Trumping the News:

A High-Frequency Analysis

Jaime Marques Pereira

University of Lancaster

EEA-ESEM 2024, Rotterdam

"Political Economy: Media I" Contributed Session

August 26, 2024

Motivation

- Politicians increasingly use social media (Pew, 2021a).
- Social media messages more sentimental than in other media.
- What about social media on other forms of media (say, e.g., TV news)?

$\Longrightarrow$ Amplification of online statements towards a significant share of voters, those that use TV as main news source, still a political majority (Pew, 2021b).

Motivation

- Politicians increasingly use social media (Pew, 2021a).
- Social media messages more sentimental than in other media.
- What about social media on other forms of media (say, e.g., TV news)?

$\Longrightarrow$ Amplification of online statements towards a significant share of voters, those that use TV as main news source, still a political majority (Pew, 2021b).

Motivation

- Politicians increasingly use social media (Pew, 2021a).
- Social media messages more sentimental than in other media.
- What about social media on other forms of media (say, e.g., TV news)?

$\Longrightarrow$ Amplification of online statements towards a significant share of voters, those that use TV as main news source, still a political majority (Pew, 2021b).

Motivation

- Politicians increasingly use social media (Pew, 2021a).
- Social media messages more sentimental than in other media.
- What about social media on other forms of media (say, e.g., TV news)?

$\Longrightarrow$ Amplification of online statements towards a significant share of voters, those that use TV as main news source, still a political majority (Pew, 2021b).

Motivation

- Politicians increasingly use social media (Pew, 2021a).
- Social media messages more sentimental than in other media.
- What about social media on other forms of media (say, e.g., TV news)?

$\Longrightarrow$ Amplification of online statements towards a significant share of voters, those that use TV as main news source, still a political majority (Pew, 2021b).

Motivation

- Politicians increasingly use social media (Pew, 2021a).
- Social media messages more sentimental than in other media.
- What about social media on other forms of media (say, e.g., TV news)?

$\Longrightarrow$ Amplification of online statements towards a significant share of voters, those that use TV as main news source, still a political majority (Pew, 2021b).

Motivation

- Politicians increasingly use social media (Pew, 2021a).
- Social media messages more sentimental than in other media.
- What about social media on other forms of media (say, e.g., TV news)?

$\Longrightarrow$ Amplification of online statements towards a significant share of voters, those that use TV as main news source, still a political majority (Pew, 2021b).

This paper

- Case-study: Donald Trump's use of Twitter and U.S. cable news outlets.

1. Whether and to what extent did cable outlets cover Donald Trump's tweets?
    - Donald J. Trump's tweets were covered *live* by cable news channels.
    - Coverages were not driven by tweets related to pressing news events;
        - Donald Trump had an *agenda-setting power* over cable news.
2. How did this coverage affect the political opinions of these outlets' audiences?
    - Prime-time coverages caused significant changes in Trump's ratings.
    - Asymmetric across outlets and driven by combination of phenomena;
        - TV coverage of social media posts had a *polarizing* effect over audiences

This paper

- Case-study: Donald Trump's use of Twitter and U.S. cable news outlets.

1. Whether and to what extent did cable outlets cover Donald Trump's tweets?
   - Donald J. Trump's tweets were covered *live* by cable news channels.
   - Coverages were not driven by tweets related to pressing news events;
     - Donald Trump had an *agenda-setting power* over cable news.
2. How did this coverage affect the political opinions of these outlets' audiences?
   - Prime-time coverages caused significant changes in Trump's ratings.
   - Asymmetric across outlets and driven by combination of phenomena;
     - TV coverage of social media posts had a *polarizing* effect over audiences.

This paper

- Case-study: Donald Trump's use of Twitter and U.S. cable news outlets.

1. Whether and to what extent did cable outlets cover Donald Trump's tweets?
    - Donald J. Trump's tweets were covered *live* by cable news channels.
    - Coverages were not driven by tweets related to pressing news events;
        - Donald Trump had an *agenda-setting power* over cable news.
2. How did this coverage affect the political opinions of these outlets' audiences?
    - Prime-time coverages caused significant changes in Trump's ratings.
    - Asymmetric across outlets and driven by combination of phenomena;
        - TV coverage of social media posts had a *polarizing* effect over audiences.

This paper

- Case-study: Donald Trump's use of Twitter and U.S. cable news outlets.

1. Whether and to what extent did cable outlets cover Donald Trump's tweets?
    - Donald J. Trump's tweets were covered *live* by cable news channels.
    - Coverages were not driven by tweets related to pressing news events;
        - Donald Trump had an *agenda-setting power* over cable news.

2. How did this coverage affect the political opinions of these outlets' audiences?
    - Prime-time coverages caused significant changes in Trump's ratings.
    - Asymmetric across outlets and driven by combination of phenomena;
        - TV coverage of social media posts had a *polarizing* effect over audiences.

This paper

- Case-study: Donald Trump's use of Twitter and U.S. cable news outlets.

1. Whether and to what extent did cable outlets cover Donald Trump's tweets?
   - Donald J. Trump's tweets were covered *live* by cable news channels.
   - Coverages were not driven by tweets related to pressing news events;
     - Donald Trump had an *agenda-setting power* over cable news.
2. How did this coverage affect the political opinions of these outlets' audiences?
   - Prime-time coverages caused significant changes in Trump's ratings.
   - Asymmetric across outlets and driven by combination of phenomena;
     - TV coverage of social media posts had a *polarizing* effect over audiences.

This paper

- Case-study: Donald Trump's use of Twitter and U.S. cable news outlets.

1. Whether and to what extent did cable outlets cover Donald Trump's tweets?
    - Donald J. Trump's tweets were covered *live* by cable news channels.
    - Coverages were not driven by tweets related to pressing news events;
        - Donald Trump had an *agenda-setting power* over cable news.
2. How did this coverage affect the political opinions of these outlets' audiences?
    - Prime-time coverages caused significant changes in Trump's ratings.
    - Asymmetric across outlets and driven by combination of phenomena;
        - TV coverage of social media posts had a *polarizing* effect over audiences.

Related literature

- **Agenda-setting power**. McCombs and Shaw (1972), Iyengar and Kinder (1987), Krosnick and Kinder (1990), Iyengar and Kinder (2010), Barberá et al. (2019).

  → First *causal* account of an agenda-setting power by politicians.

- **Political effects of social media**. Enikolopov et al. (2020), Allcott et al. (2020), Mosquera et al. (2020), Levy (2021), Melnikov (2021), Fujiwara et al. (2023).

