Marketplace of Ideas. *Journal of Communication*, 43(2):58–67. [URL].

Melnikov, N. (2021). Mobile Internet and Political Polarization. *SSRN Research Paper Series*. SSRN 3937760 [URL].

Mosquera, R., Odunowo, M., McNamara, T., Guo, X., and Petrie, R. (2020). The Economic Effects of Facebook. *Experimental Economics*, 23(2):575–602. [URL].

Mullainathan, S. and Shleifer, A. (2005). The Market for News. *American Economic Review*, 95(4):1031–1053. [URL].

Müller, K. and Schwarz, C. (2018). From Hashtag to Hate Crime: Twitter and Anti-minority Sentiment. *SSRN Research Paper Series*. RN 3149103 [URL].

Müller, K. and Schwarz, C. (2021). Fanning the flames of hate: Social media and hate crime. *Journal of the European Economic Association*, 19(4):2131–2167. [URL].

Mäntylä, M. V., Claes, M., and Farooq, U. (2018). Measuring LDA Topic Stability from Clusters of Replicated Runs. In *Proceedings of the 12th ACM/IEEE International Symposium on Empirical Software Engineering and Measurement*, pages 1–4. [URL].

Olken, B. A. (2009). Do Television and Radio Destroy Social Capital? Evidence from Indonesian Villages. *American Economic Journal: Applied Economics*, 1(4):1–33. [URL].

Pennebaker, J. W., Boyd, R. L., Jordan, K., and Blackburn, K. (2015). The Development and Psychometric Properties of LIWC2015. Technical report.

Pew (2020). Cable TV and COVID-19: How Americans Perceive the Outbreak and View Media Coverage Differ by Main News Source. Written by Mark Jurkowitz and Amy Mitchell, Washington D.C. [URL].

Pew (2021). More than Eight-in-Ten Americans get News from Digital Devices. Written by Elisa Shearer, Pew Research Center, Washington D.C. [URL].

Pew (2021). State of The News Media – Cable News Fact Sheet. Written by Mason Walker and Naomi Forman-Katz, Washington D.C. [URL].

@realDonaldTrump (Link). https://twitter.com/realdonaldtrump/ [URL].

Rotesi, T. (2019). The Impact of Twitter on Political Participation. *Mimeo*. [URL].

Sun, L. and Abraham, S. (2021). Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects. *Journal of Econometrics*, 225(2):175–199. [URL].

Trump Twitter Archive (Link). https://www.trumptwitterarchive.com/archive/ [URL].

TV News Archive (Link). https://archive.org/details/tv/ [URL].

Twitter API (Link). https://developer.twitter.com/docs/twitter-api/ [URL].

Widmer, P., Ash, E., and Galletta, S. (2020). Media Slant is Contagious. *SSRN Research Paper Series*. SSRN 3712218 [URL].

Wooldridge, J. M. (2021). Two-Way Fixed Effects, the Two-Way Mundlak Regression, and Difference-in-Differences Estimators. *SSRN Research Paper Series*. SSRN 3906345 [URL].

Zhuravskaya, E., Hatte, S., and Madinier, E. (2021). Reading Twitter in the Newsroom: How Social Media Affects Traditional-Media Reporting of Conflicts. *SSRN Research Paper Series*. SSRN 3845739 [URL].

Zhuravskaya, E., Petrova, M., and Enikolopov, R. (2020). Political Effects of the Internet and Social Media. *Annual Review of Economics*, 12:415–438. [URL].

. Appendix

A.1 Cable Coverage of Trump's Tweets

A.1.1 Variables

A.1.1.1 Trump Tweets

Definition

The count variable for Donald J. Trump's tweets is defined as follows:

$$\text{tweets}_{\text{t}} = \left|\{\text{tweet}: \text{ timestamp(tweet)} \in \text{t}\}\right| \tag{9}$$

where *tweet* stands for a Trump tweet; *timestamp*(*tweet*) stands for when in time was that *tweet* posted; t stands for a 15-minute time interval (e.g., first 15 minutes of 1pm).

Methodological note. As described in Section 2.1.2.1, I filter out "*short*" tweets. To be more specific, I start by pre-processing each tweet, i.e.,: (i) I erase non-letter characters; (ii) I cast aside words with a character length lower than 4; (iii) I filter out all English stopwords; (iv) I delete URL links. Afterwards, I rank all pre-processed tweets from shortest to longest (in terms of the number of characters). I label those tweets included in the first ten percentiles of this ranking as "*short*".

Descriptives

Table A.1.1: **Trump tweets – descriptive statistics**

	'15-'20	'15	'16	'17	'18	'19	'20
Total tweets	20,568	2,644	3,408	2,249	3,002	4,472	4,793
Total 15-minutes	15,607	2,122	2,682	1,897	2,478	3,195	3,233
Tweets per 15-minutes	'15-'20	'15	'16	'17	'18	'19	'20
Min.	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p25	1	1	1	1	1	1	1
Median	1	1	1	1	1	1	1
p75	1	1	1	1	1	2	2
Max.	18.0	9.0	14.0	8.0	5.0	13.0	18.0

Notes: The table shows descriptive statistics on a sample of @realDonaldTrump tweets that does not include retweets nor short tweets (i.e., tweets have been "winsorized" according to their dimension, measured by the number of characters; bottom ten percentiles dropped; from 2015 to 2020).

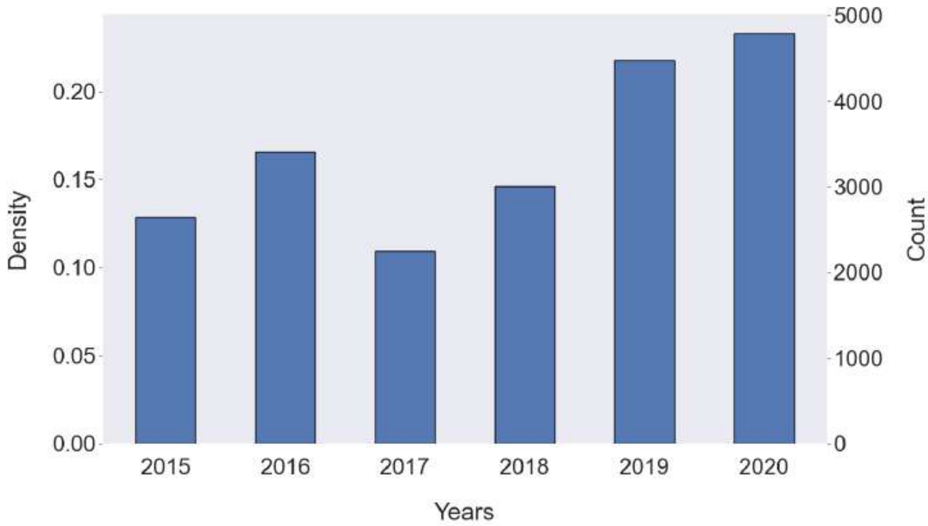


Figure A.1.1: **@realDonaldTrump tweets per year**. The figure plots the number of Trump tweets posted per year, covering a period that goes from 2015 to 2020. It focuses on a specific class of Trump tweets (as in Table A.1.1; no retweets, no short tweets).

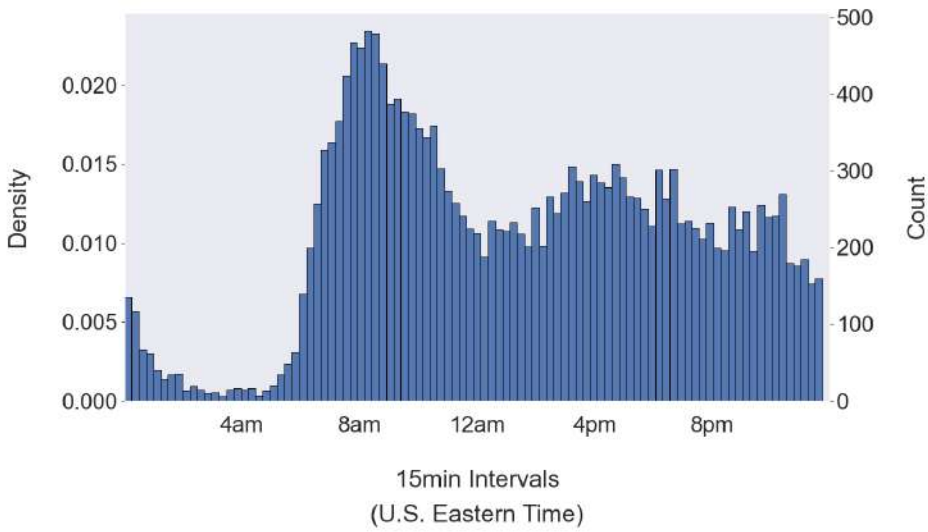


Figure A.1.2: **@realDonaldTrump tweets within a day**. The figure plots the number of Trump tweets posted within a day, per 15 minute interval. It focuses on a specific class of Trump tweets (as in Table A.1.1; no retweets, no short tweets, from 2015 to 2020).

A.1.1.1.1 Event-Windows

Figure A.1.3, below, illustrates a generic event-window:

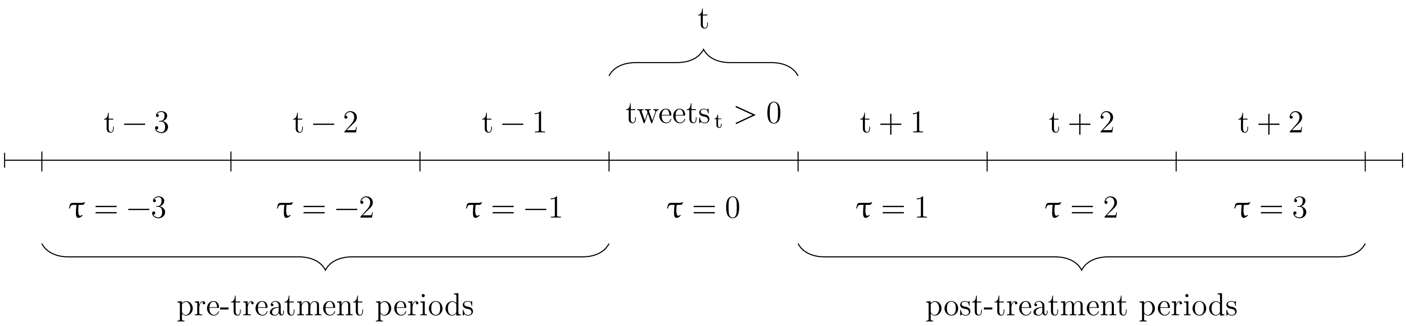


Figure A.1.3: **Event-window.** The figure illustrates a generic event-window with 7 periods, 1 treatment period ($\tau = 0$) and 6 relative-to-treatment periods ($\tau \neq 0$). t stands for absolute time, τ stands for relative-to-treatment time.

In formal terms, let a treatment period be a period in which Donald J. Trump tweeted at least once (i.e., a period in which $tweets_t > 0$). This treatment period defines an event window w composed of k pre-treatment and k post-treatment periods (e.g., if $k = 3$ then each event-window will have a duration of 1h45m – throughout the paper, measures are constructed at a quarter-hourly frequency).

A.1.1.2 Coverage Measures

A.1.1.2.1 Extent of Coverage

Definition.

The extent of coverage measure is defined as follows:

$$\text{extent\_of\_coverage}_{\text{n,w,}\tau} = \sum_{\substack{\text{intervention} \in \\ \text{interventions}_{\text{n,w,}\tau}}} \text{sim}\begin{pmatrix}\text{trigrams(intervention)}, \\ \text{trigrams(tweets}_{\text{w,0}})\end{pmatrix} \tag{10}$$

where $\textit{interventions}_{n,w,\tau}$ stands for every single-person intervention spoken on network n during relative time period τ of window w. *sim* stands for a generic similarity metric.[56]. $\textit{trigrams}\ (\textit{intervention}_{\text{n,w,}\tau})$ stands for every 3-word phrase used in a single-person intervention.[57]. $\textit{trigrams}\ (\textit{tweets}_{w,0})$ stands for every 3-word phrase used in tweets posted during relative time period 0 of event window w.

In essence, $\textit{extent\_of\_coverage}_{n,w,\tau}$ stands for the number of trigrams shared between (a) network n's transcripts from time period (w, τ) and (b) the tweets posted by President Trump during time period $(\text{w}, 0)$.

Descriptives.

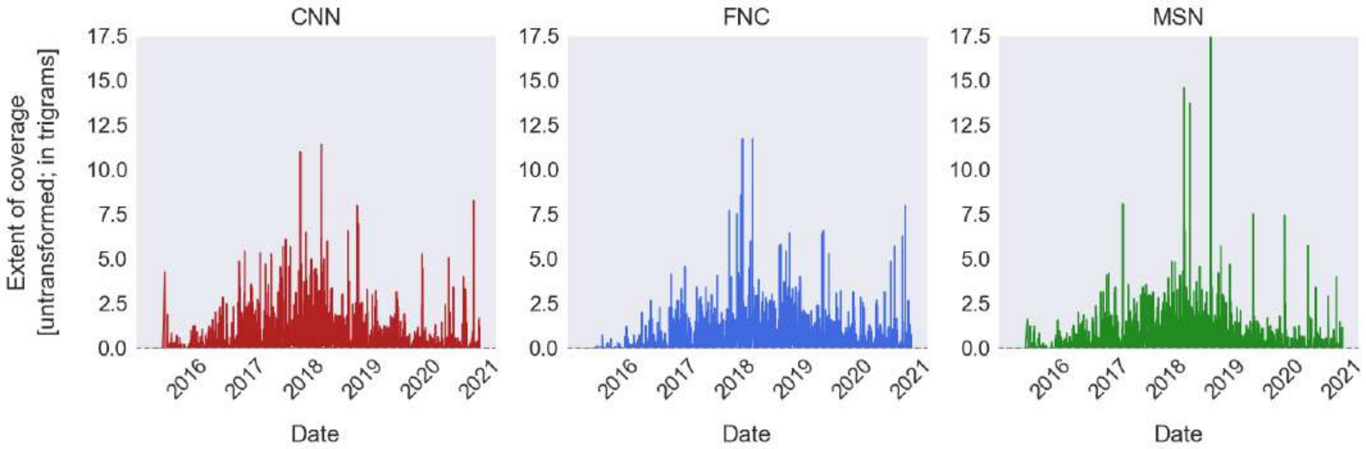
Table A.1.2: **Extent of coverage – descriptive statistics**

	Mean	Std. Dev.	Min.	p25	Median	p75	Max.	Observations
CNN	0.50	3.65	0.00	0.00	0.00	0.00	126.00	79,387
FNC	0.51	3.69	0.00	0.00	0.00	0.00	127.00	79,387
MSN	0.44	3.45	0.00	0.00	0.00	0.00	154.00	79,387

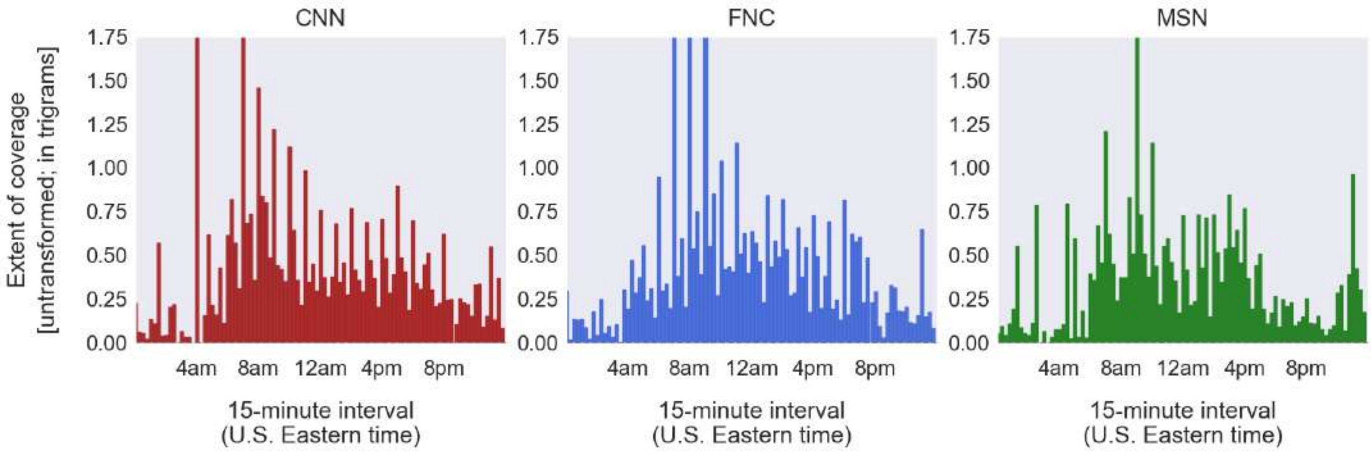
Notes: Statistics built using observations belonging to event windows that did not partially overlap over time and content in simultaneous. These amount to a total of 11,341 windows and cover a total of 59,540 hours of cable news content (≈ 2,480 days).

[56] Throughout the paper, I take *sim* as the intersection of phrases used in a pair of text documents.

[57] I choose to focus on phrases composed by 3 words to minimize the number of times that I erroneously link a cable news passage to a Trump tweet.



(a) **Measure by day**. The figure plots the average extent of coverage of Donald J. Trump's tweets, per day, by network, for event windows that did not overlap over time and content.



(b) **Measure within day**. The figure plots the average extent of coverage of Donald J. Trump's tweets, per day, by network, for event windows that did not overlap over time and content.

Figure A.1.4: **Extent of coverage – descriptive statistics**.

A.1.1.2.2 Intensity of Coverage

Definition

The intensity of coverage measure is defined as:

$$\text{intensity\_of\_coverage}_{n,w,\tau} = \sum_{\substack{\text{intervention} \in \\ \in \text{neighborhoods}_{n,w,\tau}}} \text{duration(intervention)} \times \frac{1}{60} \tag{11}$$

where

$$\text{neighborhoods}_{n,w,\tau} = \left\{ \begin{matrix} \text{intervention} \in \text{interventions}_{n,w,\tau}\text{: } \exists \text{ match} \in \\ \text{matches}_{n,w,\tau}\text{, distance(intervention,match)} \leqslant 8 \end{matrix} \right\}$$

and

$$\text{matches}_{n,w,\tau} = \left\{ \text{intervention} \in \text{interventions}_{n,w,\tau} : \mathbb{1}\left\{ \text{sim}\begin{pmatrix} \text{trigrams(intervention),} \\ \text{trigrams(tweets}_{w,0}) \end{pmatrix} > 0 \right\} \right\}$$

where $duration(intervention_{n,w,\tau})$ stands for how many seconds *intervention* took to be said. $\mathbb{1}\{sim(trigrams(intervention_{n,w,\tau}), trigrams(tweets_{w,0})) > 0\}$ stands for an indicator variable equal to 1 if and only if *intervention* shares at least one 3-word expression with the tweets posted by President Trump during window w.

$matches_{n,w,\tau}$ stands for the set of single-person interventions said during cell (n, w, τ) that shared at least one 3-word expression with the tweets posted by President Trump during window w. $neighborhoods_{n,w,\tau}$ is the set of single-person interventions said during cell (n, w, τ) that are at most 8 interventions away from a "match".

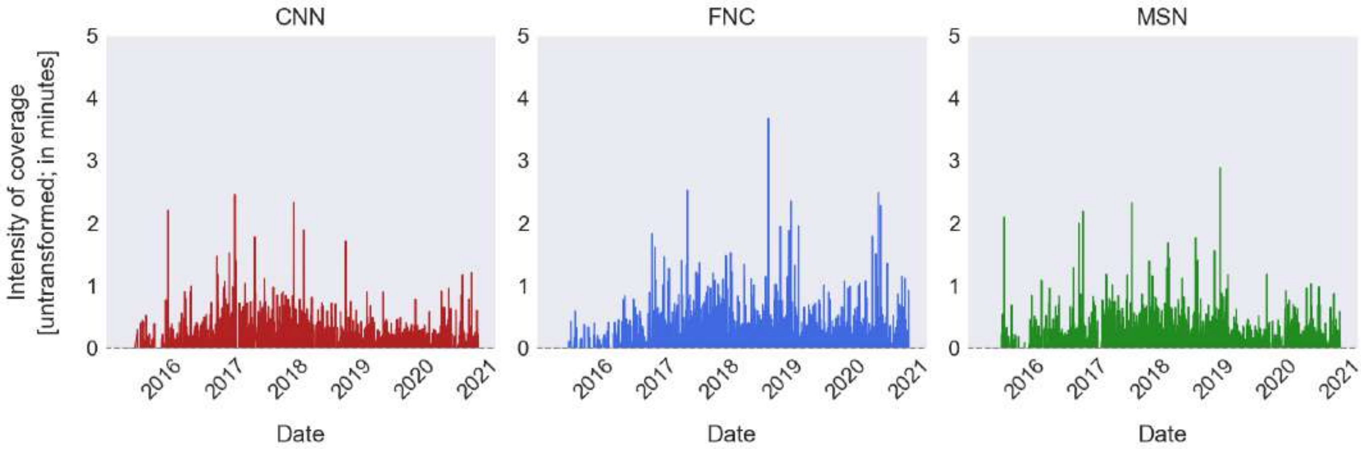
In summary, $intensity\_of\_coverage_{n,w,\tau}$ measures how much time network n spent during cell (w, τ) on issues tweeted by Trump during window w. This measure accounts for interventions taking place close to explicit mentions of tweet-related issue. To take into account that the addressing of an issue is not circumscribed to an explicit mention.

Descriptives

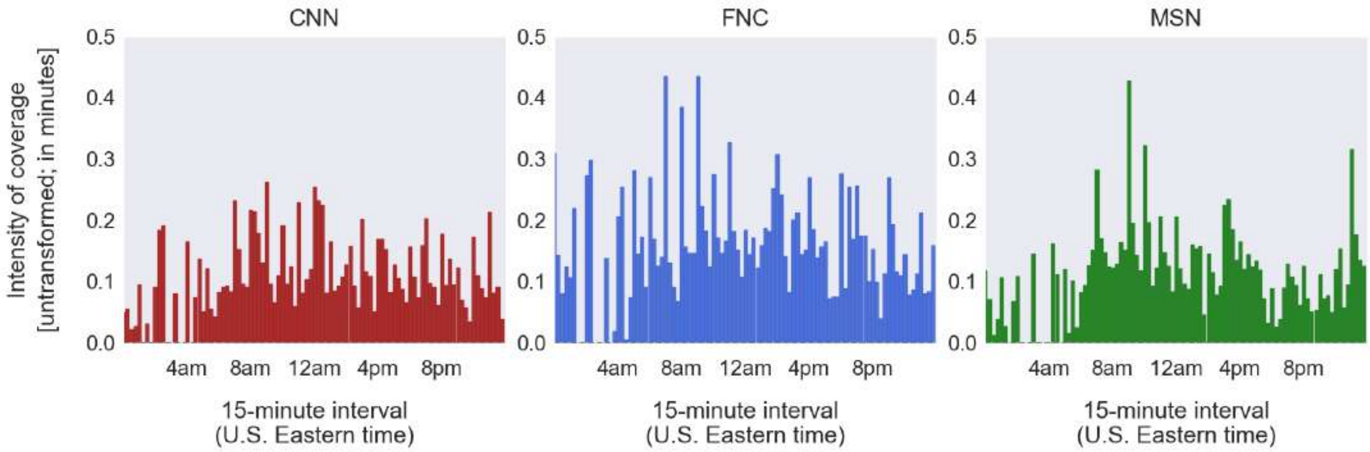
Table A.1.3: **Intensity of coverage – descriptive statistics**

	Mean	Std. Dev.	Min.	p25	Median	p75	Max.	Observations
CNN	0.12	0.99	0.00	0.00	0.00	0.00	15.00	79,387
FNC	0.17	1.21	0.00	0.00	0.00	0.00	15.00	79,387
MSN	0.13	1.04	0.00	0.00	0.00	0.00	15.00	79,387

Notes: Statistics built using observations belonging to event windows that did not partially overlap over time and content in simultaneous. These amount to a total of 11,341 windows and cover a total of 59,540 hours of cable news content (≈ 2,480 days).



(a) **Measure by day**. The figure plots the average intensity of coverage of Donald J. Trump's tweets, per day, by network, for event windows that did not overlap over time and content.



(b) **Measure within day**. The figure plots the average intensity of coverage of Donald J. Trump's tweets, per day, by network, for event windows that did not overlap over time and content.

Figure A.1.5: **Intensity of coverage – descriptive statistics**.

A.1.1.2.3 Sentiment of Coverage

Definition

The sentiment of coverage measure is defined as:

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

where *sentiment* stands for a dictionary-based sentiment score computed at a single-person intervention level. Note that a "*dictionary-based sentiment measure*" stands for the difference between the number of positive and negative words used in a given text document. A word is taken as positive or negative if it is featured in an external dictionary of positive or negative words (LIWC, a set of categorized lexicons ratified by linguistic psychologists; Pennebaker et al., 2015).

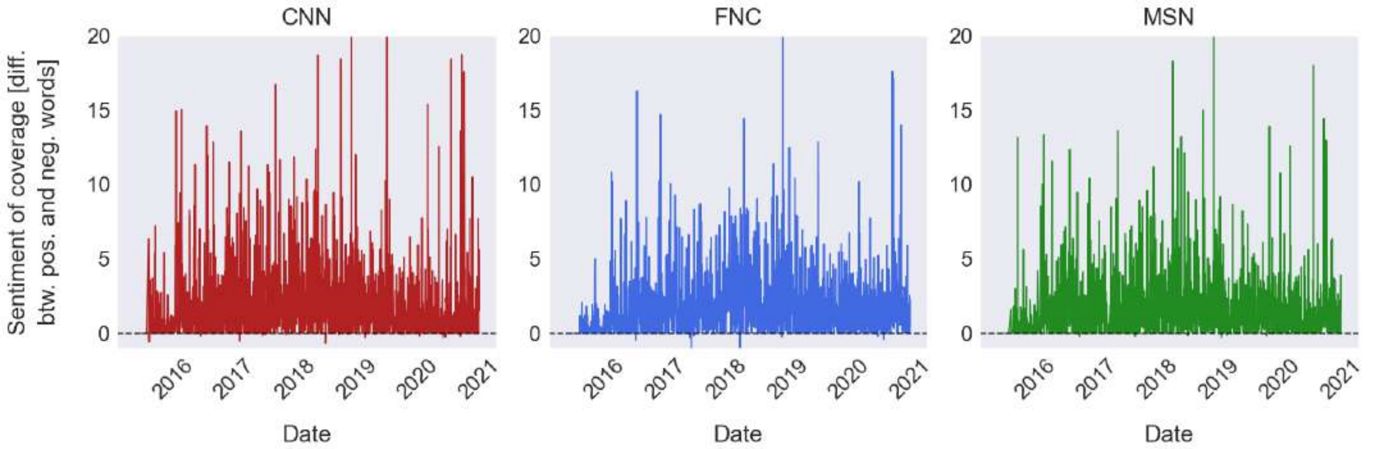
In effect, $\textit{sentiment\_of\_coverage}_{n,w,\tau}$ measures the tone with which network n covered tweet-related issues during (w, τ). As with the intensity of coverage measure, the current variable measures the sentiment of those transcripts neighboring a segment in which a tweet-related issue was explicitly mentioned.

Descriptives

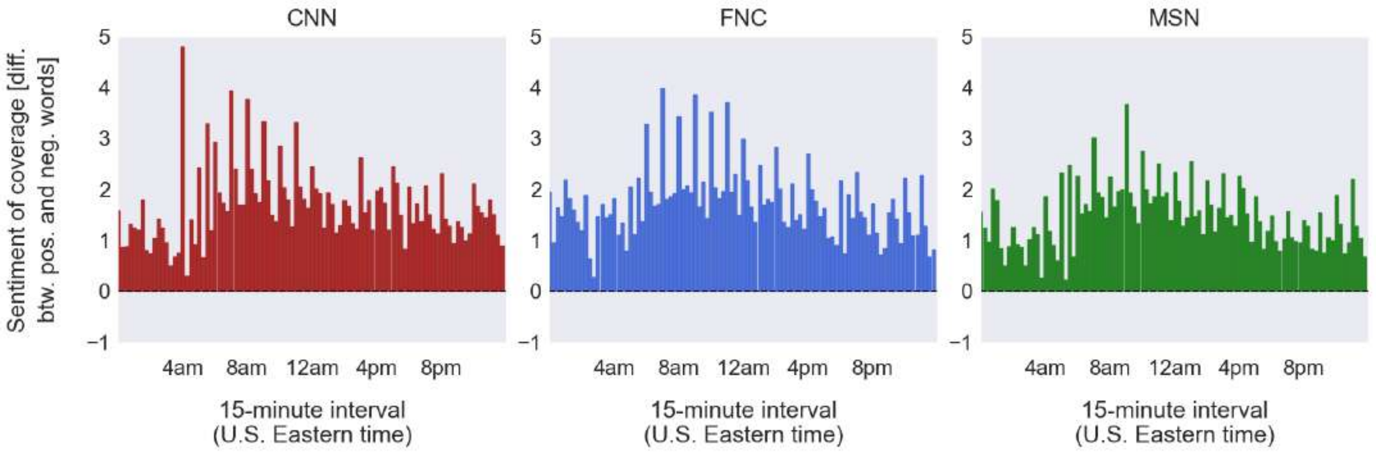
Table A.1.4: **Sentiment of coverage – descriptive statistics**

	Mean	Std. Dev.	Min.	p25	Median	p75	Max.	Observations
CNN	1.84	7.40	-33.00	0.00	0.00	0.00	172.00	79,387
FNC	1.88	7.23	-25.00	0.00	0.00	0.00	198.00	79,387
MSN	1.63	6.72	-19.00	0.00	0.00	0.00	160.00	79,387

Notes: Statistics built using observations belonging to event windows that did not partially overlap over time and content in simultaneous. These amount to a total of 11,341 windows and cover a total of 59,540 hours of cable news content (≈ 2,480 days).



(a) **Measure by day**. The figure plots the average sentiment of coverage of Donald J. Trump's tweets, per day, by network, for event windows that did not overlap over time and content.



(b) **Measure within day**. The figure plots the average sentiment of coverage of Donald J. Trump's tweets, per day, by network, for event windows that did not overlap over time and content.

Figure A.1.6: **Sentiment of coverage – descriptive statistics**.

A.1.1.3 Relation with Online News

Descriptives

Facebook handles for newspapers included in FB and 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.

Note: Newspapers featured in CrowdTangle (Link)'s "US Political Media", "US General Media" and "US Top Newspapers" newspaper groups.

Table A.1.5: **Facebook news corpus – descriptive statistics**

General news	'15-'20	'15	'16	'17	'18	'19	'20
Total news	7,953,900	860,200	1,231,600	1,361,000	1,450,200	1,514,600	1,536,300
Total newspapers	141	134	137	139	140	140	137
News not mentioning "Trump"	'15-'20	'15	'16	'17	'18	'19	'20
Total news	6,801,354	834,700	1,051,083	1,101,706	1,213,318	1,291,541	1,309,006
Total newspapers	141	134	137	139	140	140	137
News mentioning "Trump"	'15-'20	'15	'16	'17	'18	'19	'20
Total news	1,152,546	834,700	180,517	259,294	236,882	223,059	227,294
Total newspapers	139	139	134	136	137	134	133

Notes: The table shows statistics referent to an online news corpus focused entirely on Facebook (FB). This corpus has been assembled through CrowdTangle (Link) and it includes all Facebook posts released from 2015 until 2020 by those newspapers featured in CrowdTangle (Link)'s "US Political Media", "US General Media" and "US Top Newspapers" newspaper groups.

Table A.1.6: **Twitter news corpus – descriptive statistics**

General news	’15-’20	’15	’16	’17	’18	’19	’20
Total news	20,621,888	2,721,936	3,314,085	3,613,063	3,517,615	3,343,896	4,111,293
Total newspapers	139	133	135	135	134	134	135
News not mentioning ”Trump”	**’15-’20**	**’15**	**’16**	**’17**	**’18**	**’19**	**’20**
Total news	17,858,757	2,650,766	2,852,966	3,034,213	3,064,069	2,957,565	3,299,178
Total newspapers	138	133	135	134	134	134	135
News mentioning ”Trump”	**’15-’20**	**’15**	**’16**	**’17**	**’18**	**’19**	**’20**
Total news	2,763,131	71,170	461,119	578,850	453,546	386,331	812,115
Total newspapers	139	131	134	135	133	133	134

Notes: The table shows statistics referent to an online news corpus focused entirely on Twitter. This corpus has been assembled through Twitter API (Link) and, as before, it includes all tweets posted from 2015 until 2020 by those newspapers featured in CrowdTangle (Link)’s “US Political Media”, “US General Media” and “US Top Newspapers” newspaper groups.

A.1.2 Empirical Strategy

A.1.2.1 Overlap Across Event-Windows

A.1.2.1.1 Definition

Overlapping across calendar time. Figure A.1.7 illustrates a pair of windows overlapping across calendar time:

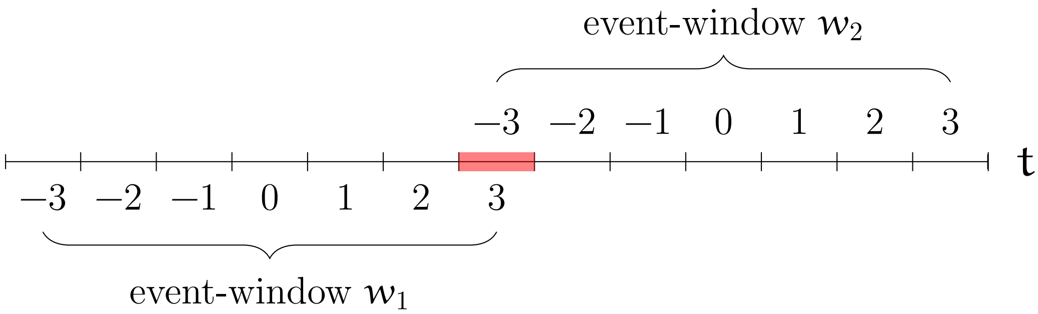
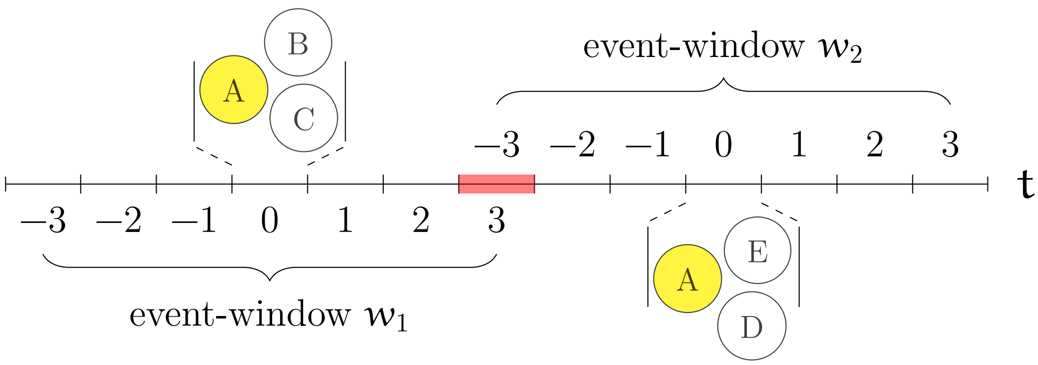


Figure A.1.7: **Overlapping event-window across calendar time.** The figure shows a scenario in which two event-windows partially overlap across calendar time. Shaded areas stand for overlaps, numbers stand for relative time periods.

Overlapping across calendar time and content. Figure A.1.8 illustrates a pair of windows overlapping in simultaneous across calendar time and content:



where A, B, C, D, E, ... are 3-word phrases
(e.g., "*great american people*" or "*fake news channel*")

Figure A.1.8: **Overlapping event-window across calendar time and content.** The figure shows a scenario in which two event-windows partially overlap across calendar time and content. Shaded areas stand for overlaps, numbers stand for relative time periods, letters stand for trigrams posted in tweets.

A.1.2.1.2 Descriptives

Table A.1.7: **Non-overlapping Trump tweets – descriptive statistics**

	'15-'20	'15	'16	'17	'18	'19	'20
Total Non-Overlapping Tweets	18,491	2,525	3,076	2,150	2,656	3,977	4,107
Total Non-Overlapping 15 Minutes	14,344	2,038	2,510	1,825	2,215	2,894	2,862
Share on Total Tweets	0.899	0.955	0.903	0.956	0.885	0.889	0.857
Share on Total 15 Minutes	0.919	0.96	0.936	0.962	0.894	0.906	0.885
Per 15Min w/ > 0 Tweets	'15-'20	'15	'16	'17	'18	'19	'20
Min.	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p25	1	1	1	1	1	1	1
Median	1	1	1	1	1	1	1
p75	1	1	1	1	1	2	2
Max.	18.0	8.0	6.0	8.0	5.0	13.0	18.0

Notes: The table shows descriptive statistics on the subset of @realDonaldTrump tweets that generate non-overlapping event-windows (across calendar time and content). This subset is included in a sample of Trump tweets that does not include retweets nor short tweets.

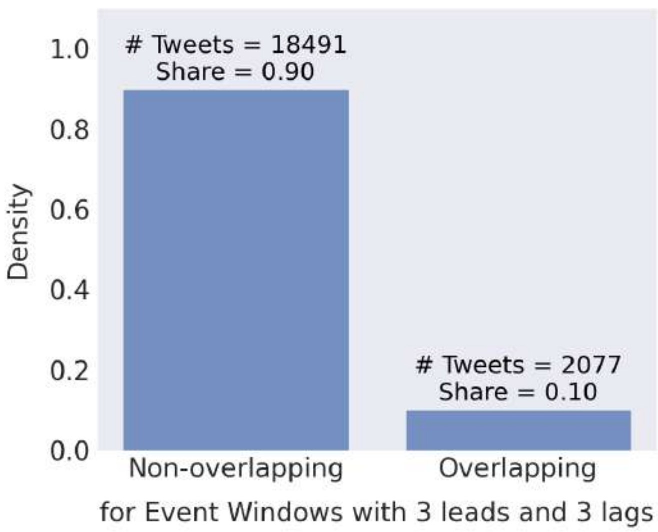


Figure A.1.9: **Overlapping vs. non-overlapping tweets, in total**. The figure plots the number of Trump tweets that generate overlapping and non-overlapping event-windows (across calendar time and content), per year, from 2015 to 2020. It focuses on a specific class of Trump tweets (as in Table ; no retweets, no short tweets).

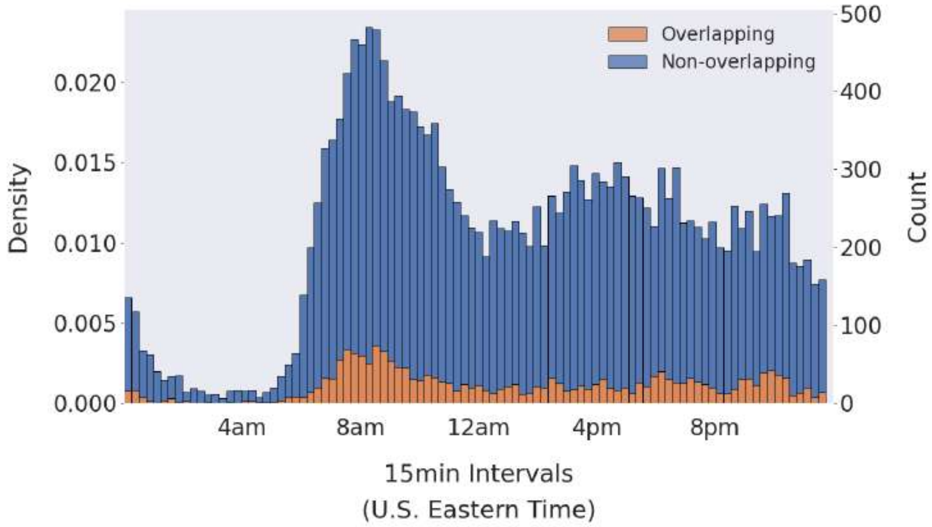


Figure A.1.10: **Overlapping vs. non-overlapping tweets, within a day**. The figure plots the number of Trump tweets that generate overlapping and non-overlapping event-windows (across calendar time and content), within a day, from 2015 to 2020. It focuses on a specific class of Trump tweets (as in Table ; no retweets, no short tweets).

A.1.3 Main Results

A.1.3.1 Pre-Posts

A.1.3.1.1 Extent of Coverage

Table A.1.8: **Extent of coverage**.

	(1)	(2)	(3)
CNN	2.019***	2.944***	3.671***
	(0.224)	(0.310)	(0.387)
FNC	1.919***	2.926***	3.914***
	(0.198)	(0.289)	(0.359)
MSN	1.768***	2.613***	3.306***
	(0.186)	(0.257)	(0.332)
Observations	75,408	68,322	62,920
Adjusted R^2	0.068	0.089	0.098
Pre-tweet CNN avg.	0.234	0.422	0.586
Pre-tweet FNC avg.	0.437	0.783	1.041
Pre-tweet MSN avg.	0.205	0.357	0.496
Event window	±45m	±1h30m	±2h15m

Note: The table shows post coefficients from a pre-post Equation as in (2) where the dependent variable is an extent of coverage measure (in trigrams; defined in A.1.1.2.1). Each column refers to an estimation sample where each event window has a particular "radius". Column (1) refers to an estimation sample using event-windows where pre and post periods stand for 45m time periods; column (2) refers to event-windows with pre and post periods of 1h30m; column (3) refers to event-windows of 2h15m. Standard errors in parenthesis, clustered at a network × window level.