  → First account of *indirect* effects of social media over political opinions.

- **Social media and news**. Hatte et al. (2021), Cagé et al. (2022).

  → Additional channel through which social media impacts news.

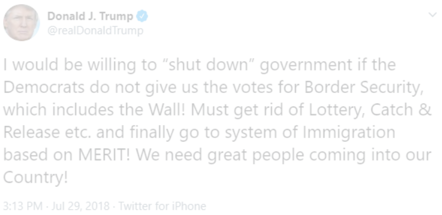
  → First measure for how social media shaped news affect public opinion.

1

Whether and to what extent did cable outlets cover Donald Trumps' tweets?

1 / Data

A. Timestamps / texts for tweets posted by Donald Trump (2015 - 2020).



- Approximately 20K statements:
  - timestamps used for events;
  - texts used for studying TV news.

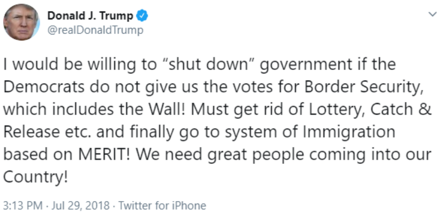
B. Timestamps / texts for transcripts aired by cable news outlets (2015 - 2020).

```
[000:13:11;123] THIS MORNING THE PRESIDENT IN
[000:13:13;058] ADDITION TO SPEAKING TO TROOPS
[000:13:14;827] ALSO USED TWITTER FOR ONE OF HIS
[000:13:17;129] MORE TYPICAL BROADSIDES AGAINST
[000:13:18;464] THE MEDIA WHERE HE TWEETS,
[000:13:20;633] PERHAPS IN RESPONSE TO "THE NEW
[000:13:22;768] YORK TIMES" STORY OR OTHER
[000:13:23;569] COVERAGE, THE FAKE NEWS REFUSES
[000:13:25;204] TO TALK HOW BIG AND HOW STRONG
[000:13:26;739] OUR BASE IS.
[000:13:27;940] THEY SHOW FAKE POLLS JUST LIKE
[000:13:30;309] THEY REPORT FAKE NEWS.
[000:13:32;011] DESPITE ONLY NEGATIVE REPORTING,
[000:13:33;445] WE ARE DOING WELL.
[000:13:34;446] NOBODY IS GOING TO BEAT US.
[000:13:36;215] MAKE AMERICA GREAT AGAIN.
```

- Approximately 75M subtitles:
  - used for coverage measures;
  - extent, intensity and sentiment.

1 / Data

A. Timestamps / texts for tweets posted by Donald Trump (2015 - 2020).



- Approximately 20K statements:
  - timestamps used for events;
  - texts used for studying TV news.

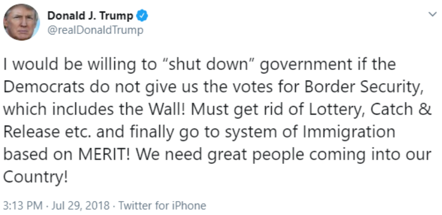
B. Timestamps / texts for transcripts aired by cable news outlets (2015 - 2020).

```
[000:13:11;123] THIS MORNING THE PRESIDENT IN
[000:13:13;058] ADDITION TO SPEAKING TO TROOPS
[000:13:14;827] ALSO USED TWITTER FOR ONE OF HIS
[000:13:17;129] MORE TYPICAL BROADSIDES AGAINST
[000:13:18;464] THE MEDIA WHERE HE TWEETS,
[000:13:20;633] PERHAPS IN RESPONSE TO "THE NEW
[000:13:22;768] YORK TIMES" STORY OR OTHER
[000:13:23;569] COVERAGE, THE FAKE NEWS REFUSES
[000:13:25;204] TO TALK HOW BIG AND HOW STRONG
[000:13:26;739] OUR BASE IS.
[000:13:27;940] THEY SHOW FAKE POLLS JUST LIKE
[000:13:30;309] THEY REPORT FAKE NEWS.
[000:13:32;011] DESPITE ONLY NEGATIVE REPORTING,
[000:13:33;445] WE ARE DOING WELL.
[000:13:34;446] NOBODY IS GOING TO BEAT US.
[000:13:36;215] MAKE AMERICA GREAT AGAIN.
```

- Approximately 75M subtitles:
  - used for coverage measures;
  - extent, intensity and sentiment.

1 / Data

A. Timestamps / texts for tweets posted by Donald Trump (2015 - 2020).



Donald J. Trump
@realDonaldTrump

I would be willing to "shut down" government if the Democrats do not give us the votes for Border Security, which includes the Wall! Must get rid of Lottery, Catch & Release etc. and finally go to system of Immigration based on MERIT! We need great people coming into our Country!

3:13 PM · Jul 29, 2018 · Twitter for iPhone

B. Timestamps / texts for transcripts aired by cable news outlets (2015 - 2020).

```
[000:13:11;123] THIS MORNING THE PRESIDENT IN
[000:13:13;058] ADDITION TO SPEAKING TO TROOPS
[000:13:14;827] ALSO USED TWITTER FOR ONE OF HIS
[000:13:17;129] MORE TYPICAL BROADSIDES AGAINST
[000:13:18;464] THE MEDIA WHERE HE TWEETS,
[000:13:20;633] PERHAPS IN RESPONSE TO "THE NEW
[000:13:22;768] YORK TIMES" STORY OR OTHER
[000:13:23;569] COVERAGE, THE FAKE NEWS REFUSES
[000:13:25;204] TO TALK HOW BIG AND HOW STRONG
[000:13:26;739] OUR BASE IS.
[000:13:27;940] THEY SHOW FAKE POLLS JUST LIKE
[000:13:30;309] THEY REPORT FAKE NEWS.
[000:13:32;011] DESPITE ONLY NEGATIVE REPORTING,
[000:13:33;445] WE ARE DOING WELL.
[000:13:34;446] NOBODY IS GOING TO BEAT US.
[000:13:36;215] MAKE AMERICA GREAT AGAIN.
```

- Approximately 20K statements:
  - timestamps used for events;
  - texts used for studying TV news.
- Approximately 75M subtitles:
  - used for coverage measures;
  - extent, intensity and sentiment.

1 / Empirical strategy

Overlap

- High-frequency event-study specification:

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

- $\beta^{\cdots}_{\cdots}$ can be interpreted as causal if and only if:
  - **No omitted variables**;
  - **No reverse causality**;
  - **No treatment overlap**.