A.1.3.1.2 Intensity of Coverage

Table A.1.9: **Intensity of coverage**.

	(1)	(2)	(3)
CNN	0.351***	0.670***	1.100***
	(0.036)	(0.058)	(0.091)
FNC	0.375***	0.754***	1.311***
	(0.042)	(0.080)	(0.102)
MSN	0.430***	0.778***	1.216***
	(0.040)	(0.062)	(0.093)
Observations	75,408	68,322	62,920
Adjusted R^2	0.030	0.000	-0.005
Pre-tweet CNN avg.	0.162	0.261	0.363
Pre-tweet FNC avg.	0.313	0.570	0.723
Pre-tweet MSN avg.	0.134	0.246	0.335
Event window	±45m	±1h30m	±2h15m

Note: The table shows post coefficients from a pre-post Equation as in (2) where the dependent variable is an intensity of coverage measure (in minutes; defined in A.1.1.2.2). Each column refers to an estimation sample where each event window has a particular "radius". Column (1) refers to an estimation sample using event-windows where pre and post periods stand for 45m time periods; column (2) refers to event-windows with pre and post periods of 1h30m; column (3) refers to event-windows of 2h15m. Standard errors in parenthesis, clustered at a network × window level.

A.1.3.1.3 Sentiment of Coverage

Table A.1.10: **Sentiment of coverage**.

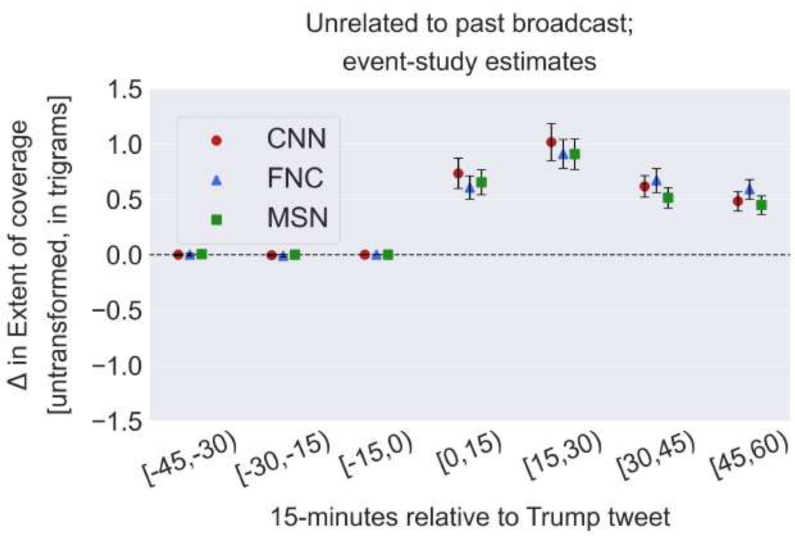
	(1)	(2)	(3)
CNN	3.023***	3.904***	4.745***
	(0.297)	(0.411)	(0.521)
FNC	2.668***	3.279***	4.176***
	(0.252)	(0.374)	(0.496)
MSN	2.580***	3.677***	4.486***
	(0.238)	(0.361)	(0.498)
Observations	75,408	68,322	62,920
Adjusted R^2	0.403	0.490	0.525
Pre-tweet CNN avg.	4.046	7.868	11.145
Pre-tweet FNC avg.	4.755	9.179	12.780
Pre-tweet MSN avg.	3.768	7.025	10.129
Event window	$\pm$45m	$\pm$1h30m	$\pm$2h15m

Note: The table shows post coefficients from a pre-post Equation as in (2) where the dependent variable is a sentiment of coverage measure (based on a dictionary-based sentiment score; defined in A.1.1.2.3). Each column refers to an estimation sample where each event window has a particular "radius". Column (1) refers to an estimation sample using event-windows where pre and post periods stand for 45m time periods; column (2) refers to event-windows with pre and post periods of 1h30m; column (3) refers to event-windows of 2h15m. Standard errors in parenthesis, clustered at a network $\times$ window level.

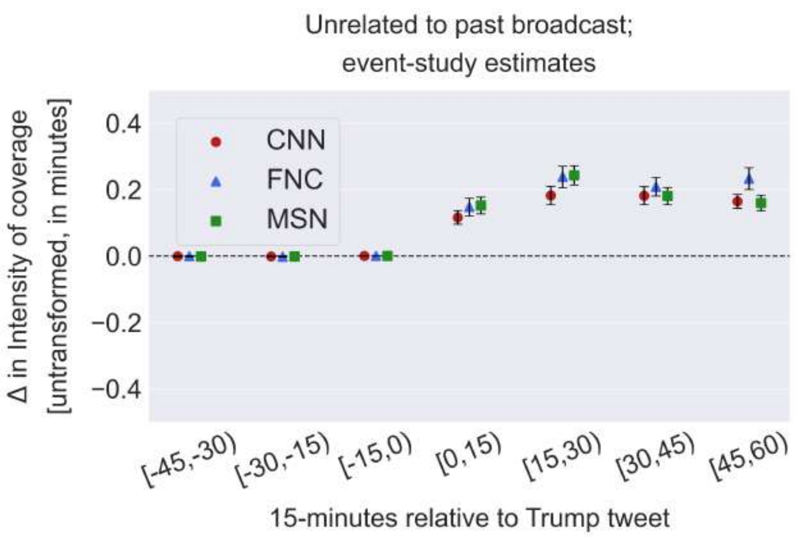
A.1.4 Robustness Checks

A.1.4.1 Reverse Causality Concerns

A.1.4.1.1 Extent and Intensity of Coverage

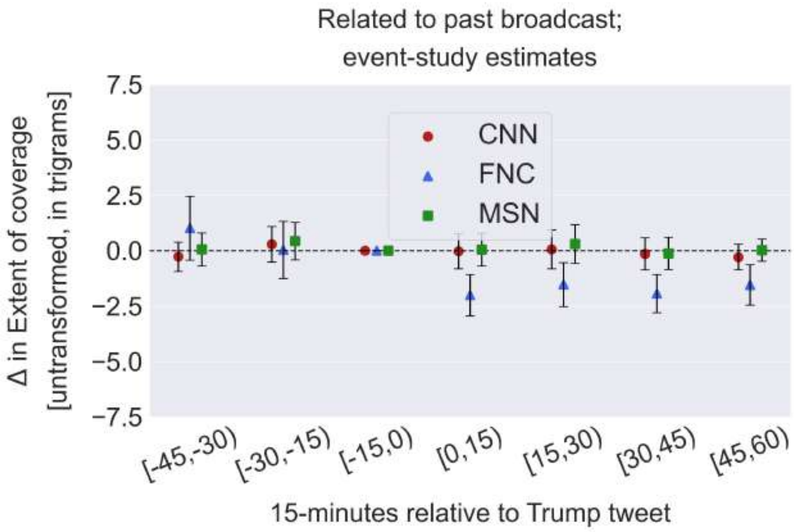


(a) **Extent of coverage**.

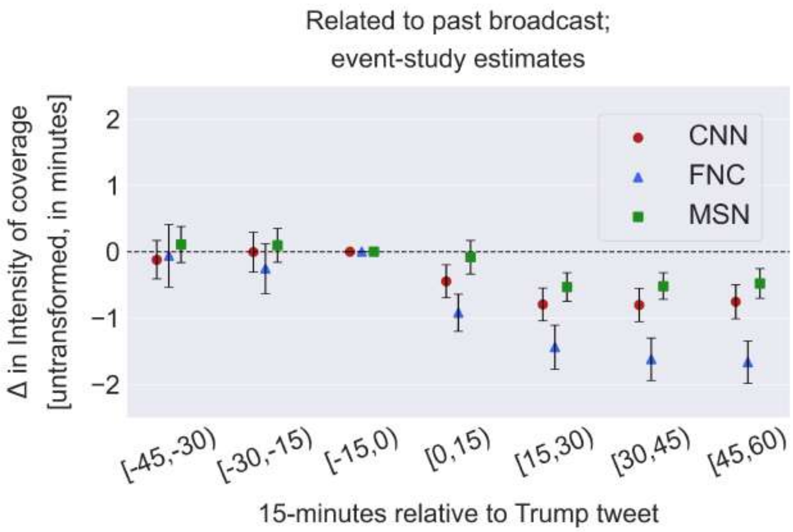


(b) **Intensity of coverage**.

Figure A.1.11: **Extent and intensity of coverage – unrelated to past broadcast**. Panel (a) and (b) plot coefficients from different event-study regressions, as in Equation 3. Panel (a) refers to a regression where the dependent variable is an extent of coverage measure (in trigrams; as defined in A.1.1.2.1). Panel (b) refers to a regression where the dependent variable is an intensity of coverage measure (in minutes; as defined in A.1.1.2.2). Each coefficient refers exclusively to Trump tweets seemingly unrelated to past cable news broadcast. The error bars refer to 95% confidence intervals drawn from standard errors clustered at a network × window level.



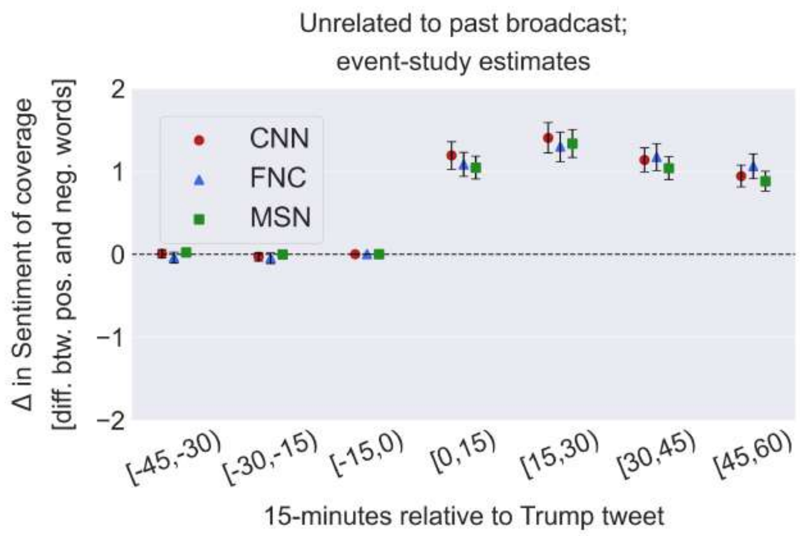
(a) **Extent of coverage**.



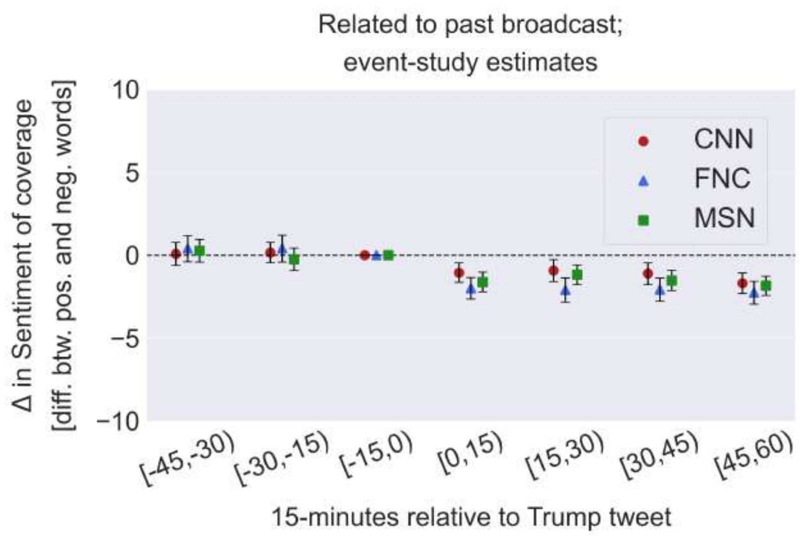
(b) **Intensity of coverage**.

Figure A.1.12: **Extent and intensity of coverage – related to past broadcast**. Panel (a) and (b) plot coefficients from different event-study regressions, as in Equation 3. Panel (a) refers to a regression where the dependent variable is an extent of coverage measure (in trigrams; as defined in A.1.1.2.1). Panel (b) refers to a regression where the dependent variable is an intensity of coverage measure (in minutes; as defined in A.1.1.2.2). Each coefficient refers exclusively to Trump tweets seemingly related to past cable news broadcast. The error bars refer to 95% confidence intervals drawn from standard errors clustered at a network × window level.

A.1.4.1.2 Sentiment of Coverage



(a) **Unrelated to past broadcast**.

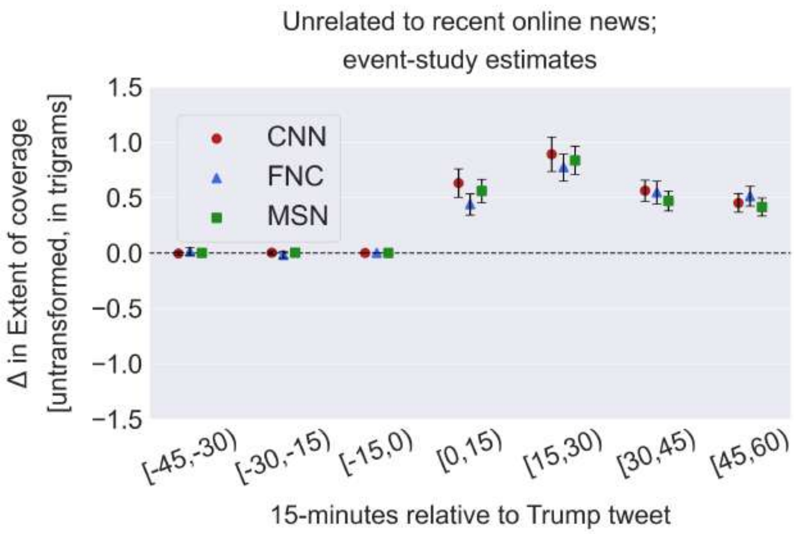


(b) **Related to past broadcast**.

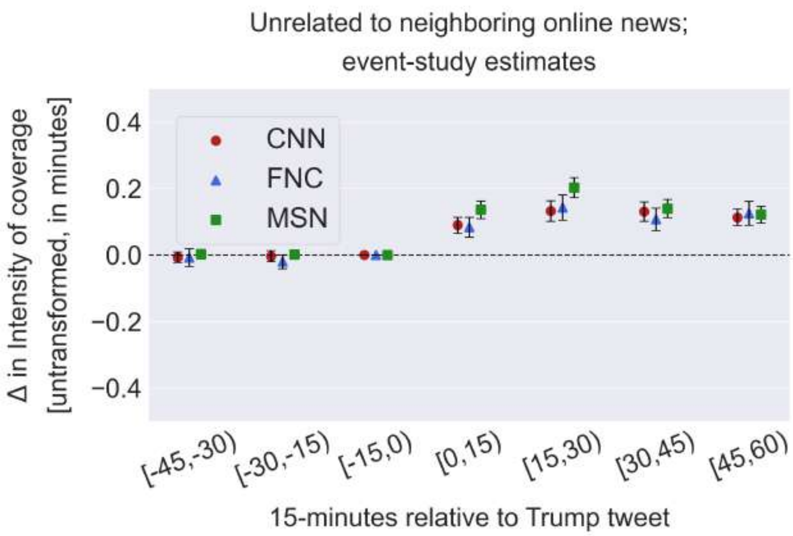
Figure A.1.13: **Sentiment of coverage – unrelated / related to past broadcast**. Panel (a) and (b) plot the coefficients from an event-study regression as in Equation 3 where the dependent variable is a sentiment coverage measure (based on a dictionary-based sentiment score; defined in A.1.1.2.3). Panel (a) refers exclusively to Trump tweets seemingly unrelated to past cable news broadcast. Panel (b) refers exclusively to Trump tweets seemingly related to past coverage. The error bars refer to 95% confidence intervals drawn from standard errors clustered at a network × window level.

A.1.4.2 Omitted Variable Concerns

A.1.4.2.1 Extent and Intensity of Coverage

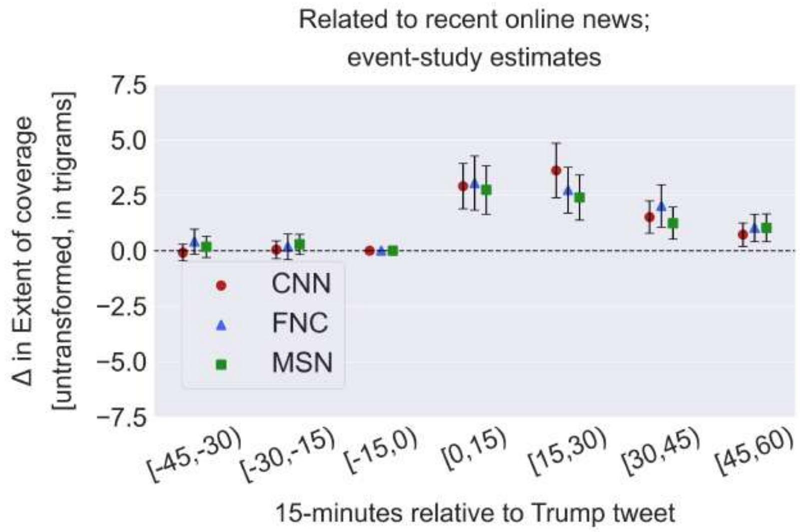


(a) **Extent of coverage**.

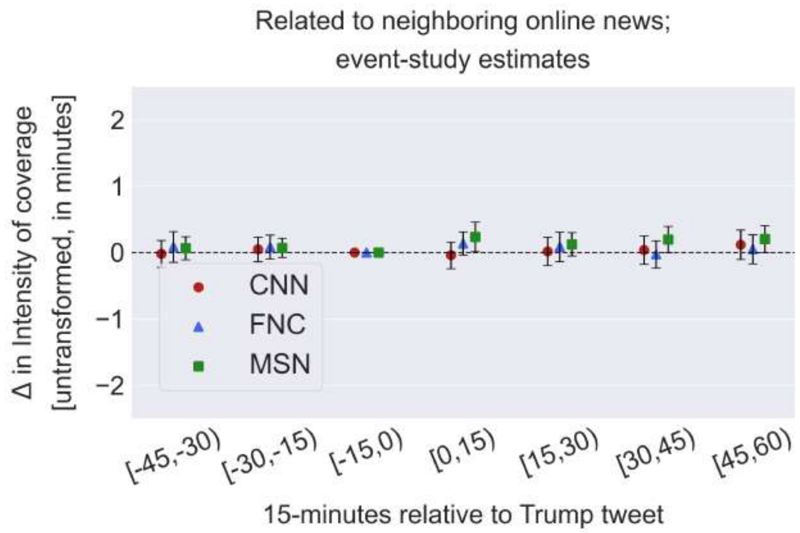


(b) **Intensity of coverage**.

Figure A.1.14: **Extent and intensity of coverage – unrelated to news events**. Panel (a) and (b) plot coefficients from different event-study regressions, similar to Equation 3 only that focused on windows related and unrelated to neighboring news events. Panel (a) refers to a regression where the dependent variable is an extent of coverage measure (in trigrams; as defined in A.1.1.2.1). Panel (b) refers to a regression where the dependent variable is an intensity of coverage measure (in minutes; as defined in A.1.1.2.2). Each coefficient refers exclusively to Trump tweets seemingly unrelated to recent news events. The error bars refer to 95% confidence intervals drawn from standard errors clustered at a network × window level.



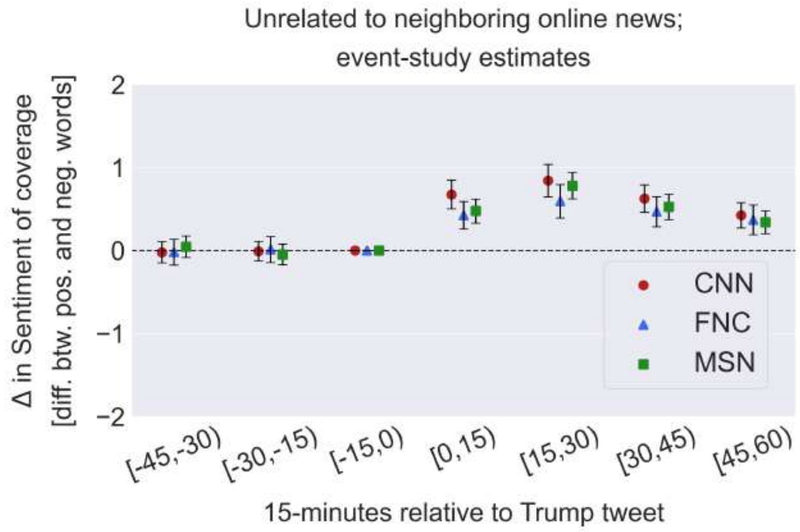
(a) **Extent of coverage**.