- High-frequency event-study specification:

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

- $\beta_{\cdots}^{\cdots}$ can be interpreted as causal if and only if:
  - No omitted variables;
  - No reverse causality;
  - No treatment overlap.

Overlap

- High-frequency event-study specification:

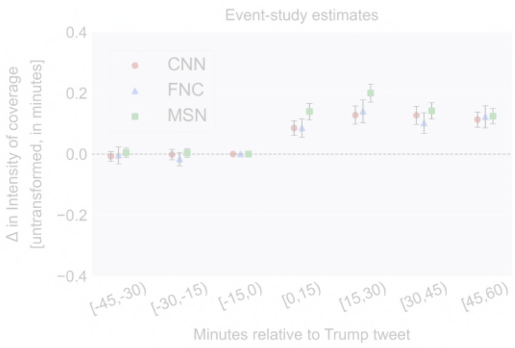
$$y_{n,w,\tau} = \alpha_{n,w} + \sum_{\eta \in \{C,F,M\}} \sum_{\substack{k=-3,\\ k\neq -1}}^{3} \mathbb{1}\begin{Bmatrix} n=\eta, \\ \tau=k \end{Bmatrix} \times \text{tweets}_{w,0} \times \beta_k^{\eta} + \varepsilon_{n,w,\tau}$$

- $\beta_{\cdots}^{\cdots}$ can be interpreted as causal if and only if:
  - **No omitted variables**;
  - **No reverse causality**;
  - **No treatment overlap**.

1 / Main results

Extent Sentiment

- Trump tweets caused cable outlets to shift their coverage towards "tweeted" issues.



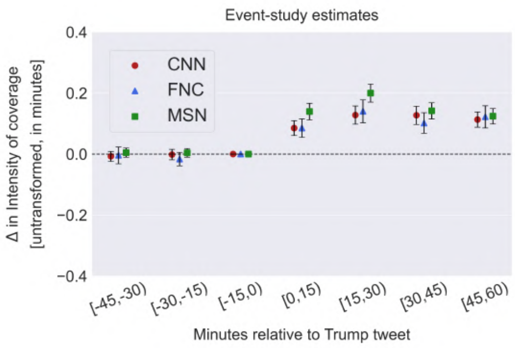
- A tweet on a given issue caused outlets to cover issue by an additional ≈ 1m12s.

	CNN	FNC	MSN
±2h15m	1.100***	1.311***	1.216***
	(0.091)	(0.102)	(0.093)
Obs.	62,920	62,920	62,920
Adj. R^2	-0.005	-0.005	-0.005
"Pre" avg.	0.363	0.723	0.335

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Main results

- Trump tweets caused cable outlets to shift their coverage towards "tweeted" issues.



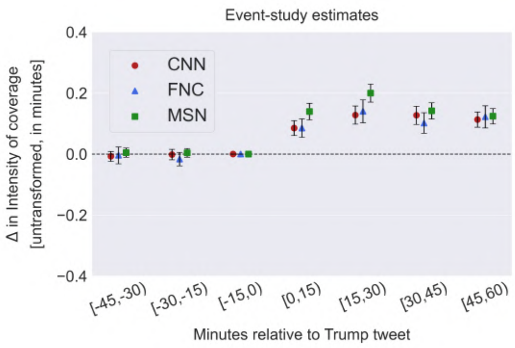
- A tweet on a given issue caused outlets to cover issue by an additional ≈ 1m12s.

	CNN	FNC	MSN
±2h15m	1.100***	1.311***	1.216***
	(0.091)	(0.102)	(0.093)
Obs.	62,920	62,920	62,920
Adj. R^2	-0.005	-0.005	-0.005
"Pre" avg.	0.363	0.723	0.335

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

- Trump tweets caused cable outlets to shift their coverage towards "tweeted" issues.

- A tweet on a given issue caused outlets to cover issue by an additional $\approx$ 1m12s.



	CNN	FNC	MSN
$\pm$2h15m	1.100***	1.311***	1.216***
	(0.091)	(0.102)	(0.093)
Obs.	62,920	62,920	62,920
Adj. R^2	-0.005	-0.005	-0.005
"Pre" avg.	0.363	0.723	0.335

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

1 / More

- Results are robust to...
  - reverse causality concerns: i.e., outlets shifted coverage towards tweets unrelated to (recent) past cable news stories;
  - omitted variable concerns: cable outlets's reaction was not driven by tweets that seemed to tackle pressing news events.
- **Donald J. Trump had an agenda-setting power over U.S. cable news**.
- In addition...
  - outlets reacted similarly to different topics;
  - cable outlets covered Trump's tweets prior to his presidency.
  - other prominent U.S. politicians did not see their tweets receive *same* coverage.

1 / More

- Results are robust to...
  - reverse causality concerns: i.e., outlets shifted coverage towards tweets unrelated to (recent) past cable news stories;
  - omitted variable concerns: cable outlets's reaction was not driven by tweets that seemed to tackle pressing news events.
- **Donald J. Trump had an agenda-setting power over U.S. cable news**.
- In addition...
  - outlets reacted similarly to different topics;
  - cable outlets covered Trump's tweets prior to his presidency.
    - other prominent U.S. politicians did not see their tweets receive *same* coverage.

1 / More

- Results are robust to...
  - reverse causality concerns: i.e., outlets shifted coverage towards tweets unrelated to (recent) past cable news stories;
  - omitted variable concerns: cable outlets's reaction was not driven by tweets that seemed to tackle pressing news events.
- **Donald J. Trump had an agenda-setting power over U.S. cable news**.
- In addition...
  - outlets reacted similarly to different topics;
  - cable outlets covered Trump's tweets prior to his presidency.
    - other prominent U.S. politicians did not see their tweets receive *same* coverage.

1 / More

- Results are robust to...
  - reverse causality concerns: i.e., outlets shifted coverage towards tweets unrelated to (recent) past cable news stories;
  - omitted variable concerns: cable outlets's reaction was not driven by tweets that seemed to tackle pressing news events.
- **Donald J. Trump had an agenda-setting power over U.S. cable news**.
- In addition...
  - outlets reacted similarly to different topics;
  - cable outlets covered Trump's tweets prior to his presidency.
    - other prominent U.S. politicians did not see their tweets receive *same* coverage.