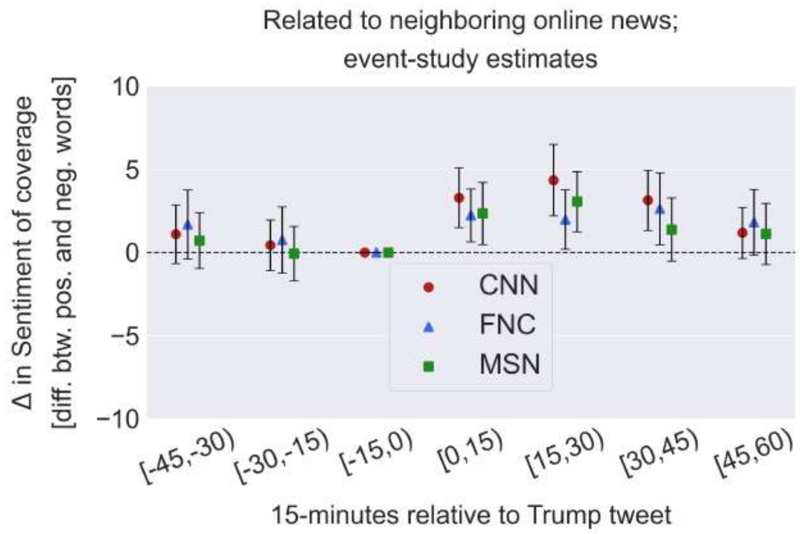
(b) **Intensity of coverage**.

Figure A.1.15: **Extent and intensity of coverage – related to news events**. Panel (a) and (b) plot coefficients from different event-study regressions, similar to Equation 3 only that focused on windows related and unrelated to neighboring news events. Panel (a) refers to a regression where the dependent variable is an extent of coverage measure (in trigrams; as defined in A.1.1.2.1). Panel (b) refers to a regression where the dependent variable is an intensity of coverage measure (in minutes; as defined in A.1.1.2.2). Each coefficient refers exclusively to Trump tweets seemingly related to recent news events. The error bars refer to 95% confidence intervals drawn from standard errors clustered at a network × window level.

A.1.4.2.2 Sentiment of Coverage



(a) **Unrelated to recent news**.



(b) **Related to recent news**.

Figure A.1.16: **Sentiment of coverage – unrelated / related to news events**. Panel (a) and (b) plot the coefficients from an event-study regression similar to Equation 3 (only that focused on windows related and unrelated to neighboring news events) where the dependent variable is a sentiment coverage measure (based on a dictionary-based sentiment score; defined in A.1.1.2.3). Panel (a) refers exclusively to Trump tweets seemingly unrelated to recent news events. Panel (b) refers exclusively to Trump tweets seemingly related recent news events. The error bars refer to 95% confidence intervals drawn from standard errors clustered at a network × window level.

A.1.5 Heterogeneity Analyses

A.1.5.1 Heterogeneity by Year

A.1.5.1.1 Results

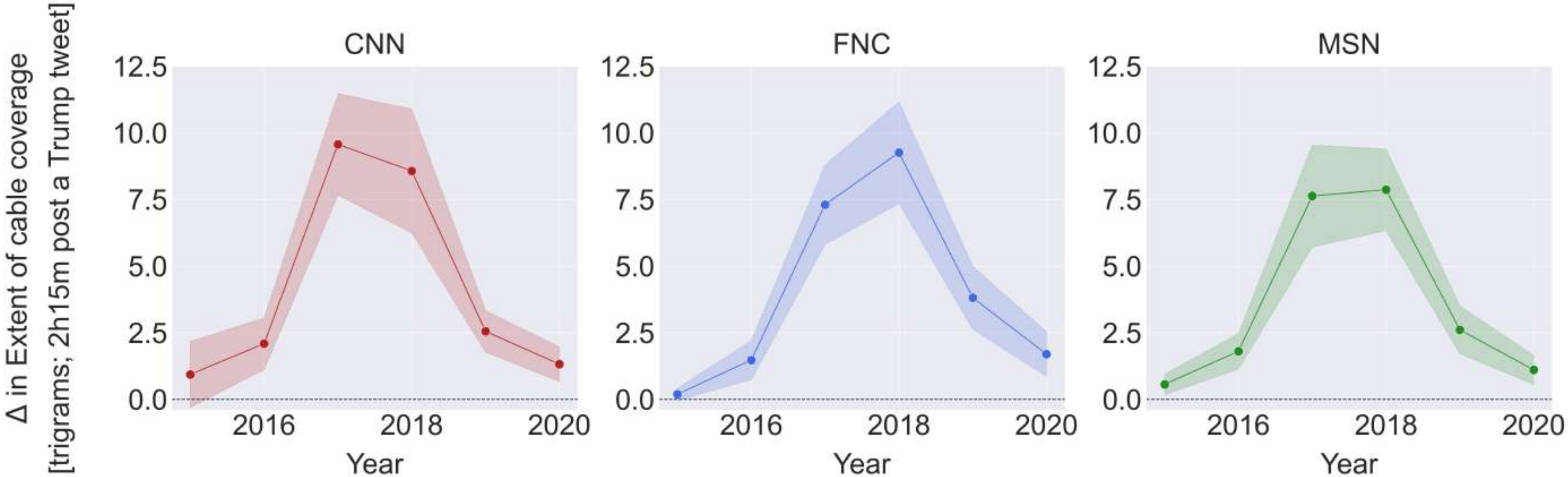


Figure A.1.17: **Extent of coverage – pre-post estimates by year**. The figure plots the post coefficients from a pre-post Equation as in (4) where the dependent variable is an extent of coverage measure (in trigrams; defined in A.1.1.2.1). Each subplot refers to a set of network-specific post coefficients, from left to right – CNN, Fox News and MSNBC. The confidence bands refer to 95% confidence intervals computed using standard errors clustered at a network × window level.

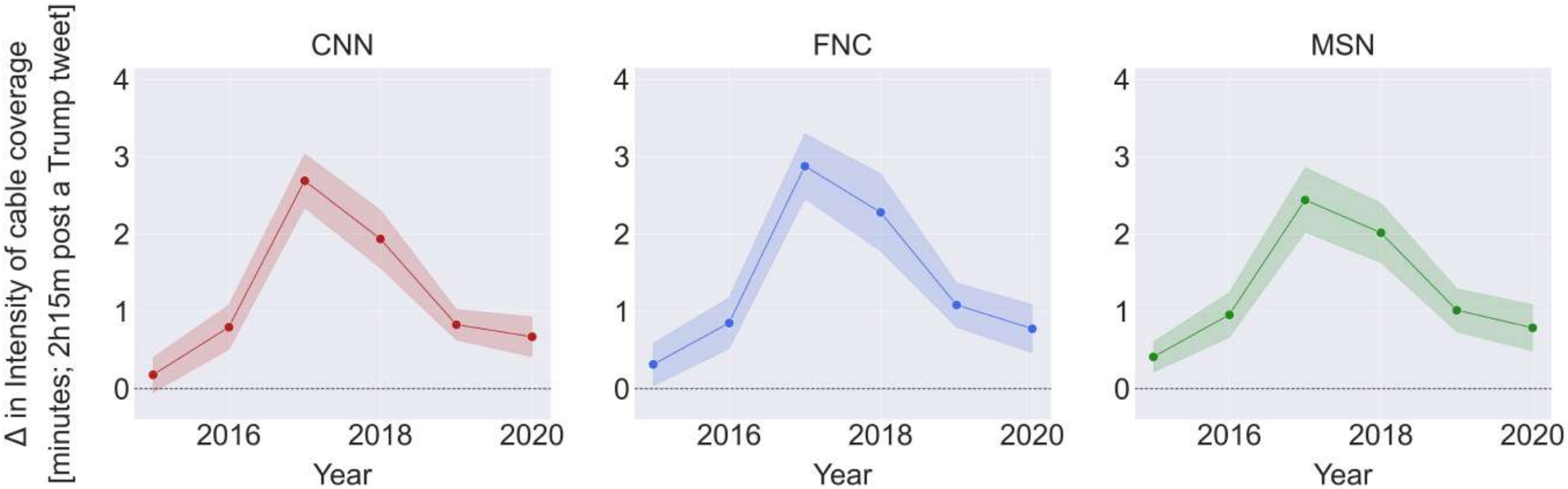


Figure A.1.18: **Intensity of coverage – pre-post estimates by year**. The figure plots the post coefficients from a pre-post Equation as in (4) where the dependent variable is an intensity of coverage measure (in minutes; defined in A.1.1.2.2). Each subplot refers to a set of network-specific post coefficients, from left to right – CNN, Fox News and MSNBC. The confidence bands refer to 95% confidence intervals computed using standard errors clustered at a network × window level.

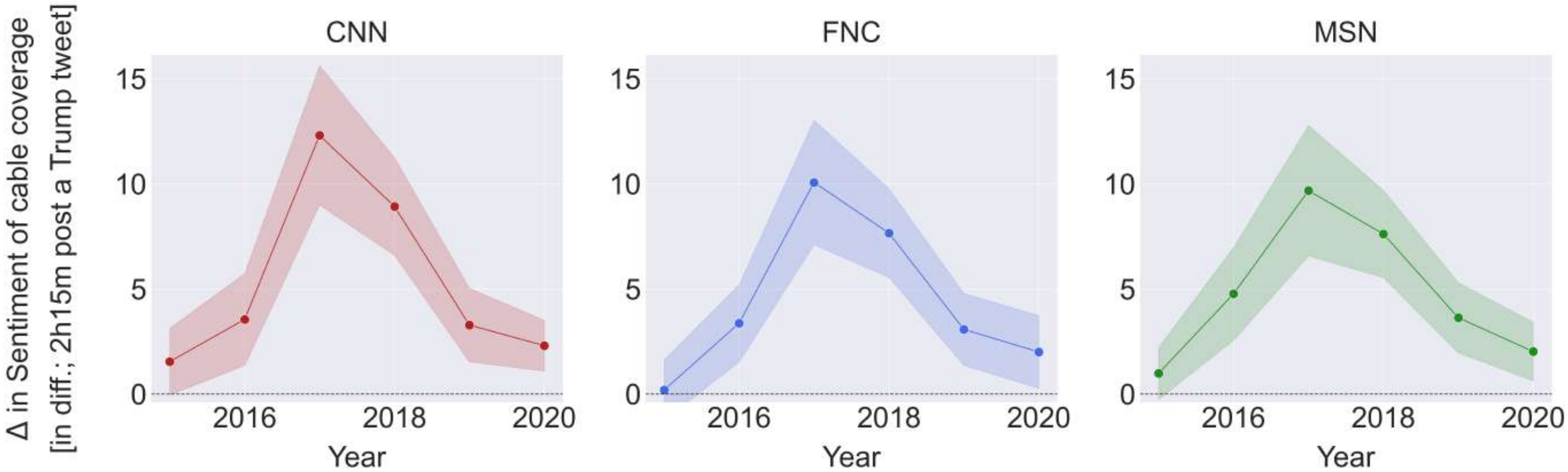


Figure A.1.19: **Sentiment of coverage – pre-post estimates by year**. The figure plots the post coefficients from a pre-post Equation as in (4) where the dependent variable is a sentiment of coverage measure (based on a dictionary-based sentiment score; defined in A.1.1.2.3). Each subplot refers to a set of network-specific post coefficients, from left to right – CNN, Fox News and MSNBC. The confidence bands refer to 95% confidence intervals computed using standard errors clustered at a network × window level.

A.1.5.2 Heterogeneity by Topic

A.1.5.2.1 Descriptives

Table A.1.11: **Trump tweets – Topic-word distribution**.

Topic	Theme	Words
1	Democrats / Congress	republican, democrat, radical_left, dems, supreme_court, senate, impeachment, house, election, ballot, nancy_pelosi, justice, court, crime, judge, allow, pelosi, congress, party, process
2	Trade Policy	china, tariff, trade, deal, north_korea, dollar, company, farmer, united_states, trade_deal, product, mexico, money, relationship, plant, nafta, inflation, federal_reserve, many_year, interest_rate
3	Shootings / Disasters	family, honor, police, hero, great_honor, nation, american, america, whitehouse, bless, stand, celebrate, shooting, thought_prayer, life, community, enforcement, brave, flag, prayer
4	Republicans / Congress	endorsement, complete_total, congressman, governor, strong_crime, amendment, love_military, second_amendment, taxis, senator, georgia, military, support, need, louisiana, fight, tough_crime, border, strong, usdot
5	News Media	fake_news, medium, story, fake, nytime, write, report, rating, dishonest, fail_, media, show, cnn, wrong, reporting, fact, cover, news, nytimes, foxnews
6	Political Campaigning	rally, join, tonight, crowd, makeamericagreatagain, trump2016, tomorrow, maga, pennsylvania, ticket, evening, south_carolina, north_carolina, fantastic, florida, iowa, hshire, amazing, votetrump, ohio
7	Corruption Scandals	witch_hunt, crooked_hillary, collusion, mueller, investigation, russia, schiff, clinton, comey, caign, ukraine, mueller_report, hoax, james_comey, fraud, report, lawyer, hunt, evidence, investigate
8	Immigration	border, wall, immigration, southern_border, border_security, mexico, crime, drug, build_wall, daca, border_patrol, congress, criminal, want_open, need, military, illegal_immigration, stop, open_border, illegal_immigrant
9	Foreign Policy	north_korea, iran, china, world, meeting, trade, united_states, syria, deal, japan, prime_minister, turkey, france, nato, meet, sanction, leader, testing, europe, south_korea
10	Economy	economy, stock_market, high, china, unemployment, biden, record, american, price, dollar, growth, worker, increase, america, regulation, strong, economic, number, create, well

Note: Topics via a semi-supervised topic model (a CorEx topic model; Gallagher et al., 2017) which is estimated using a set of topic anchors that are instead inferred from a bootstrap-like routine à la Mäntylä et al. (2018).

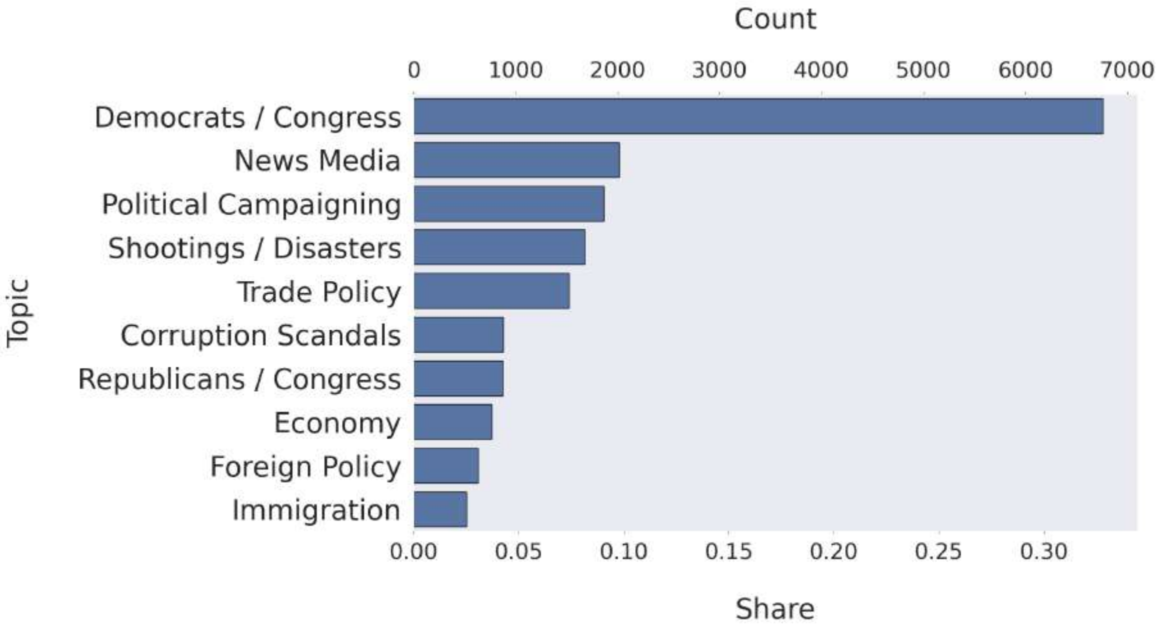


Figure A.1.20: **Trump tweets – Topic distribution**. The figure plots the distribution of topics tweeted by Donald J. Trump, from 2015 to 2020. Topics are inferred via a semi-supervised topic model (a CorEx topic model; Gallagher et al., 2017) which is estimated using a set of topic anchors that are instead inferred from a bootstrap-like routine à la Mäntylä et al. (2018).

A.1.5.2.2 Results

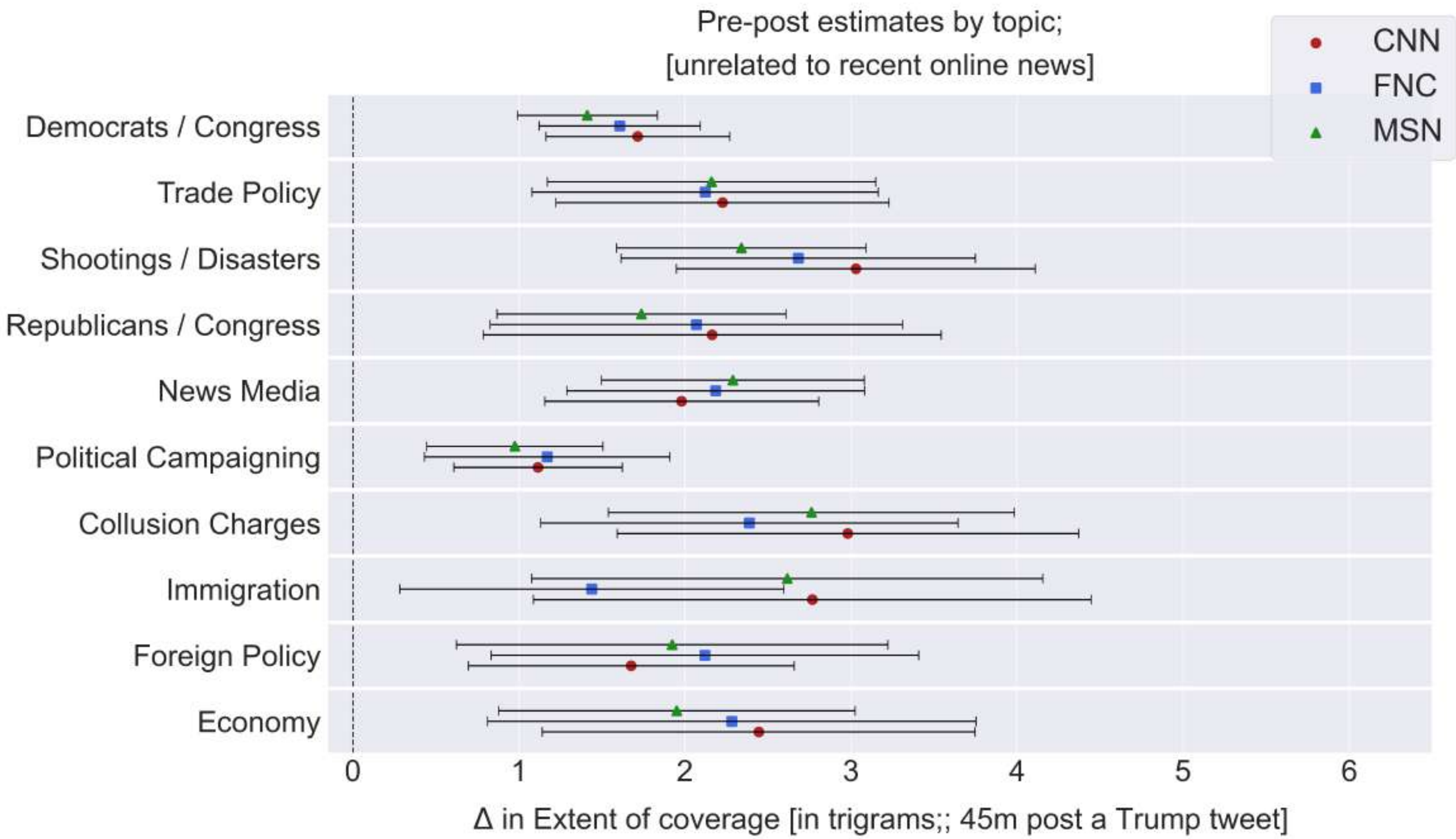


Figure A.1.21: **Extent of coverage – pre-post estimates by topic**. The figure plots post coefficients from a pre-post equation extended similarly as in (4) where outlets react differently to Trump tweets depending on the topics of these statements. The dependent variable is an extent of coverage measure (in minutes; as in A.1.1.2.2). Each row refers to a set of topic-specific post coefficients, one for each outlet, from up to down – MSNBC, Fox News, CNN. The confidence errors refer to 95% confidence intervals computed using standard errors clustered at a network × window level. Topics are inferred via a semi-supervised topic model (a CorEx topic model; Gallagher et al., 2017) estimated using a set of topic anchors instead inferred from a bootstrap routine à la Mäntylä et al. (2018).

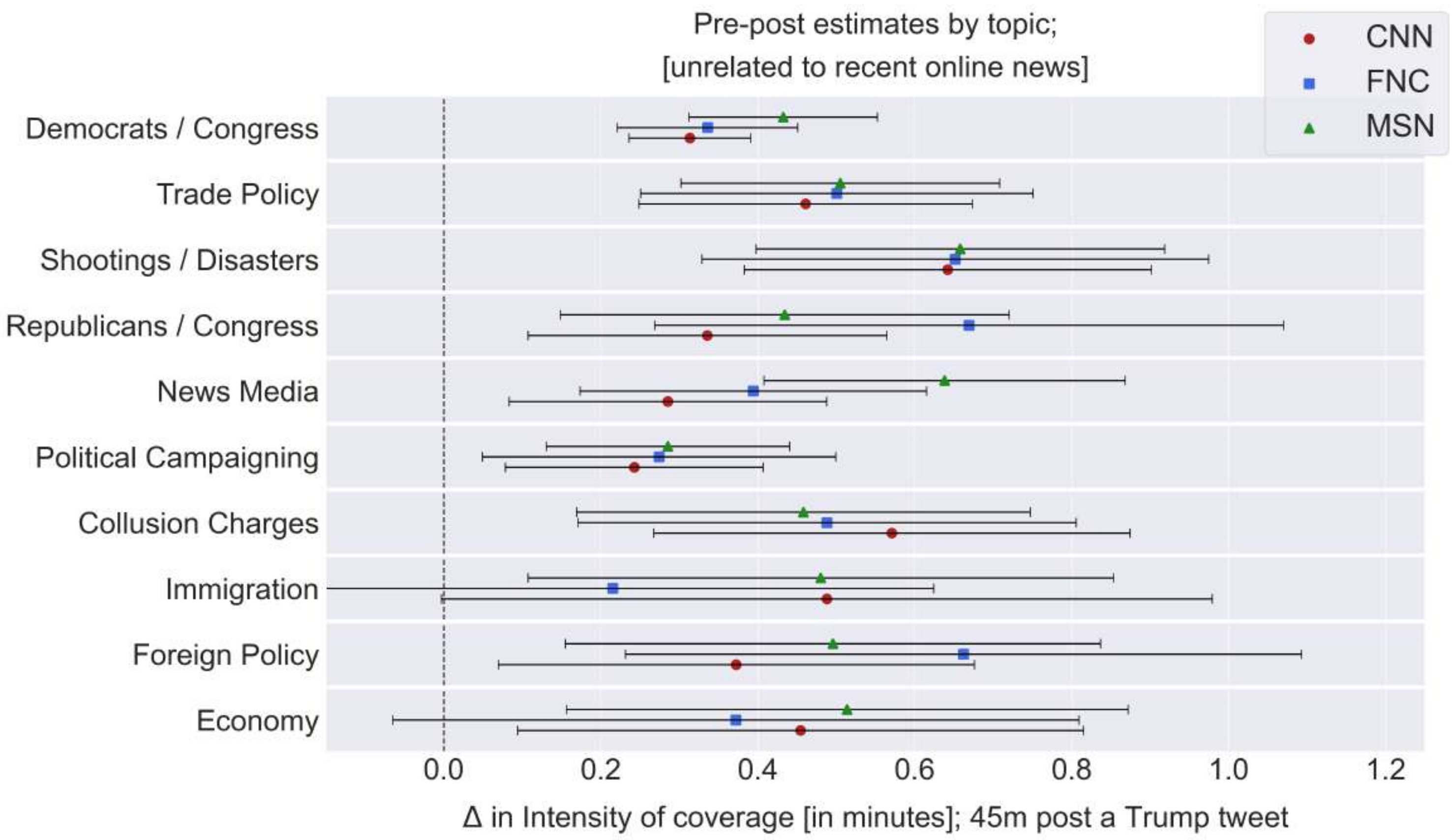


Figure A.1.22: **Intensity of coverage – pre-post estimates by topic**. The figure plots post coefficients from a pre-post equation extended similarly as in (4) where outlets react differently to Trump tweets depending on the topics of these statements. The dependent variable is an intensity of coverage measure (in minutes; as in A.1.1.2.2). Each row refers to a set of topic-specific post coefficients, one for each outlet, from up to down – MSNBC, Fox News, CNN. The confidence errors refer to 95% confidence intervals computed using standard errors clustered at a network × window level. Topics are inferred via a semi-supervised topic model (a CorEx topic model; Gallagher et al., 2017) estimated using a set of topic anchors instead inferred from a bootstrap routine à la Mäntylä et al. (2018).

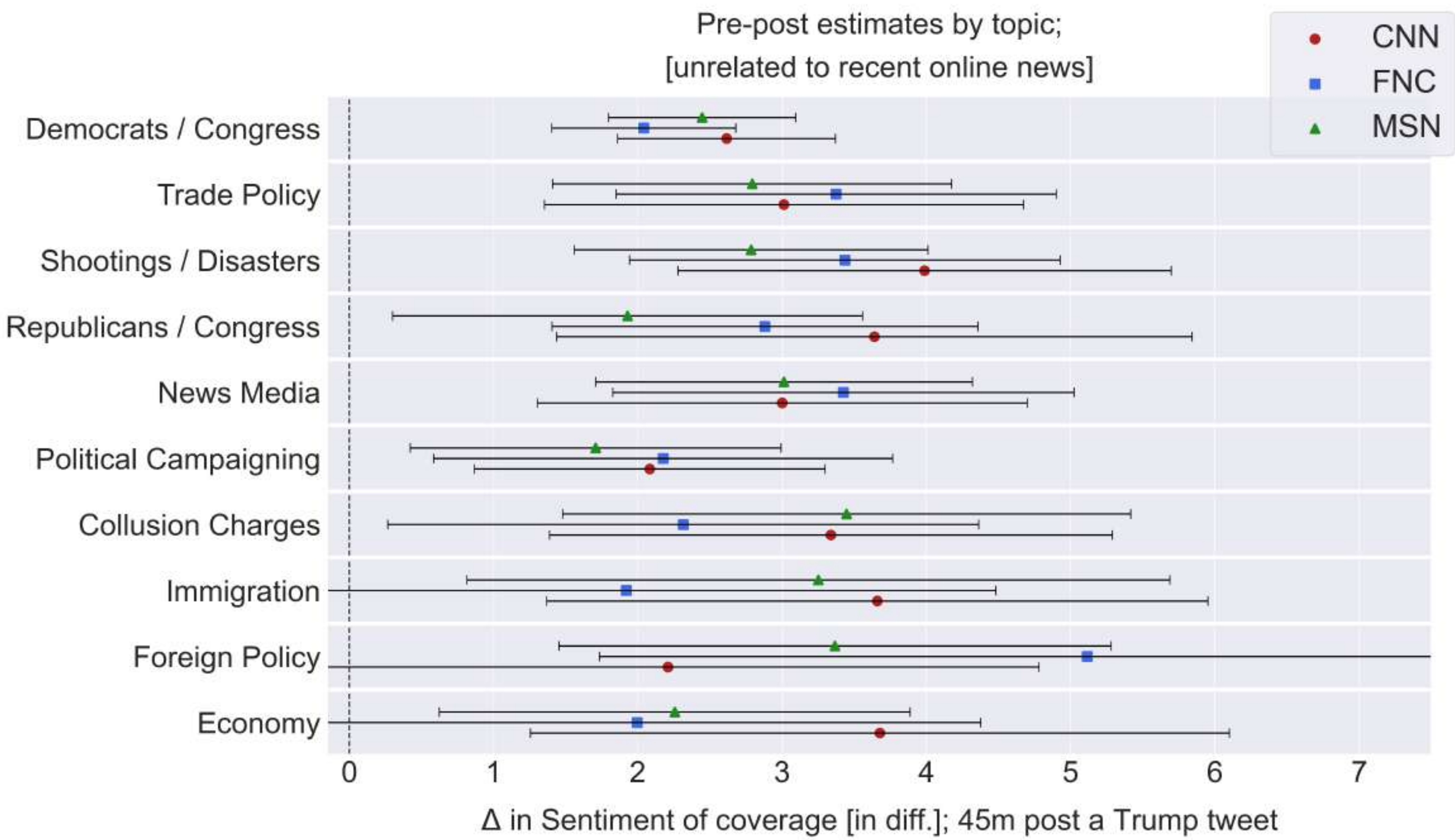


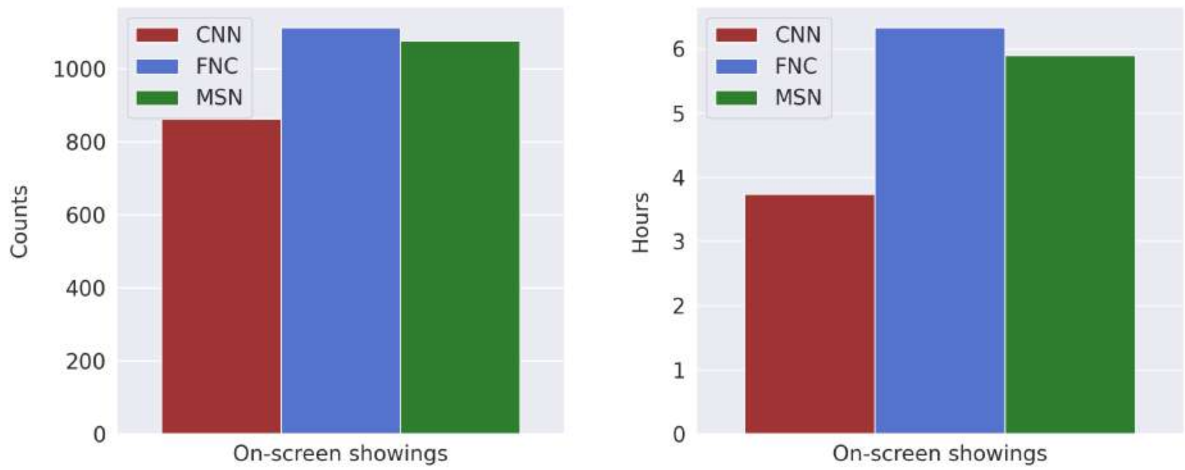
Figure A.1.23: **Sentiment of coverage – pre-post estimates by topic**. The figure plots post coefficients from a pre-post equation extended similarly as in (4) where outlets react differently to tweets depending on their topics. The dependent variable is a sentiment of coverage measure (based on a dictionary-based sentiment score; as in A.1.1.2.3). Each row refers to a set of topic-specific post coefficients, one for each outlet, from up to down – MSNBC, Fox News, CNN. The confidence errors refer to 95% confidence intervals computed using standard errors clustered at a network × window level. Topics are inferred via a semi-supervised topic model (a CorEx topic model; Gallagher et al., 2017) estimated using a set of topic anchors instead inferred from a bootstrap routine à la Mäntylä et al. (2018).

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

A.2.1 Variables

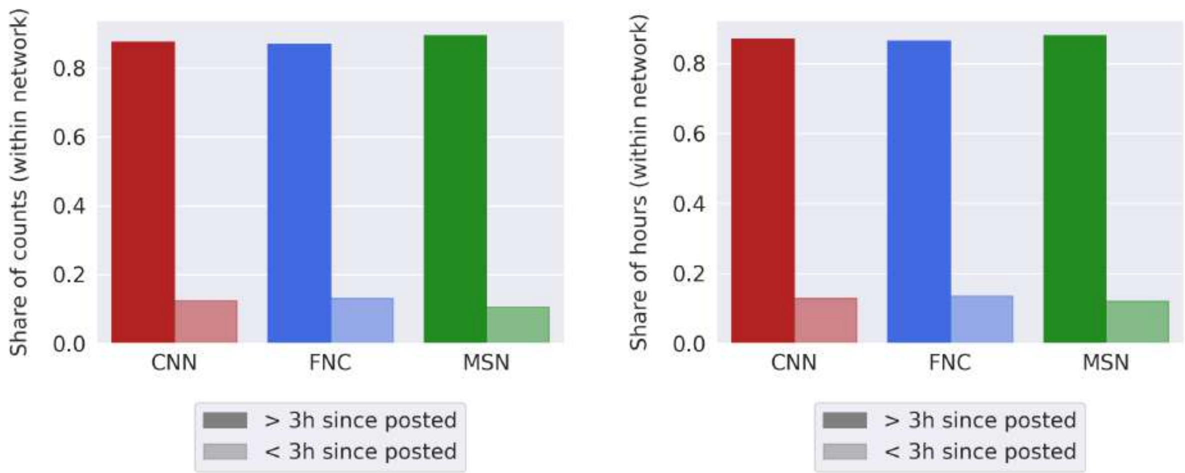
A.2.1.1 Broadcasts of Trump Tweets

Descriptives



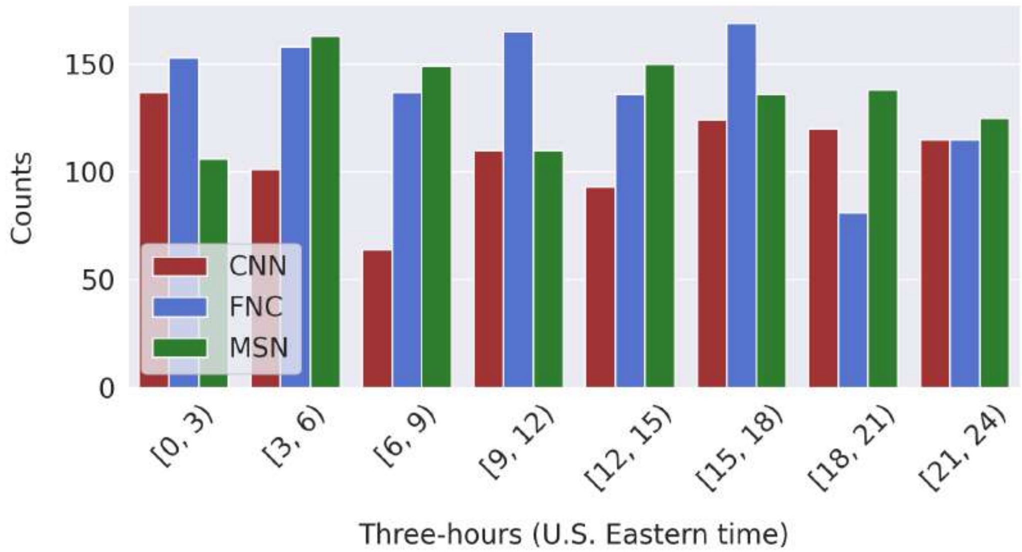
(a) **Number of broadcasts.** (b) **Duration of broadcasts.**

Figure A.2.1: **Broadcasts of Trump tweets – in total**. The figure plots the number and the duration of explicit coverages of Trump tweets by cable news outlets (by network). Panel (a) refers to the number of explicit coverages done by each network during 2020. Panel (b) instead plots the amount of airtime that these coverages took on each station.

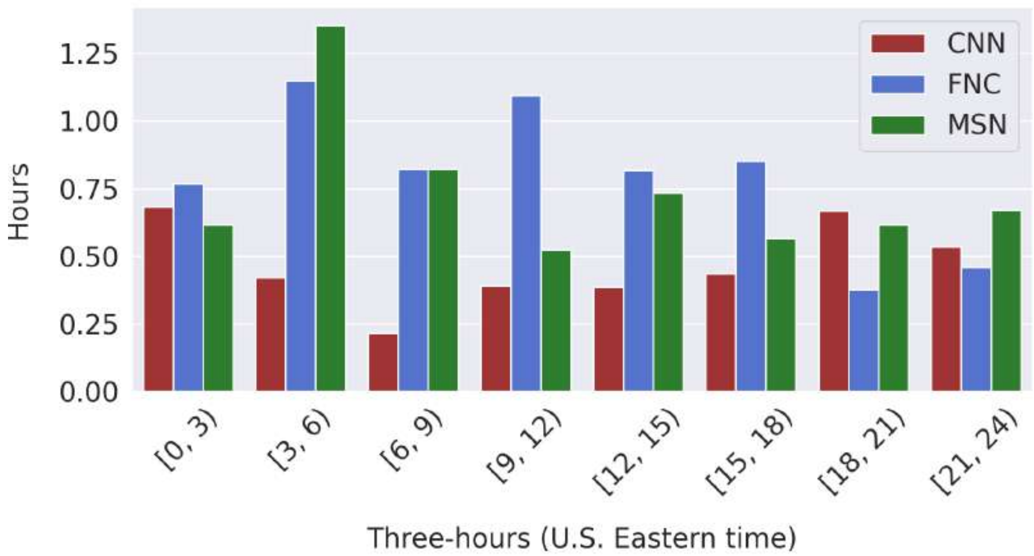


(a) **Number of broadcasts.** (b) **Duration of broadcasts.**

Figure A.2.2: **Broadcasts of Trump tweets – by "speed" of broadcast**. The figure plots the number and the duration of explicit coverages of Trump tweets by cable news outlets (by network). It makes a distinction between showings of tweets that were posted (a) less than or (b) more than 3 hours after a showing.



(a) **Number of broadcasts**.



(b) **Duration of broadcasts**.

Figure A.2.3: **Broadcasts of Trump tweets – within a day**. The figure plots the number and the duration of explicit coverages of Trump tweets by cable news outlets (by network and within a day). Panel (a) refers to the number of explicit coverages done by each network within a day (where a day is divided into 8 within-day periods, each of 3 hours). Panel (b) instead plots the amount of airtime that these coverages took on each station, for each within-day slot.

A.2.1.2 Trump Approval Rating

Descriptives

Table A.2.1: **Estimation sample – "*offline*" respondents**

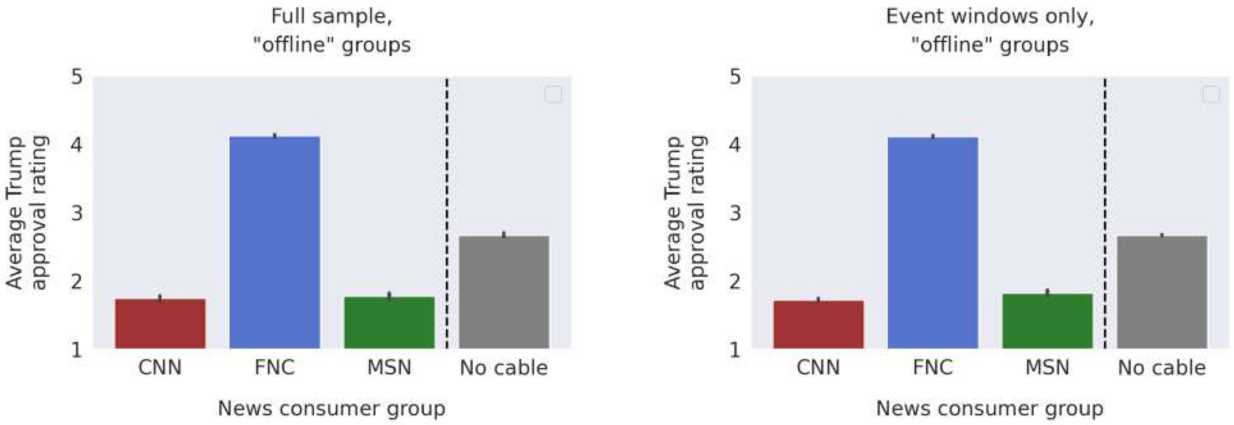
	CNN	FNC	MSN
Windows	638	745	710
Control	66,503	75,191	70,908
Treated	13,651	29,162	5,318

Notes: The table shows: (1) number of non-overlapping event windows, per network (i.e., windows that do not partially overlap across time with other windows in which a Trump tweet was shown for an abnormally long amount of time); (2) number of control units, per network (individuals that do not watch any cable news and do not use social media to gather their news); (3) number of treated units, per network (individuals that watch only that given network and do not use social media to gather their news).

Table A.2.2: **Estimation sample – "*online or not*" respondents**

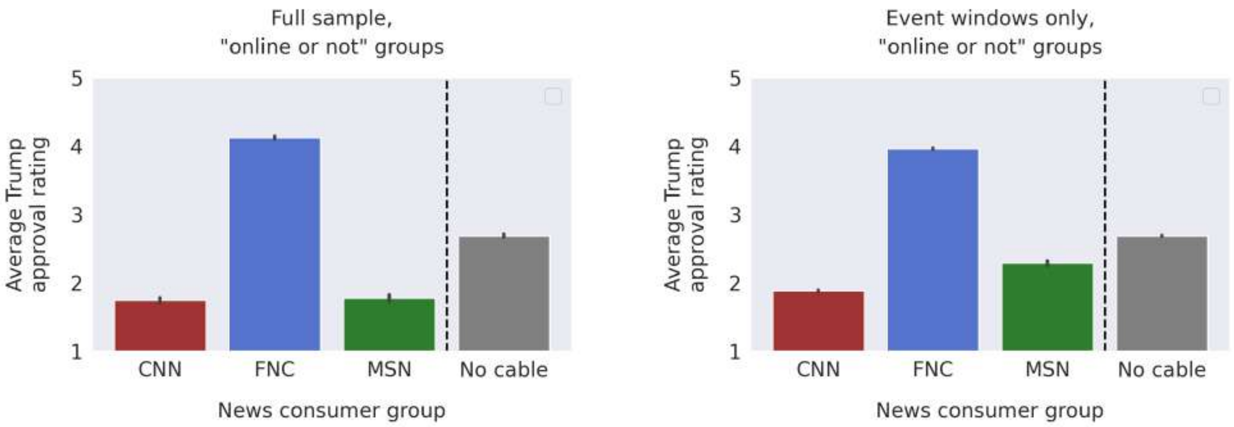
	CNN	FNC	MSN
Windows	638	745	710
Control	177,431	201,830	190,301
Treated	54,310	88,767	18,178

Notes: The table shows: (1) number of non-overlapping event windows, per network (i.e., windows that do not partially overlap across time with other windows in which a Trump tweet was shown for an abnormally long amount of time); (2) number of control units, per network (individuals that do not watch any cable news); (3) number of treated units, per network (individuals that watch only that given network).