1 / More

- Results are robust to...
  - reverse causality concerns: i.e., outlets shifted coverage towards tweets unrelated to (recent) past cable news stories;
  - omitted variable concerns: cable outlets's reaction was not driven by tweets that seemed to tackle pressing news events.
- **Donald J. Trump had an agenda-setting power over U.S. cable news**.
- In addition...
  - outlets reacted similarly to different topics;
  - cable outlets covered Trump's tweets prior to his presidency.
    - other prominent U.S. politicians did not see their tweets receive *same* coverage.

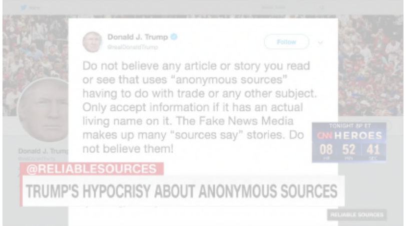
1 / More

- Results are robust to...
  - reverse causality concerns: i.e., outlets shifted coverage towards tweets unrelated to (recent) past cable news stories;
  - omitted variable concerns: cable outlets's reaction was not driven by tweets that seemed to tackle pressing news events.
- **Donald J. Trump had an agenda-setting power over U.S. cable news**.
- In addition...
  - outlets reacted similarly to different topics;
  - cable outlets covered Trump's tweets prior to his presidency.
    - other prominent U.S. politicians did not see their tweets receive *same* coverage.

2 | How did this coverage affect the political opinions of these outlets' audiences?

2 / Data

A. Text shown on-screen by cable outlets at a secondly frequency (2020 only).

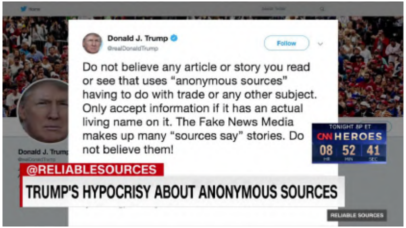


- $\approx$ 100M annotated images:
  - Timestamps for on-screen showings of tweets on cable.

B. Timestamped interviews on news consumption and opinions (2019 - 2021).

- Approximately 400k interviews:
  - High-frequency approval ratings of Trump for alternative news audiences.

A. Text shown on-screen by cable outlets at a secondly frequency (2020 only).



- ≈ 100M annotated images:
  - Timestamps for on-screen showings of tweets on cable.

B. Timestamped interviews on news consumption and opinions (2019 - 2021).

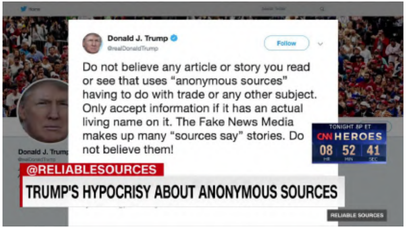
democracy fund
VOTER STUDY GROUP

UCLA

- Approximately 400k interviews:
  - High-frequency approval ratings of Trump for alternative news audiences.

2 / Data

A. Text shown on-screen by cable outlets at a secondly frequency (2020 only).



- ≈ 100M annotated images:
  - Timestamps for on-screen showings of tweets on cable.

B. Timestamped interviews on news consumption and opinions (2019 - 2021).

democracy fund
VOTER STUDY GROUP

UCLA

- Approximately 400k interviews:
  - High-frequency approval ratings of Trump for alternative news audiences.

Overlap

- High-frequency *difference-in-difference* event-study specification:

$$\text{trump\_approval}_{\text{i, g, n, w}, \tau} = \alpha_{\text{g, n, w}} + \mathbf{X}_{\text{i}} + \mathbb{1}\{\text{g: ``}\textit{watches n}\text{''}\} \times$$

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

- $\beta_{\dots}^{\dots}$ can be interpreted as causal if and only if:
  - **Parallel trends**;
  - **No treatment overlap**.

- High-frequency *difference-in-difference* event-study specification:

$$\text{trump\_approval}_{\,\text{i, g, n, w},\,\tau} = \alpha_{\,\text{g, n, w}} + \mathbf{X}_{\text{i}} + \mathbb{1}\,\{\text{g: "}\textit{watches n}\text{"}\} \times$$

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

- $\beta_{\cdots}^{\cdots}$ can be interpreted as causal if and only if:
  - Parallel trends;
  - No treatment overlap.

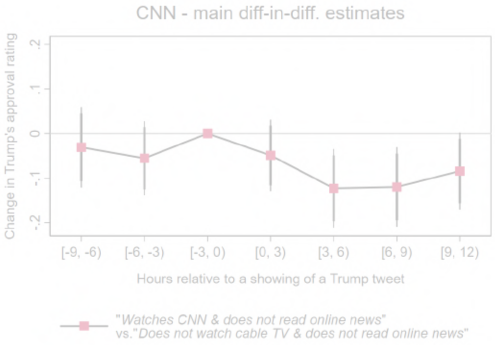
- High-frequency *difference-in-difference* event-study specification:

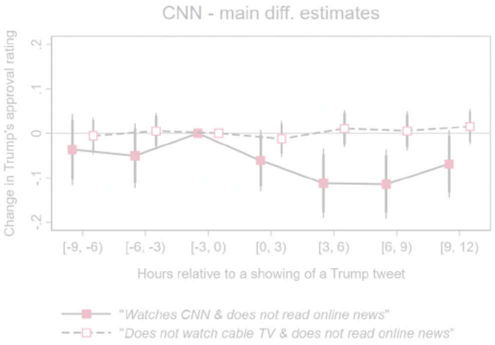
$$\text{trump\_approval}_{\,\mathrm{i,\,g,\,n,\,w},\,\tau} = \alpha_{\,\mathrm{g,\,n,\,w}} + \mathbf{X}_{\mathrm{i}} + \mathbb{1}\left\{\mathrm{g}\text{: ``}\textit{watches } n\text{''}\right\} \times$$

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

- $\beta^{\cdots}_{\cdots}$ can be interpreted as causal if and only if:
  - **Parallel trends**;
  - **No treatment overlap**.

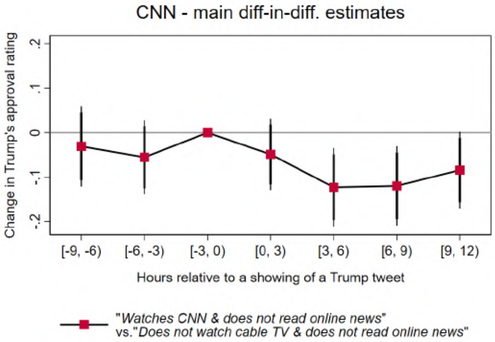
- CNN showings of Trump tweets caused CNN viewers to worsen Trump views.
- Change driven by CNN viewers deteriorating views vs. non-cable consumers.