(a) **Full sample**. (b) **Event windows**.

Figure A.2.4: **Average Trump approval rating – "*offline*" respondents**. The figure plots the average approval rating of Trump for different news audiences: individuals that only watch CNN, Fox News or MSNBC and do not use social media to gather their news ("*CNN*", "*FNC*" and "*MSN*" respectively); individuals that do not watch any cable outlet and do not use social media to gather their news ("*no cable*"). Panel (a) refers to the average approval rating for all Nationscape respondents complying with these news diets. Panel (b) refers to the average approval rating of each news audience for the periods neighboring an explicit broadcast of a Trump tweet by a cable news outlet (i.e., an "*event window*").



(a) **Full sample**. (b) **Event windows**.

Figure A.2.5: **Average Trump approval rating – "*online or not*" respondents**. The figure plots the average approval rating of Trump for different news audiences: individuals that only watch CNN, Fox News or MSNBC ("*CNN*", "*FNC*" and "*MSN*" respectively); individuals that do not watch any cable outlet ("no cable"). Contrary to A.2.4, in this figure respondents are allowed to use social media to gather their news ("online or not"). Panel (a) refers to the average approval rating for all Nationscape respondents complying with these news diets. Panel (b) refers to the average approval rating of each news audience for the periods neighboring an explicit broadcast of a Trump tweet by a cable news outlet (i.e., an "*event window*").

A.2.2 Empirical Strategy

A.2.2.1 Overlap Across Event-Windows

Descriptives

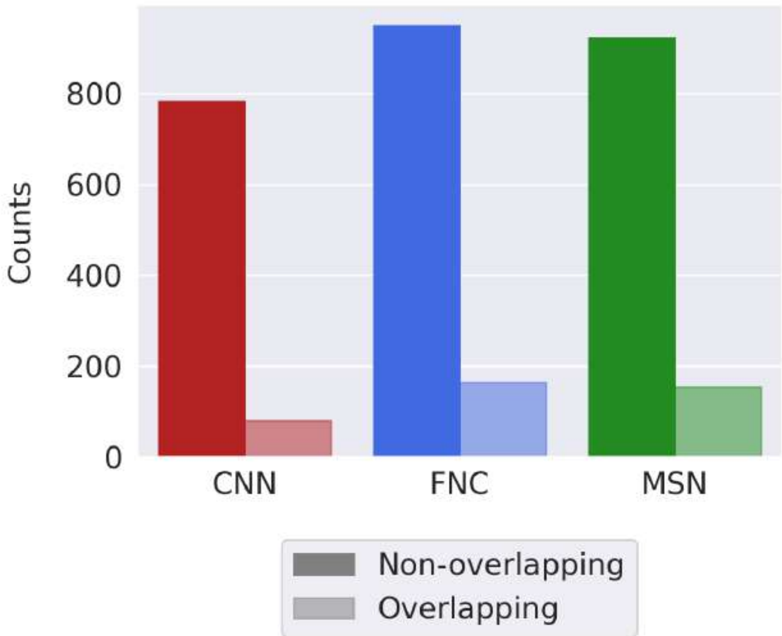


Figure A.2.6: **Overlapping vs. non-overlapping broadcasts, in total**. The figure plots the number of broadcasts that generate overlapping and non-overlapping event-windows (across calendar time). It focuses on a specific class of overlapping event windows – windows that cross over time other broadcasts from a same outlet that take an abnormally long period of time (more specifically, 2SD $\approx$ 37 seconds).

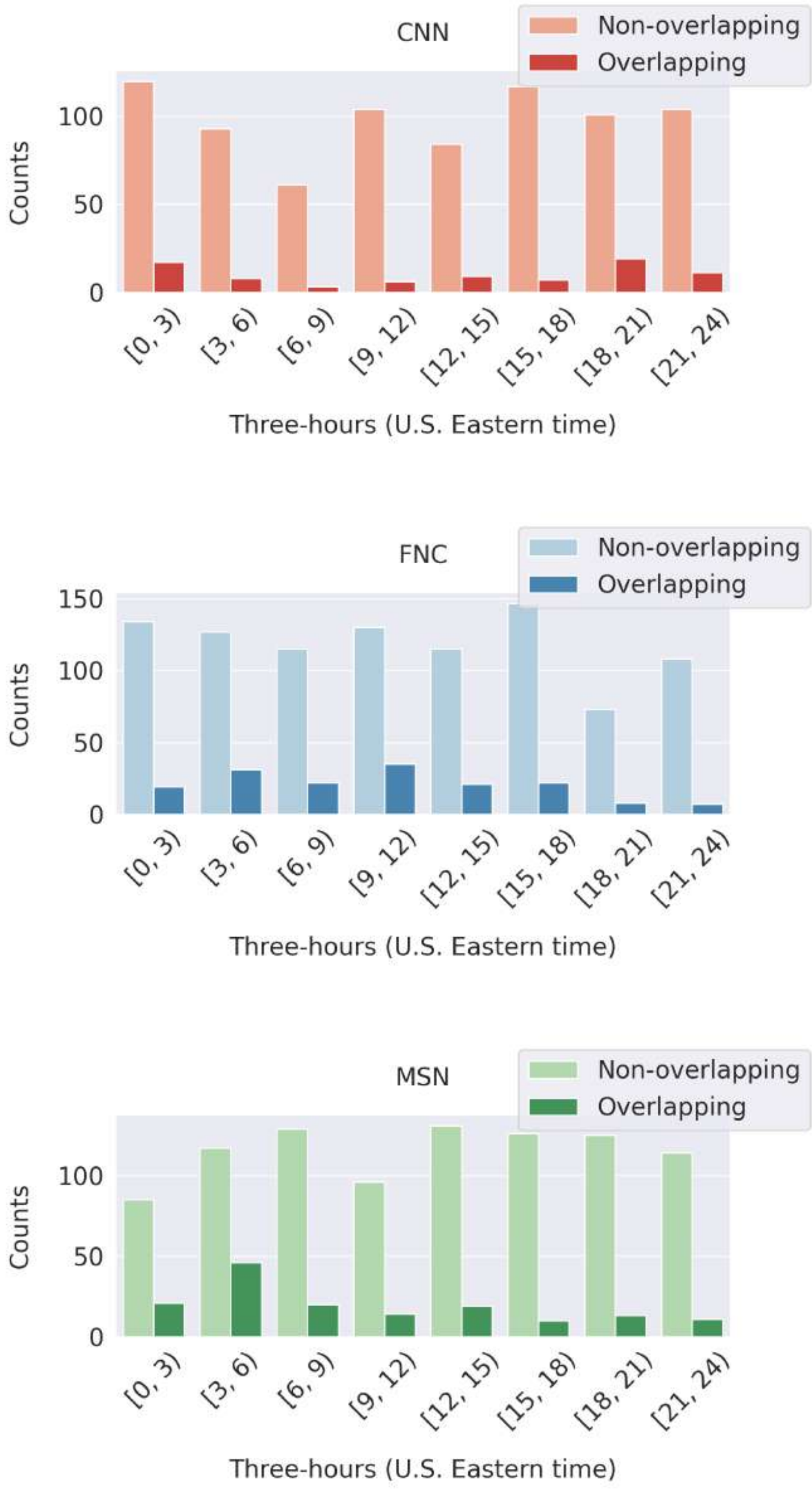
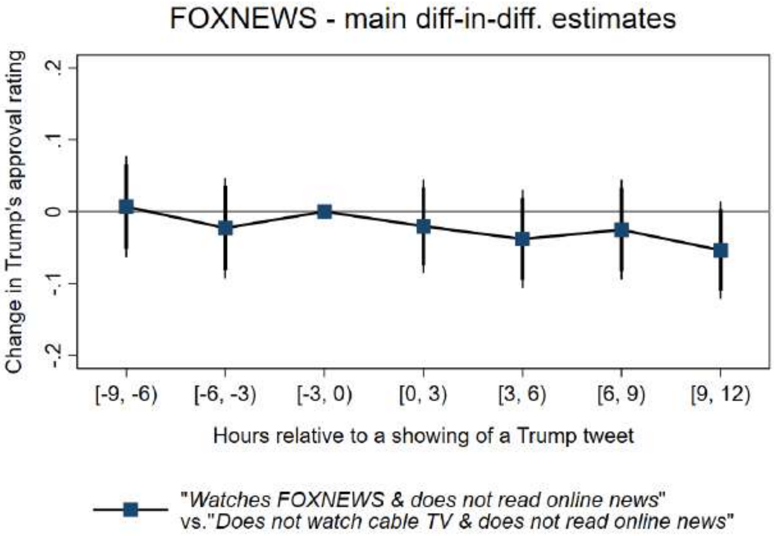


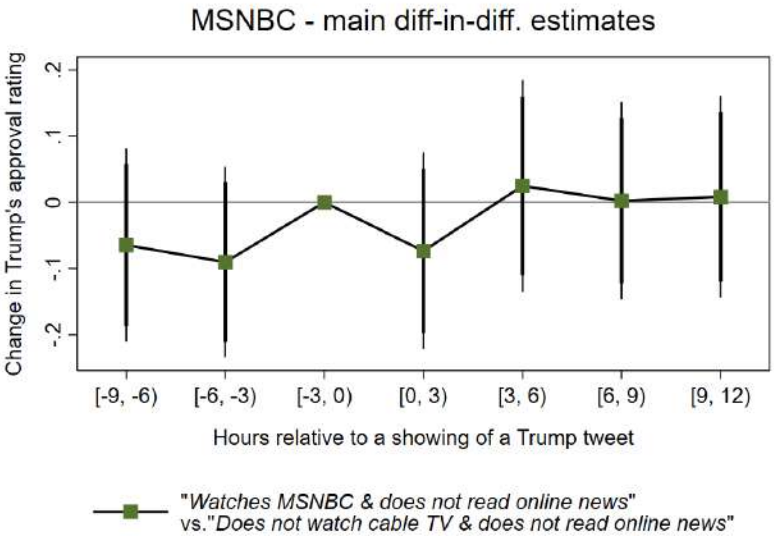
Figure A.2.7: **Overlapping vs. non-overlapping tweets, within a day**. The figure plots the number of Trump broadcasts by outlet, within a day, that generate overlapping and non-overlapping event-windows (across calendar time). It focuses on a specific class of overlapping event windows – windows that cross over time other broadcasts from a same outlet that take an abnormally long period of time (more specifically, 2SD $\approx$ 37 seconds).

A.2.3 Main Results

A.2.3.1 Event-Studies



(a) **Fox News**.



(b) **MSNBC**.

Figure A.2.8: **Differences-in-differences event-study estimates – Fox News and MSNBC**. Panel (a) and (b) plot respectively the Fox News and MSNBC coefficients from a diff.-in-diff. event-study regression as in Equation 5. The dependent variable is an approval ratings measure of Trump taking five values: (1) "*strong disapprove*", (2) "*somewhat disapprove*", (3) "*not sure*", (4) "*somewhat approve*" and (5) "*strongly approve*". The error bars refer to 95% confidence intervals drawn from standard errors clustered at a network × window level.

A.2.3.2 Pre-Posts

Table A.2.3: **Balance-check tables**

(a) **CNN**

	Pre	Post	Difference
Age	0.439	0.433	0.436
Gender	0.857	0.864	0.860
Race	0.743	0.753	0.747
Income	0.489	0.483	0.487
Education	0.937	0.939	0.938
Obs.	31,556	43,442	74,998
Clusters	638	638	638

(b) **Fox News**

	Pre	Post	Difference
Age	0.196	0.196	0.196
Gender	0.205	0.206	0.206
Race	0.590	0.591	0.591
Income	0.701	0.701	0.701
Education	0.241	0.241	0.241
Obs.	41,329	56,407	97,736
Clusters	745	745	745

(c) **MSNBC**

	Pre	Post	Difference
Age	0.667	0.680	0.673
Gender	0.354	0.337	0.346
Race	0.947	0.937	0.942
Income	0.917	0.915	0.916
Education	0.749	0.754	0.751
Obs.	31,357	39,977	71,334
Clusters	710	710	710

Notes: The tables show p-values for different balance-check regressions. Each demographic is first residualized according to those fixed effects used to estimate Equation 5. 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).

Table A.2.4: **Diff.-in-diff. pre-post estimates**.

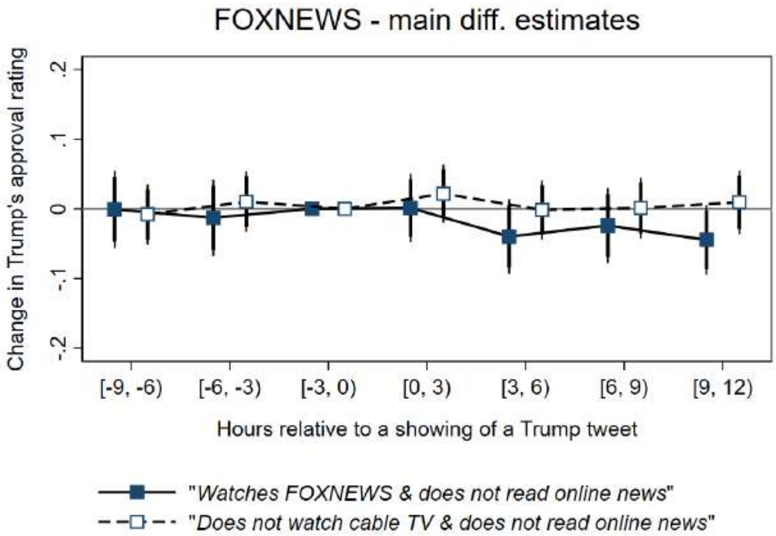
	(1)	(2)	(3)	(4)
Post × TV=1 × CNN	-0.0374	-0.0433*	-0.0366	-0.0366
	(0.0248)	(0.0259)	(0.0274)	(0.0283)
Post × TV=1 × FNC	-0.0218	-0.00730	-0.0173	-0.0173
	(0.0196)	(0.0195)	(0.0211)	(0.0204)
Post × TV=1 × MSN	0.0663*	0.0748*	0.0163	0.0163
	(0.0387)	(0.0396)	(0.0420)	(0.0476)
Observations	260183	244097	244068	244068
Adjusted R-squared	0.111	0.161	0.163	0.163
Mean dep. var.	2.759	2.761	2.761	2.761
Controls	No	Yes	Yes	Yes
Window-group FEs	No	No	Yes	Yes
Clustered SEs	No	No	No	Yes

Notes: standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table shows post coefficients from different versions of Equation 6. The dependent variable is an approval ratings measure for Trump (taking five values: (1) "*strong disapprove*", (2) "*somewhat disapprove*", (3) "*not sure*", (4) "*somewhat approve*" and (5) "*strongly approve*"). Column 1 refers to a version of Equation 6 where there are no demographic controls, no window × group fixed effects and the standard errors are not clustered. Column 2 refers to a version of Equation 6 where I control for respondents' age, gender, race, census region, household income and education (while not including window × group fixed effects nor clustering the standard errors). Column 3 refers to a pre-post regression as in Equation 6 where I control for an array of demographic controls (as in column 2) and I control for group × window fixed effects (while not clustering the standard errors). Column (4) refers to a regression identical to column 3 where the sole difference is the clustering of the standard errors at a group × window level (to adjust for sampling differences in each group of news consumers, across event-windows).

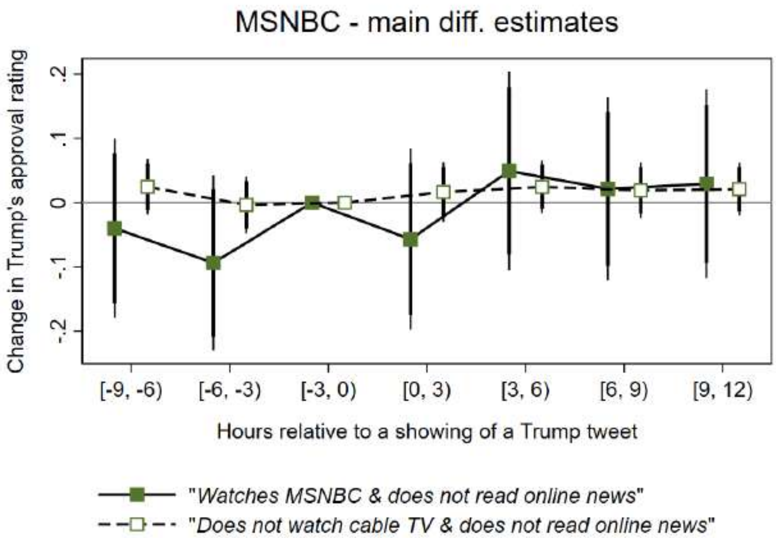
A.2.4 Robustness Checks

A.2.4.1 Parallel Trend Concerns

A.2.4.1.1 Event-Studies



(a) **Fox News**.

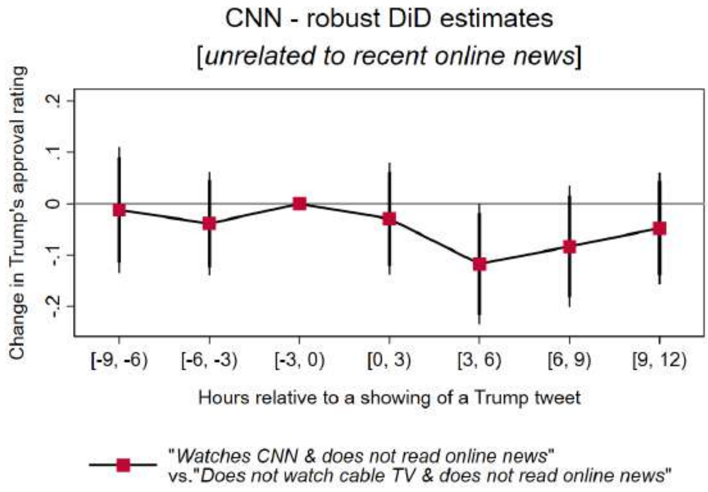


(b) **MSNBC**.

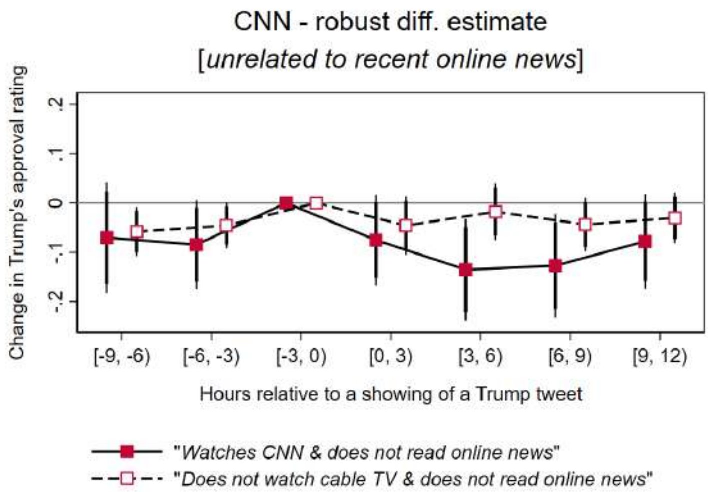
Figure A.2.9: **"Single-difference" event-study estimates – Fox News and MSNBC**. Panel (a) and (b) plot respectively the Fox News and MSNBC coefficients from an event-study regression as in Equation 7. The dependent variable is an approval ratings measure of Trump taking five values: (1) "*strong disapprove*", (2) "*somewhat disapprove*", (3) "*not sure*", (4) "*somewhat approve*" and (5) "*strongly approve*". The error bars refer to 95% confidence intervals drawn from standard errors clustered at a network $\times$ window level.

A.2.4.2 Omitted Variable Concerns

A.2.4.2.1 Event-Studies

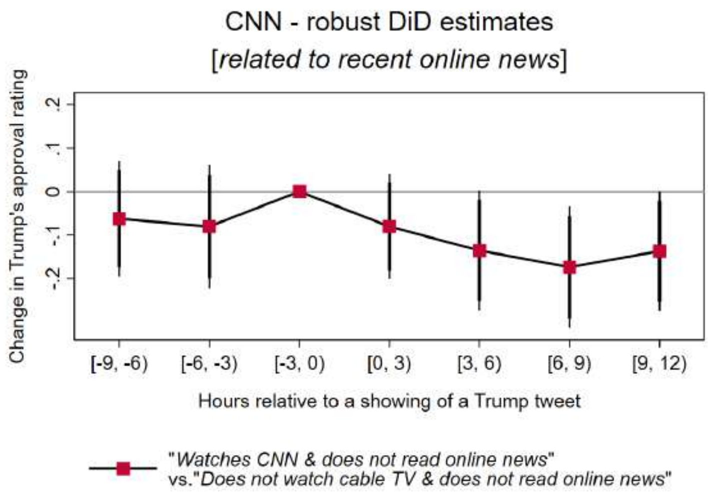


(a) **Differences-in-differences**.

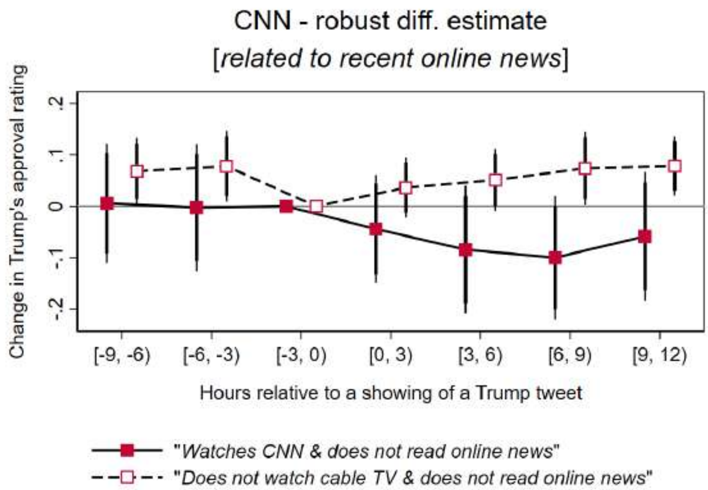


(b) **Difference**.

Figure A.2.10: **Unrelated to recent online news, diff.-in.diff. – CNN**. Panel (a) shows CNN coefficients from an extension of the diff.-in-diff. regression laid out in Equation 5. In this extension, I allow respondents to react differently to showings of Trump tweets that are seemingly related or unrelated to neighboring news events. Panel (b) instead shows CNN coefficients referent to a similar extension of that single-differences regression laid out in Equation 7. The dependent variable is an approval ratings measure of Trump taking five values: (1) "*strong disapprove*", (2) "*somewhat disapprove*", (3) "*not sure*", (4) "*somewhat approve*" and (5) "*strongly approve*". The coefficients are referent to broadcasts of tweets that are seemingly unrelated to recent news events. The error bars refer to 95% confidence intervals drawn from standard errors clustered at a network $\times$ window level.

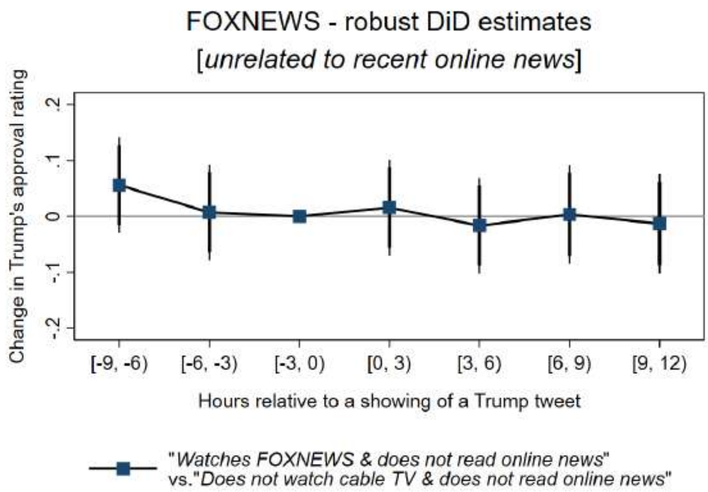


(a) **Differences-in-differences**.

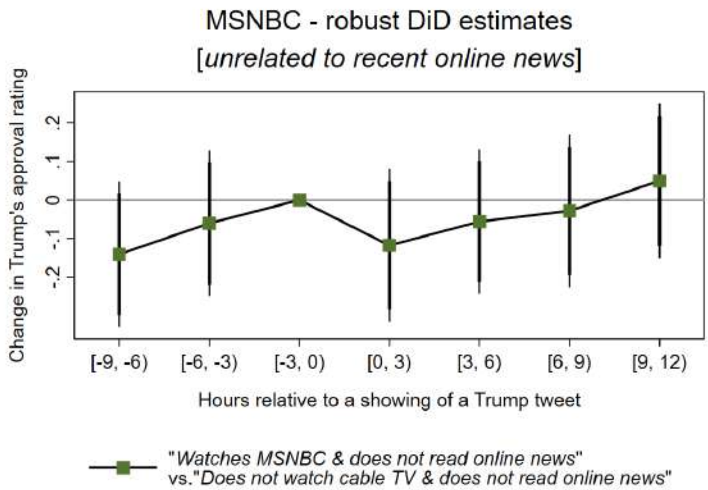


(b) **Difference**.

Figure A.2.11: **Related to recent online news, diff.-in.diff. − CNN**. Panel (a) shows CNN coefficients from an extension of the diff.-in-diff. regression laid out in Equation 5. In this extension, I allow respondents to react differently to showings of Trump tweets that are seemingly related or unrelated to neighboring news events. Panel (b) instead shows CNN coefficients referent to a similar extension of that single-differences regression laid out in Equation 7. The dependent variable is an approval ratings measure of Trump taking five values: (1) "*strong disapprove*", (2) "*somewhat disapprove*", (3) "*not sure*", (4) "*somewhat approve*" and (5) "*strongly approve*". The coefficients are referent to broadcasts of tweets that are seemingly related to recent news events. The error bars refer to 95% confidence intervals drawn from standard errors clustered at a network × window level.

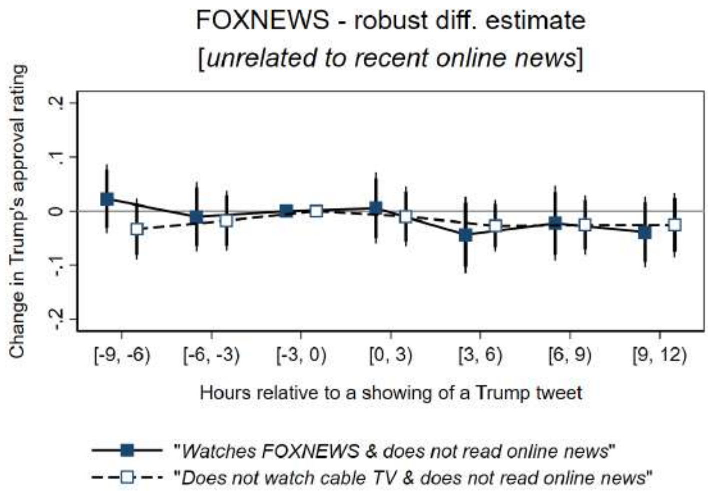


(a) **Fox News**.

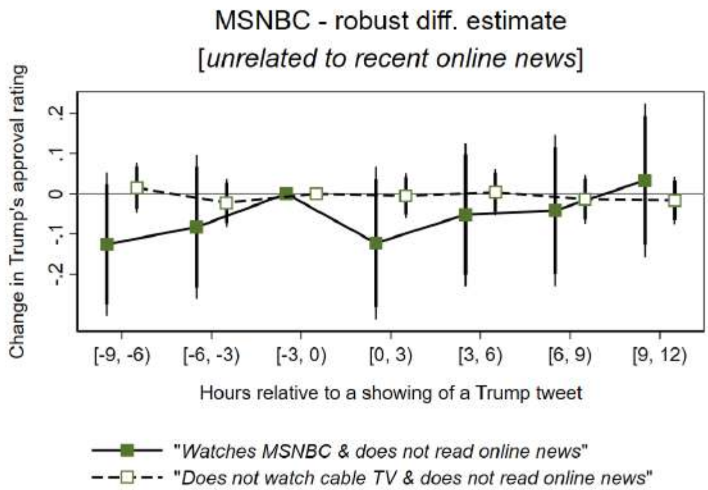


(b) **MSNBC**.

Figure A.2.12: **Unrelated to recent news, DiD – Fox News and MSNBC**. Panels (a) and (b) show different coefficients from an extension of the diff.-in-diff. (DiD) regression laid out in Equation 5. Panel (a) refers to those coefficients related to Fox News. Panel (b) instead is plotting those coefficients referent to MSNBC. As in Figure A.2.10, this extension allows respondents to react differently to showings of Trump tweets that are seemingly related or unrelated to neighboring news events (note: all coefficients, from Panel (a), Panel (b) and Figure A.2.10, are from one single regression). The dependent variable is an approval ratings measure of Trump taking five values: (1) "*strong disapprove*", (2) "*somewhat disapprove*", (3) "*not sure*", (4) "*somewhat approve*" and (5) "*strongly approve*". The coefficients are referent to broadcasts of tweets that are seemingly unrelated to recent news events. The error bars refer to 95% confidence intervals drawn from standard errors clustered at a network $\times$ window level.

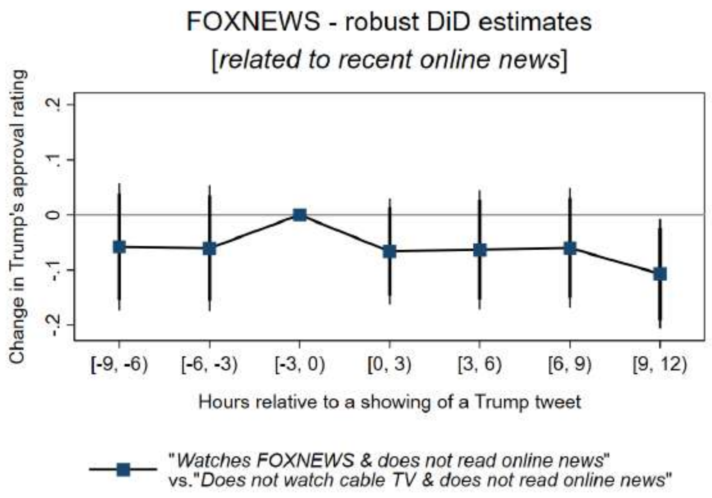


(a) **Fox News**.

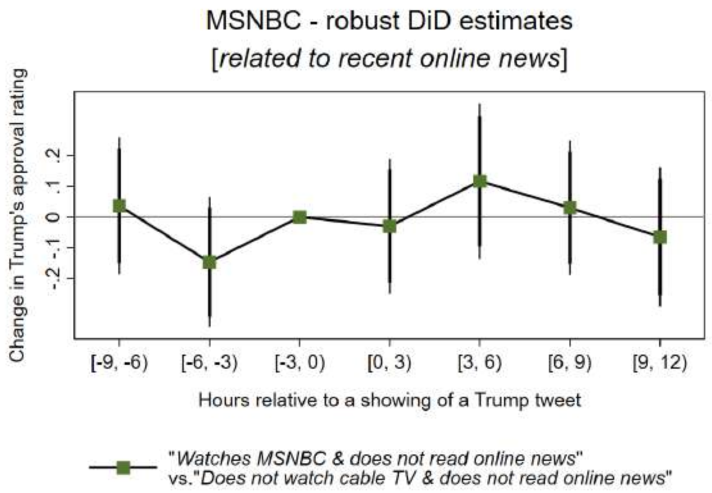


(b) **MSNBC**.

Figure A.2.13: **Unrelated to recent news, DiF – Fox News and MSNBC**. Panels (a) and (b) show different coefficients from an extension of the "single-differences" (DiF) event-study regression laid out in Equation 5. Panel (a) refers to those coefficients related to Fox News. Panel (b) instead is plotting those coefficients referent to MSNBC. As in Figure A.2.10, this extension allows respondents to react differently to showings of Trump tweets that are seemingly related or unrelated to neighboring news events (note: all coefficients, from Panel (a), Panel (b) and Figure A.2.10, are from one single regression). The dependent variable is an approval ratings measure of Trump taking five values: (1) "*strong disapprove*", (2) "*somewhat disapprove*", (3) "*not sure*", (4) "*somewhat approve*" and (5) "*strongly approve*". The coefficients are referent to broadcasts of tweets that are seemingly unrelated to recent news events. The error bars refer to 95% confidence intervals drawn from standard errors clustered at a network × window level.

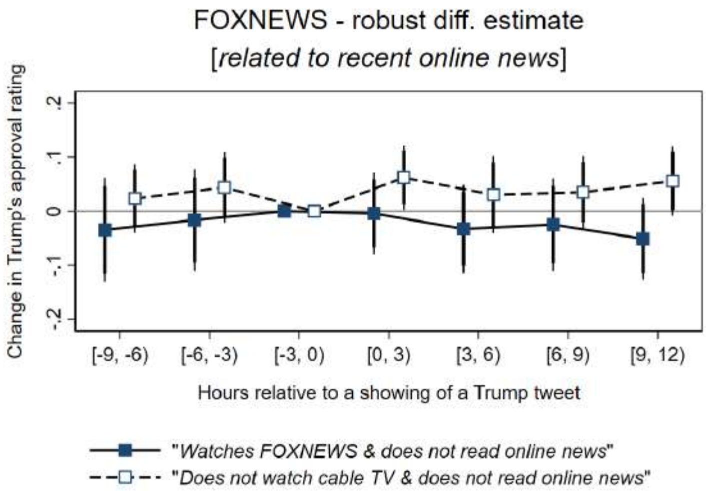


(a) **Fox News**.

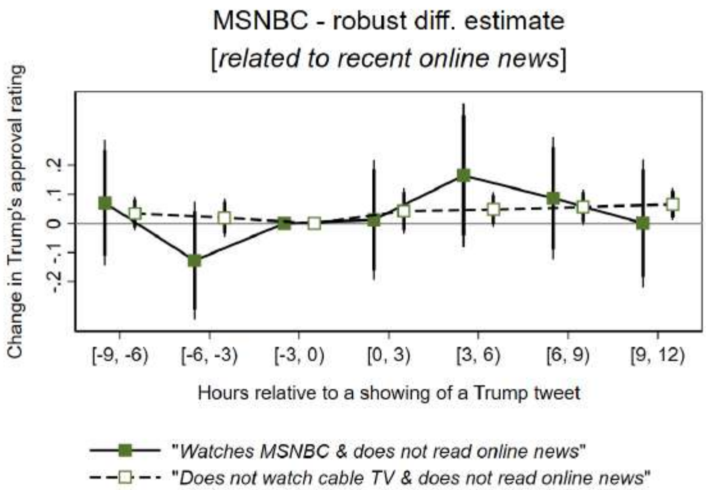


(b) **MSNBC**.

Figure A.2.14: **Related to recent news, DiD – Fox News and MSNBC**. Panels (a) and (b) show different coefficients from an extension of the diff.-in-diff. (DiD) regression laid out in Equation 5. Panel (a) refers to those coefficients related to Fox News. Panel (b) instead is plotting those coefficients referent to MSNBC. As in Figure A.2.10, this extension allows respondents to react differently to showings of Trump tweets that are seemingly related or unrelated to neighboring news events (note: all coefficients, from Panel (a), Panel (b) and Figure A.2.10, are from one single regression). The dependent variable is an approval ratings measure of Trump taking five values: (1) "*strong disapprove*", (2) "*somewhat disapprove*", (3) "*not sure*", (4) "*somewhat approve*" and (5) "*strongly approve*". The coefficients are referent to broadcasts of tweets that are seemingly related to recent news events. The error bars refer to 95% confidence intervals drawn from standard errors clustered at a network $\times$ window level.



(a) **Fox News**.

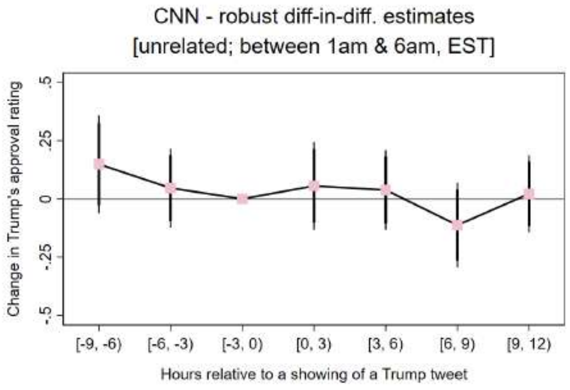


(b) **MSNBC**.

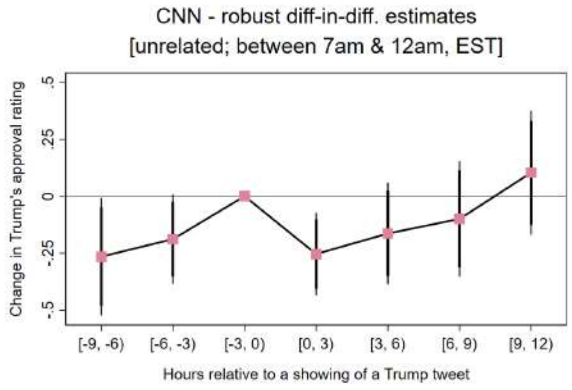
Figure A.2.15: **Related to recent news, DiF – Fox News and MSNBC**. Panels (a) and (b) show different coefficients from an extension of the "single-differences" (DiF) event-study regression laid out in Equation 5. Panel (a) refers to those coefficients related to Fox News. Panel (b) instead is plotting those coefficients referent to MSNBC. As in Figure A.2.10, this extension allows respondents to react differently to showings of Trump tweets that are seemingly related or unrelated to neighboring news events (note: all coefficients, from Panel (a), Panel (b) and Figure A.2.10, are from one single regression). The dependent variable is an approval ratings measure of Trump taking five values: (1) "*strong disapprove*", (2) "*somewhat disapprove*", (3) "*not sure*", (4) "*somewhat approve*" and (5) "*strongly approve*". The coefficients are referent to broadcasts of tweets that are seemingly related to recent news events. The error bars refer to 95% confidence intervals drawn from standard errors clustered at a network $\times$ window level.

A.2.5 Heterogeneity Analyses

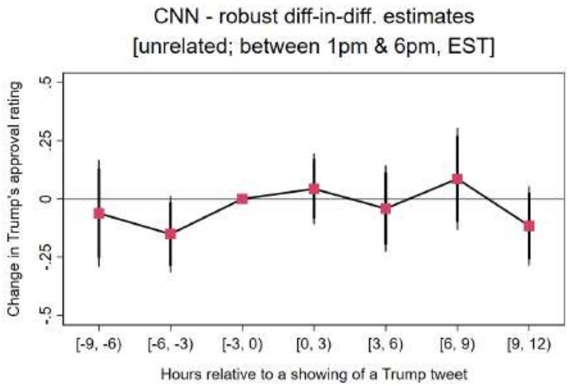
A.2.5.1 Heterogeneity by Time-Of-Day



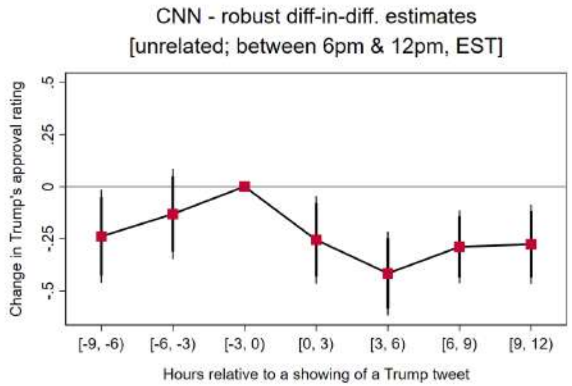
(a) **Between 1am & 6am, EST**.



(b) **Between 7am & 12am, EST**.

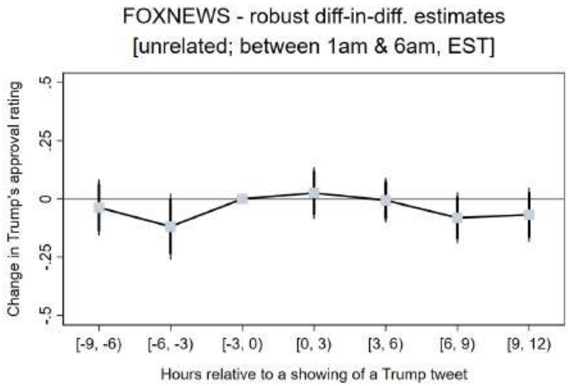


(c) **Between 1pm & 6pm, EST**.