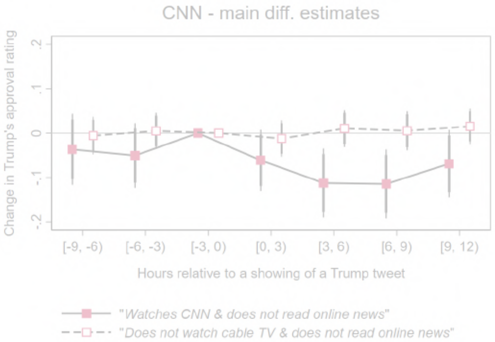




2 / Main results

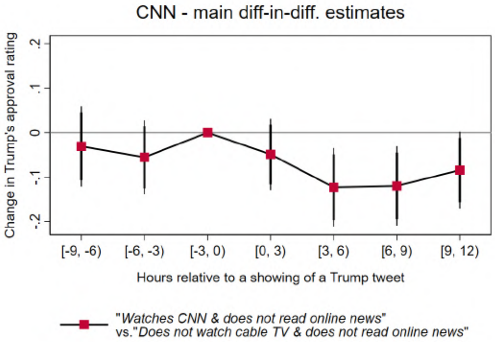
- CNN showings of Trump tweets caused CNN viewers to worsen Trump views.
- Change driven by CNN viewers deteriorating views vs. non-cable consumers.

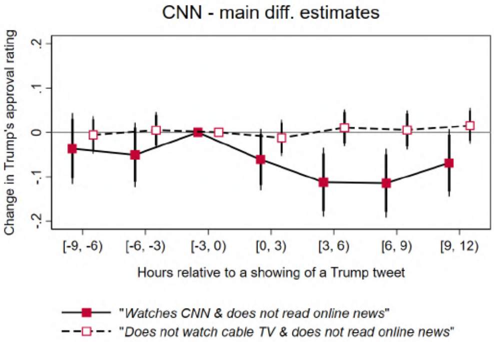




Effect size / Fox News MSNBC

- CNN showings of Trump tweets caused CNN viewers to worsen Trump views.
- Change driven by CNN viewers deteriorating views vs. non-cable consumers.





- Robust to a battery of checks (binary outcome, empirical specification, time frequency, event-window size and different variables on support for Trump [*candidate favorability*]).
- Prime-time showings caused *larger* and *asymmetric* changes in Trump ratings...
  - CNN showings caused CNN viewers to worsen Trump views;
  - Fox News showings caused Fox News viewers to improve Trump views.
- **TV showings of social media content causally affect political opinions**.
- Likely due to a combination of phenomena...
  - Trump's tweets being *filtered* differently across outlets.
  - Trump's tweets being *slanted* differently across outlets.

- Robust to a battery of checks (binary outcome, empirical specification, time frequency, event-window size and different variables on support for Trump [*candidate favorability*]).

- Prime-time showings caused *larger* and *asymmetric* changes in Trump ratings...
  - CNN showings caused CNN viewers to worsen Trump views;
  - Fox News showings caused Fox News viewers to improve Trump views.

- **TV showings of social media content causally affect political opinions.**

- Likely due to a combination of phenomena...
  - Trump's tweets being *filtered* differently across outlets.
  - Trump's tweets being *slanted* differently across outlets.

2 / More

- Robust to a battery of checks (binary outcome, empirical specification, time frequency, event-window size and different variables on support for Trump [*candidate favorability*]).
- Prime-time showings caused *larger* and *asymmetric* changes in Trump ratings...
  - CNN showings caused CNN viewers to worsen Trump views;
  - Fox News showings caused Fox News viewers to improve Trump views.
- **TV showings of social media content causally affect political opinions**.
- Likely due to a combination of phenomena...
  - Trump's tweets being *filtered* differently across outlets.
  - Trump's tweets being *slanted* differently across outlets.

2 / More

- Robust to a battery of checks (binary outcome, empirical specification, time frequency, event-window size and different variables on support for Trump [*candidate favorability*]).
- Prime-time showings caused *larger* and *asymmetric* changes in Trump ratings...
    - CNN showings caused CNN viewers to worsen Trump views;
    - Fox News showings caused Fox News viewers to improve Trump views.
- **TV showings of social media content causally affect political opinions**.
- Likely due to a combination of phenomena...
    - Trump's tweets being <u>*filtered*</u> differently across outlets.
    - Trump's tweets being <u>*slanted*</u> differently across outlets.

Conclusion

Conclusion

Truth Social

- High-frequency analysis of Trump tweets and timestamped television transcripts:
  - Donald J. Trump's tweets were covered *live* by cable news channels;
  - Donald Trump had an *agenda-setting power* over U.S. cable news outlets.
- Comparing Trump ratings across different news audiences within-day:
  - Prime-time coverages caused significant changes in Trump's ratings;
  - Asymmetric across outlets and driven by a combination of phenomena.
- This paper...

  ... new channel through which social media impacts individuals' political opinions.

Conclusion

Truth Social

- High-frequency analysis of Trump tweets and timestamped television transcripts:
  - Donald J. Trump's tweets were covered *live* by cable news channels;
  - Donald Trump had an *agenda-setting power* over U.S. cable news outlets.
- Comparing Trump ratings across different news audiences within-day:
  - Prime-time coverages caused significant changes in Trump's ratings;
  - Asymmetric across outlets and driven by a combination of phenomena.
- This paper...

  ... new channel through which social media impacts individuals' political opinions.

Conclusion

Truth Social

- High-frequency analysis of Trump tweets and timestamped television transcripts:
  - Donald J. Trump's tweets were covered *live* by cable news channels;
  - Donald Trump had an *agenda-setting power* over U.S. cable news outlets.
- Comparing Trump ratings across different news audiences within-day:
  - Prime-time coverages caused significant changes in Trump's ratings;
  - Asymmetric across outlets and driven by a combination of phenomena.
- This paper...

  ... new channel through which social media impacts individuals' political opinions.

Conclusion

▸ Truth Social

- High-frequency analysis of Trump tweets and timestamped television transcripts:
  - Donald J. Trump's tweets were covered *live* by cable news channels;
  - Donald Trump had an *agenda-setting power* over U.S. cable news outlets.
- Comparing Trump ratings across different news audiences within-day:
  - Prime-time coverages caused significant changes in Trump's ratings;
  - Asymmetric across outlets and driven by a combination of phenomena.
- This paper...

  ... new channel through which social media impacts individuals' political opinions.