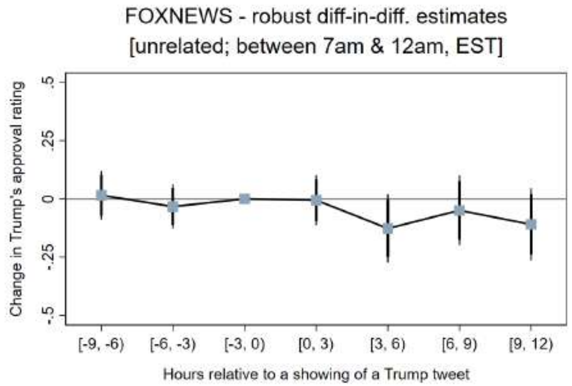


(d) **Between 7pm & 12pm, EST**.

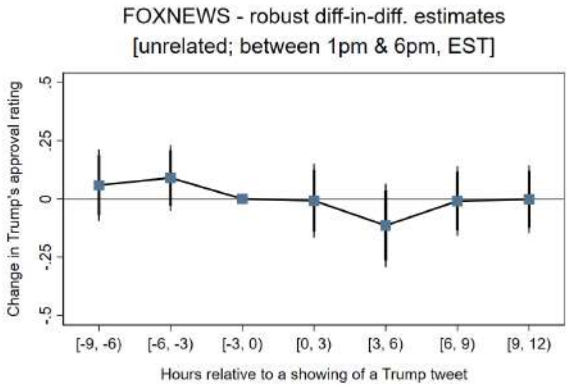
Figure A.2.16: **Heterogeneity by timing-of-day, event-study estimates – CNN, broadcasts unrelated to recent news**. Panels (a), (b), (c) and (d) plot the coefficients referent to CNN from an event-study regression similar to Eq. (8) only that extended to distinguish between showings of tweets related and unrelated to recent news events. The dependent variable is an approval ratings measure of Trump taking five values: (1) "*strong disapprove*", (2) "*somewhat disapprove*", (3) "*not sure*", (4) "*somewhat approve*" and (5) "*strongly approve*". Panel (a) refers to the CNN coefficients referent to broadcasts unrelated taking place between 1am and 6am EST. Panel (b) refers to the CNN coefficients referent to broadcasts taking place between 7am and 12am EST. Panel (c) refers to the CNN coefficients referent to broadcasts taking place between 1pm and 6pm EST. Panel (d) refers to the CNN coefficients referent to broadcasts taking place between 1pm and 6pm EST. ALL panels refer to showings referent to tweets seemingly unrelated to recent news events. The error bars refer to 95% confidence intervals drawn from standard errors clustered at a network × window level.



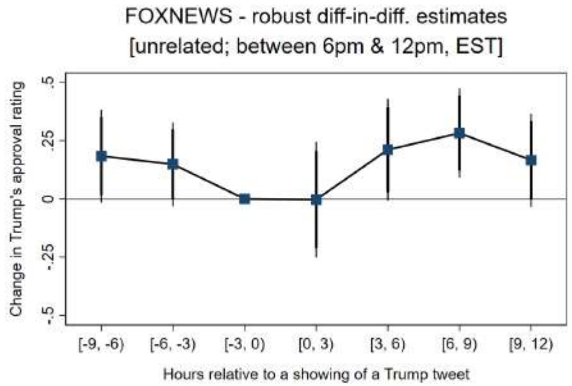
(a) **Between 1am & 6am, EST**.



(b) **Between 7am & 12am, EST**.

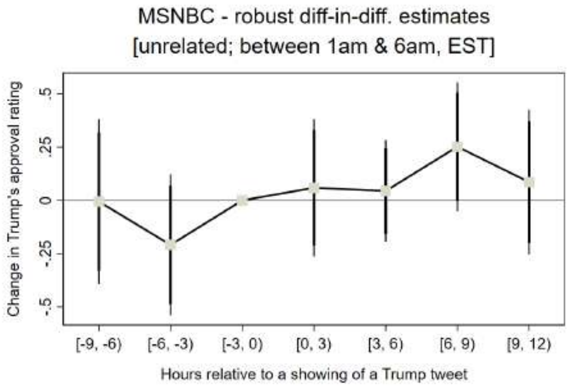


(c) **Between 1pm & 6pm, EST**.

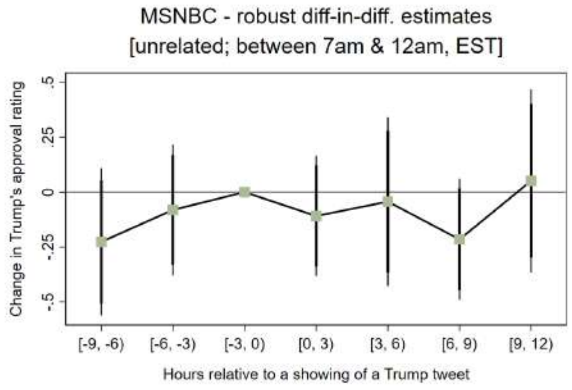


(d) **Between 7pm & 12pm, EST**.

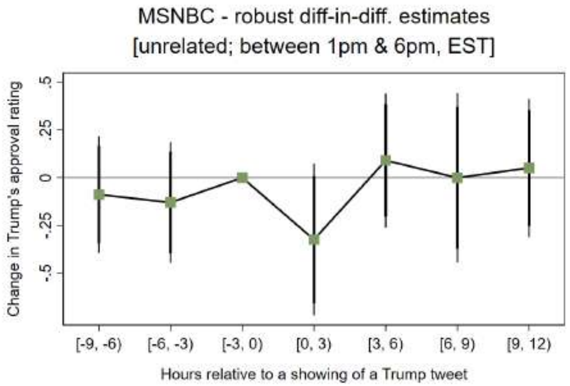
Figure A.2.17: **Heterogeneity by timing-of-day, event-study estimates – Fox News, broadcasts unrelated to recent news**. Panels (a), (b), (c) and (d) plot the coefficients referent to Fox News from an event-study regression similar to Eq. (8) only that extended to distinguish between showings of tweets related and unrelated to recent news events. The dependent variable is an approval ratings measure of Trump taking five values: (1) "*strong disapprove*", (2) "*somewhat disapprove*", (3) "*not sure*", (4) "*somewhat approve*" and (5) "*strongly approve*". Panel (a) refers to the Fox News coefficients referent to broadcasts unrelated taking place between 1am and 6am EST. Panel (b) refers to the Fox News coefficients referent to broadcasts taking place between 7am and 12am EST. Panel (c) refers to the Fox News coefficients referent to broadcasts taking place between 1pm and 6pm EST. Panel (d) refers to the Fox News coefficients referent to broadcasts taking place between 1pm and 6pm EST. ALL panels refer to showings referent to tweets seemingly unrelated to recent news events. The error bars refer to 95% confidence intervals drawn from standard errors clustered at a network $\times$ window level.



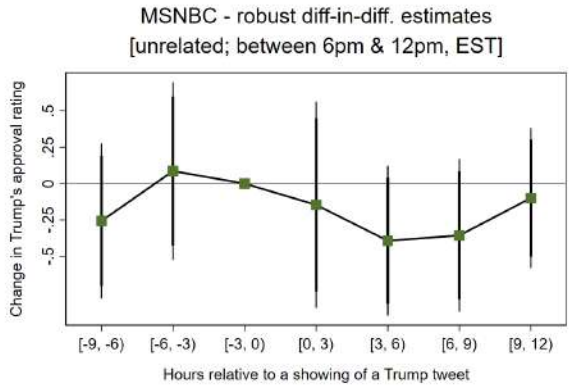
(a) **Between 1am & 6am, EST**.



(b) **Between 7am & 12am, EST**.

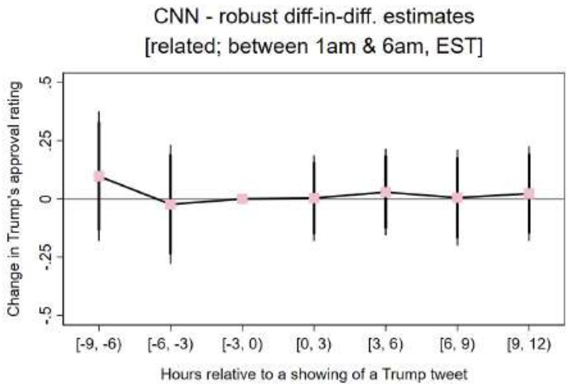


(c) **Between 1pm & 6pm, EST**.

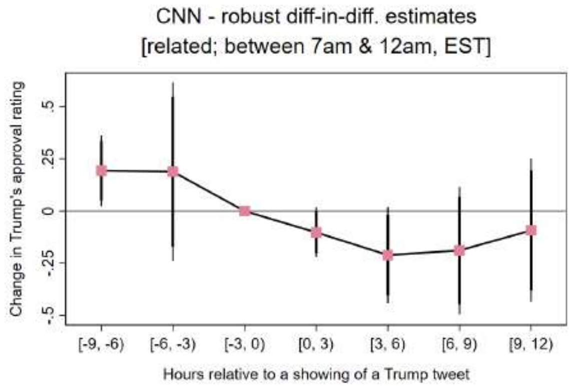


(d) **Between 7pm & 12pm, EST**.

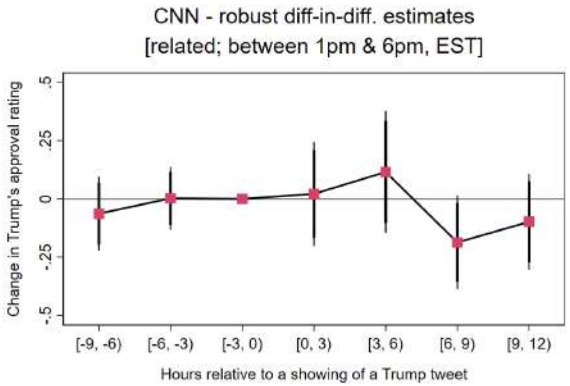
Figure A.2.18: **Heterogeneity by timing-of-day, event-study estimates – MSNBC, broadcasts unrelated to recent news**. Panels (a), (b), (c) and (d) plot the coefficients referent to Fox News from an event-study regression similar to Eq. (8) only that extended to distinguish between showings of tweets related and unrelated to recent news events. The dependent variable is an approval ratings measure of Trump taking five values: (1) "*strong disapprove*", (2) "*somewhat disapprove*", (3) "*not sure*", (4) "*somewhat approve*" and (5) "*strongly approve*". Panel (a) refers to the Fox News coefficients referent to broadcasts unrelated taking place between 1am and 6am EST. Panel (b) refers to the Fox News coefficients referent to broadcasts taking place between 7am and 12am EST. Panel (c) refers to the Fox News coefficients referent to broadcasts taking place between 1pm and 6pm EST. Panel (d) refers to the Fox News coefficients referent to broadcasts taking place between 1pm and 6pm EST. ALL panels refer to showings referent to tweets seemingly unrelated to recent news events. The error bars refer to 95% confidence intervals drawn from standard errors clustered at a network × window level.



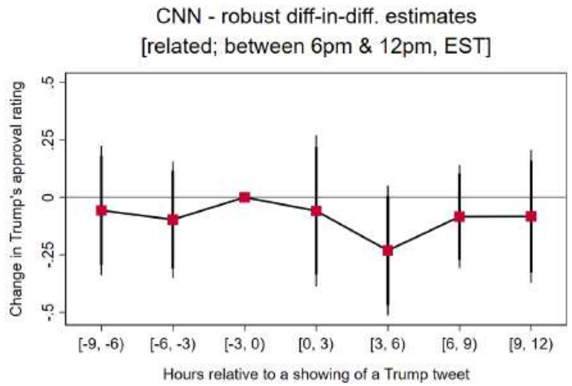
(a) **Between 1am & 6am, EST**.



(b) **Between 7am & 12am, EST**.

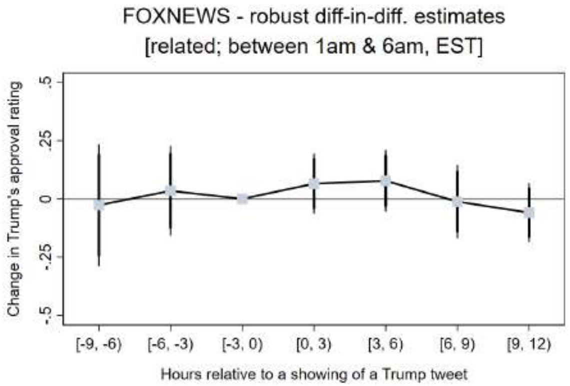


(c) **Between 1pm & 6pm, EST**.

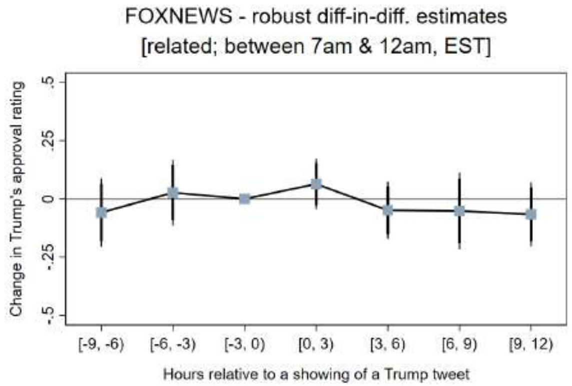


(d) **Between 7pm & 12pm, EST**.

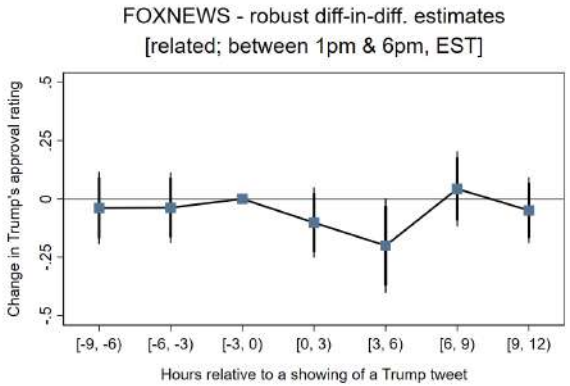
Figure A.2.19: **Heterogeneity by timing-of-day, event-study estimates – CNN, broadcasts related to recent news**. Panels (a), (b), (c) and (d) plot the coefficients referent to CNN from an event-study regression similar to Eq. (8) only that extended to distinguish between showings of tweets related and unrelated to recent news events. The dependent variable is an approval ratings measure of Trump taking five values: (1) "*strong disapprove*", (2) "*somewhat disapprove*", (3) "*not sure*", (4) "*somewhat approve*" and (5) "*strongly approve*". Panel (a) refers to the CNN coefficients referent to broadcasts unrelated taking place between 1am and 6am EST. Panel (b) refers to the CNN coefficients referent to broadcasts taking place between 7am and 12am EST. Panel (c) refers to the CNN coefficients referent to broadcasts taking place between 1pm and 6pm EST. Panel (d) refers to the CNN coefficients referent to broadcasts taking place between 1pm and 6pm EST. ALL panels refer to showings referent to tweets seemingly related to recent news events. The error bars refer to 95% confidence intervals drawn from standard errors clustered at a network × window level.



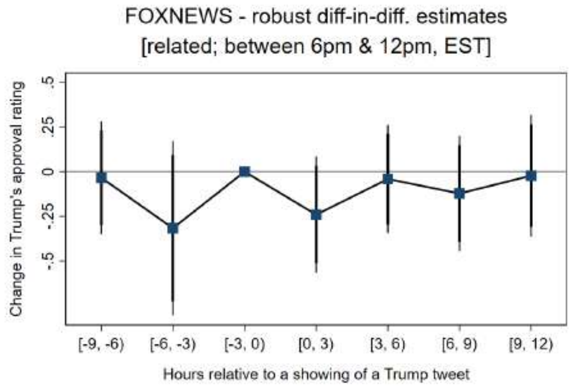
(a) **Between 1am & 6am, EST**.



(b) **Between 7am & 12am, EST**.

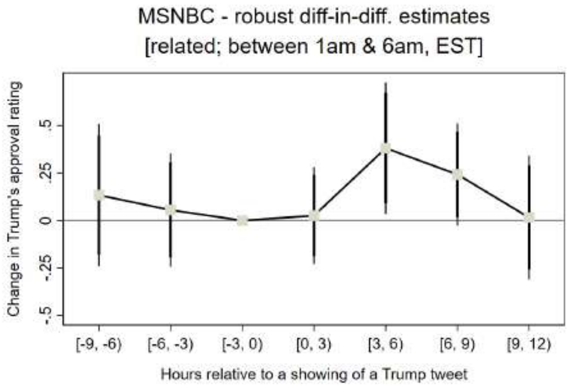


(c) **Between 1pm & 6pm, EST**.

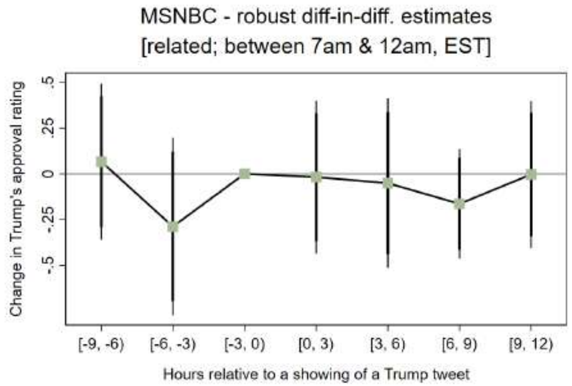


(d) **Between 7pm & 12pm, EST**.

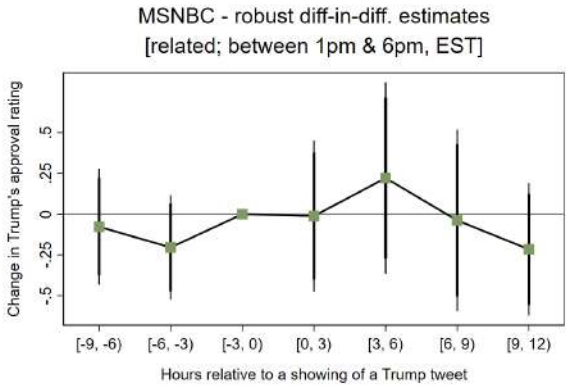
Figure A.2.20: **Heterogeneity by timing-of-day, event-study estimates – Fox News, broadcasts related to recent news**. Panels (a), (b), (c) and (d) plot the coefficients referent to Fox News from an event-study regression similar to Eq. (8) only that extended to distinguish between showings of tweets related and unrelated to recent news events. The dependent variable is an approval ratings measure of Trump taking five values: (1) "*strong disapprove*", (2) "*somewhat disapprove*", (3) "*not sure*", (4) "*somewhat approve*" and (5) "*strongly approve*". Panel (a) refers to the Fox News coefficients referent to broadcasts unrelated taking place between 1am and 6am EST. Panel (b) refers to the Fox News coefficients referent to broadcasts taking place between 7am and 12am EST. Panel (c) refers to the Fox News coefficients referent to broadcasts taking place between 1pm and 6pm EST. Panel (d) refers to the Fox News coefficients referent to broadcasts taking place between 1pm and 6pm EST. ALL panels refer to showings referent to tweets seemingly unrelated to recent news events. The error bars refer to 95% confidence intervals drawn from standard errors clustered at a network × window level.



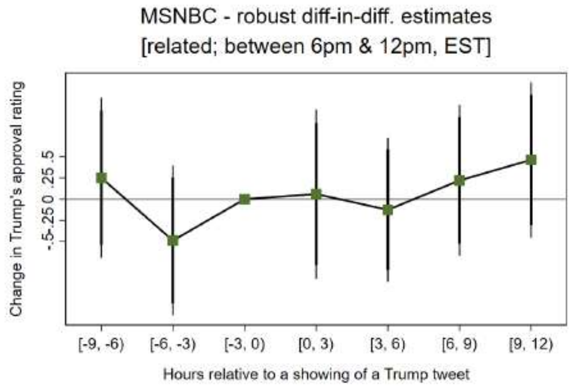
(a) **Between 1am & 6am, EST**.



(b) **Between 7am & 12am, EST**.



(c) **Between 1pm & 6pm, EST**.



(d) **Between 7pm & 12pm, EST**.

Figure A.2.21: **Heterogeneity by timing-of-day, event-study estimates – MSNBC, broadcasts related to recent news**. Panels (a), (b), (c) and (d) plot the coefficients referent to Fox News from an event-study regression similar to Eq. (8) only that extended to distinguish between showings of tweets related and unrelated to recent news events. The dependent variable is an approval ratings measure of Trump taking five values: (1) "*strong disapprove*", (2) "*somewhat disapprove*", (3) "*not sure*", (4) "*somewhat approve*" and (5) "*strongly approve*". Panel (a) refers to the Fox News coefficients referent to broadcasts unrelated taking place between 1am and 6am EST. Panel (b) refers to the Fox News coefficients referent to broadcasts taking place between 7am and 12am EST. Panel (c) refers to the Fox News coefficients referent to broadcasts taking place between 1pm and 6pm EST. Panel (d) refers to the Fox News coefficients referent to broadcasts taking place between 1pm and 6pm EST. ALL panels refer to showings referent to tweets seemingly related to recent news events. The error bars refer to 95% confidence intervals drawn from standard errors clustered at a network × window level.