Thank you!

References I

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

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].

References II

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].

DellaVigna, S. and Gentzkow, M. (2010). Persuasion: Empirical evidence. *Annual Review of Econonomics*, 2(1):643–669. [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].

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

References III

Fujiwara, T., Müller, K., and Schwarz, C. (2023). The Effect of Social Media on Elections: Evidence from the United States. *Journal of the European Economic Association*, page jvad058. [URL].

Hatte, S., Zhuravskaya, E., 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].

Iyengar, S. and Kinder, D. R. (1987). *News that Matters: Television and American Opinion*. University of Chicago Press. [URL].

Iyengar, S. and Kinder, D. R. (2010). *News that Matters: Television and American Opinion, Updated Edition*. University of Chicago Press. [URL].

References IV

Krosnick, J. A. and Kinder, D. R. (1990). Altering the Foundations of Support for the President Through Priming. *American Political Science Review*, 84(2):497–512. [URL].

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

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

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

References V

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

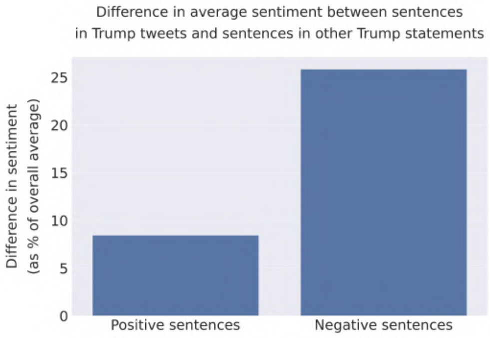
Pew (2021a). Charting Congress on Social Media in the 2016 and 2020 Elections. Written by Sono Shah, Andrew Grant and others, Pew Research Center, Washington D.C. [URL].

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

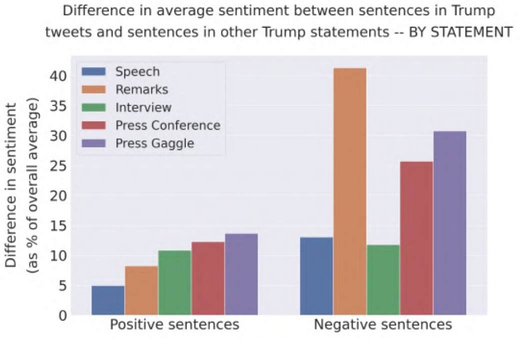
Appendix

Back

- Tweets are more sentimentally charged than other public statements by Trump.
- Same pattern holds within different types of statements (e.g., tweets vs. rallies).



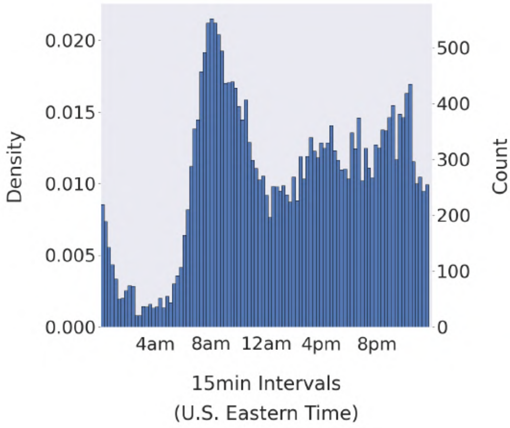
Note: Trump Twitter Archive + Factba.se; own calculations.



Note: Trump Twitter Archive + Factba.se; own calculations.

- tweets_t = number of tweets posted by President Trump during period t
- Event-windows centered on tweets.

Figure: Trump tweets within a generic day, from January 1, 2015, to January 1, 2021



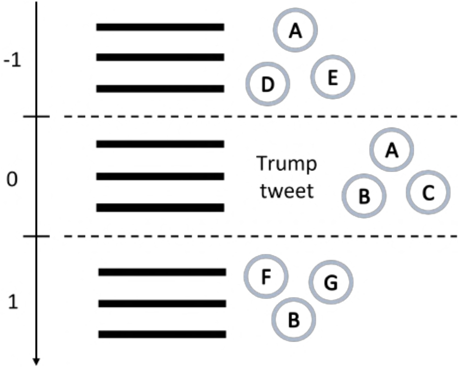
Back

- Number of 3-word expressions shared between an outlet's transcripts and Trump's tweets:

$$\text{extent\_of\_coverage}_{n,w,\tau} =$$

$$= \sum_{\text{intervention} \in \text{transcripts}_{n,w,\tau}}$$

$$= \text{sim}(\text{intervention}, \text{tweets}_w)$$



Back

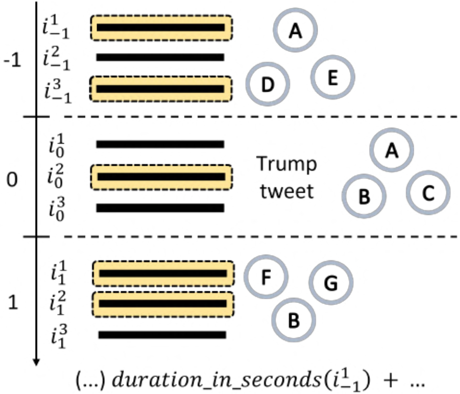
- Amount of minutes an outlet spent discussing those expressions used in Trump's tweets:

$$\text{intensity\_of\_coverage}_{\text{n,w},\tau} =$$

$$= \sum_{\text{intervention} \in \text{transcripts}_{\text{n,w},\tau}}$$

$$\text{duration\_in\_seconds}(\text{intervention}) \times$$

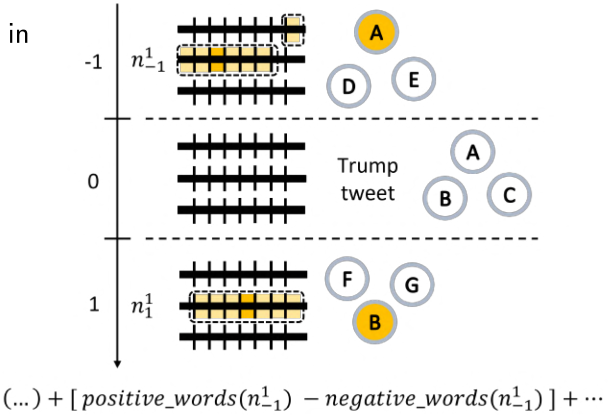
$$\times \mathbb{1}\left\{\text{sim}(\text{intervention}, \text{tweets}_{\text{w}}) > 0\right\} \times \frac{1}{60}$$



Back

- Difference in positive and negative words in neighborhoods of tweeted expressions:

$$\text{sentiment\_of\_coverage}_{\text{n,w},\tau} =$$
$$= \sum_{\text{neighborhood} \in \text{neighborhoods}_{\text{n,w},\tau}} \text{positive\_words}(\text{neighborhood}) -$$
$$- \text{negative\_words}(\text{neighborhood})$$



Overlapping Windows

Back

- **Repeated treatment**:

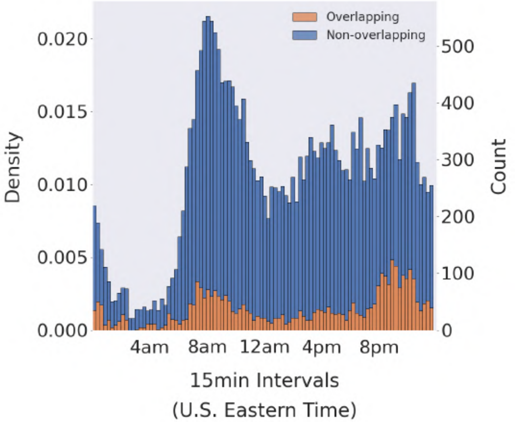
  i.e., several postings within day
  $\rightarrow$ overlapping windows.

  $\Rightarrow$ Stacked design à la Cengiz et al. (2019);

  $\Rightarrow$ Sample restriction: windows not overlapping over content:

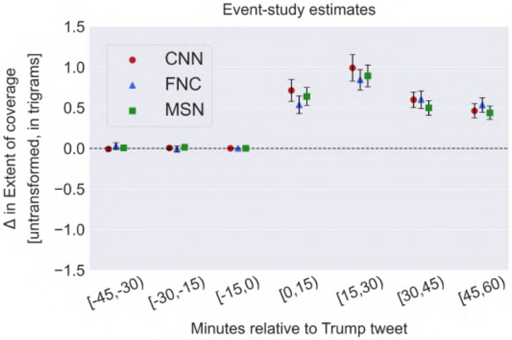
  - $\approx$ 90% of all tweets...
  - ... balanced on topics.

Figure: Overlapping vs. non-overlapping @realDonaldTrump tweets within day



Back

- Identical shift in terms of content.



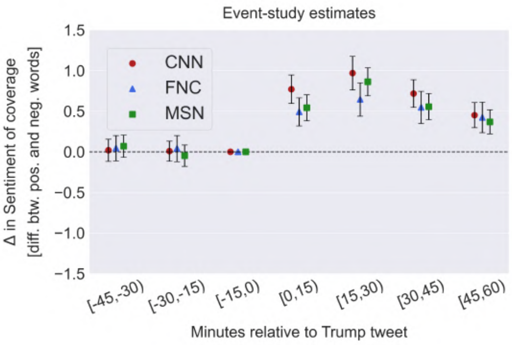
- A tweet on a given issue caused outlets to mention that issue $\approx$ 4 additional times.

	CNN	FNC	MSN
$\pm$2h15m	3.671***	3.914***	3.306***
	(0.387)	(0.359)	(0.332)
Obs.	62,920	62,920	62,920
Adj. R^2	-0.005	-0.005	-0.005
"Pre" avg.	0.586	1.041	0.496

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Back

- Same shift for sentiment of coverage.



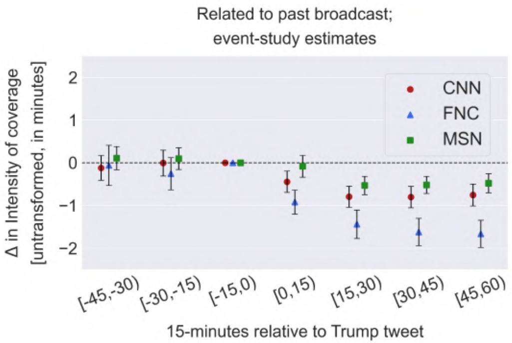
- Tweets on given issues caused outlets to immediately discuss these more positively.

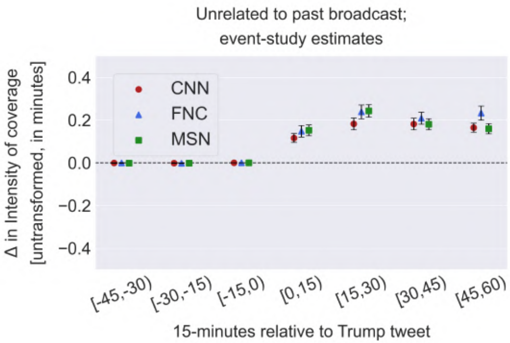
	CNN	FNC	MSN
±2h15m	4.745***	4.176***	4.486***
	(0.521)	(0.496)	(0.498)
Obs.	62,920	62,920	62,920
Adj. R^2	-0.005	-0.005	-0.005
"Pre" avg.	11.145	12.780	10.129

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Back

- Coverage diverged from “related” tweets... ... and converged to “unrelated” ones.



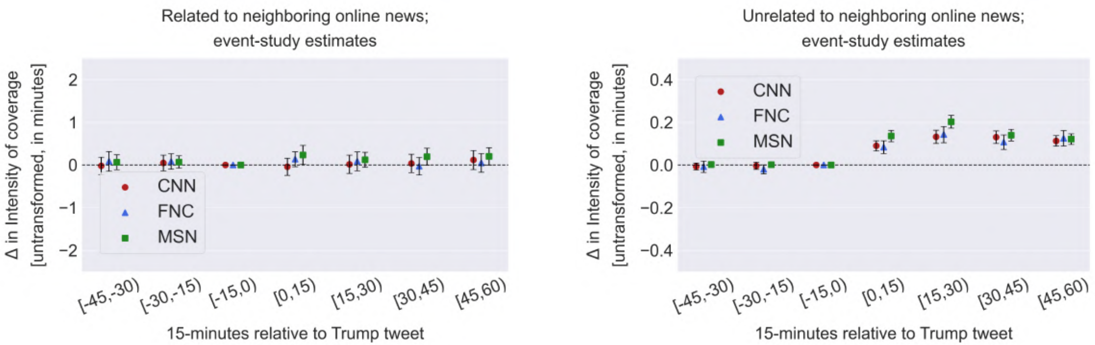


Note: “related” and “unrelated” refer to tweets correlated with past cable news stories.

Omitted variable concern

Back

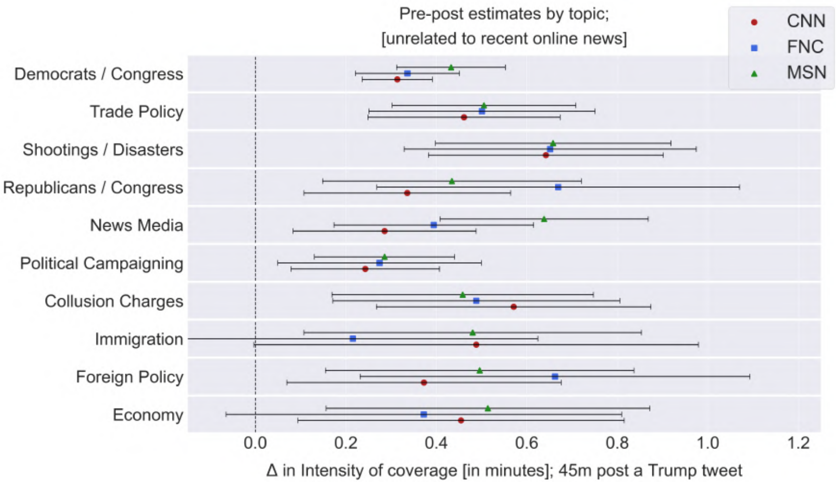
- Coverage did not converge to "related"... … only to "unrelated" statements.



Note: "related" and "unrelated" refer to tweets correlated with neighboring online news.

Back

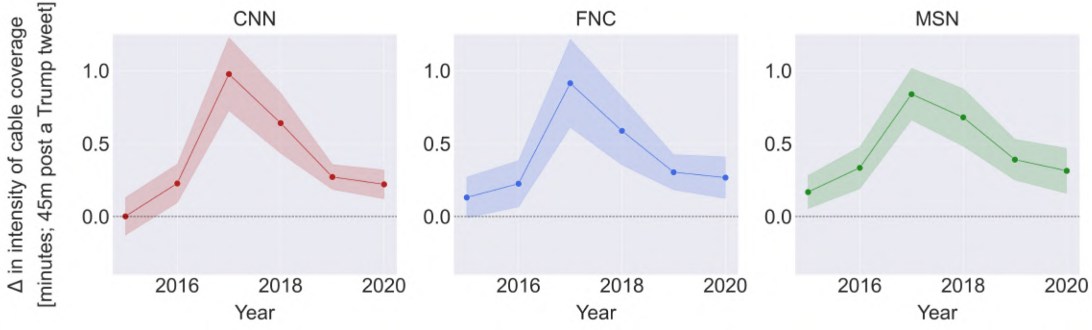
- Outlets reacted similarly to Trump tweets, irrespective of the topic.



Heterogeneity by Year

Back

- Cable outlets actively covered Donald Trump's tweets during his candidacy in 2016.

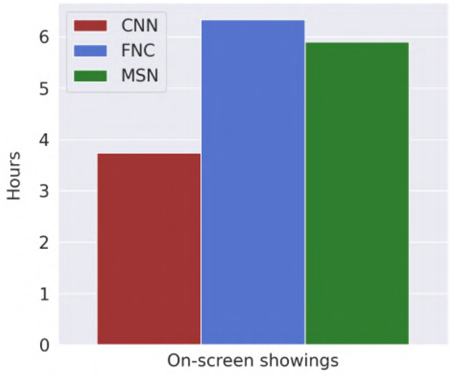


Back

- $\text{broadcast}_{n,t} = \mathbb{1}\{\text{Trump tweet shown on-screen by outlet n during period t}\}$

- Windows centered on broadcasts.

Figure: Duration of broadcasts of Trump tweets from January until December 2020, by outlet



Back

- $\text{trump\_approval}_{i,g,n,w,\tau} \in \{1, 2, 3, 4, 5\}$

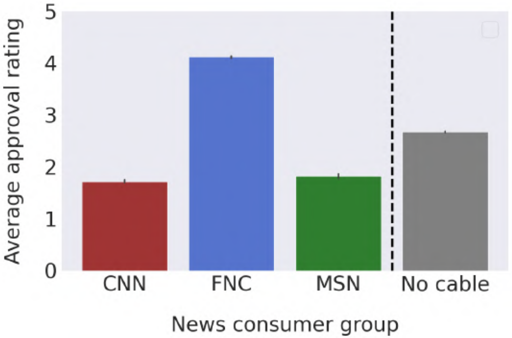
  where:

  - 1 stands for "Strongly disapprove", (...) and 5 for "Strongly approve",
  - g stands for either individuals that...

    T. only watch outlet n (that broadcasted a tweet during window w);

    C. do not watch cable TV news.

Figure: Average Trump approval rating by news consumer group (not on social media)



Back

- **Repeated / staggered treatment**:

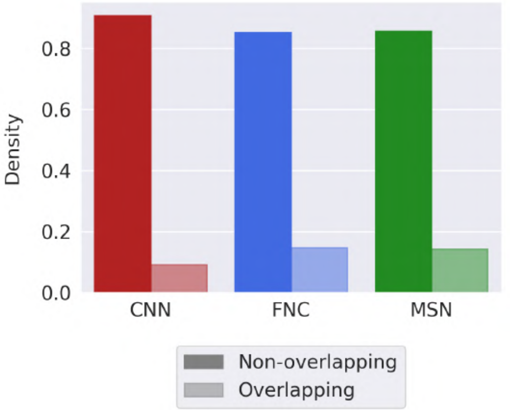
  i.e., multiple showings daily → overlapping windows, across and within.

  ⇒ "*Never-treated*" as controls (Callaway and Sant'Anna, 2021);

  ⇒ "*Stacked*" definition of treated (à la Cengiz et al., 2019);

  ⇒ Sample restriction: non-overlap with abnormally long showings.

Figure: Overlapping vs. non-overlapping Trump tweets showings within day



Back

- Media effects comparable if converted into persuasion rates à la DellaVigna and Kaplan (2007) – "*percentage of receivers that change the behavior among those that receive a message and are not already persuaded*" (DellaVigna and Gentzkow, 2010):

$$f = \frac{y_T - y_C}{e_T - e_C} \frac{1}{1 - y_0} = \frac{y_T - y_C}{1 - y_C}$$

- `Note`... only computable for binary outcomes – binary outcome $= 1$ if discrete version $\geqslant 2$ (recall, outcome values from 1 [highly disapprove] to 5 [... approve]).

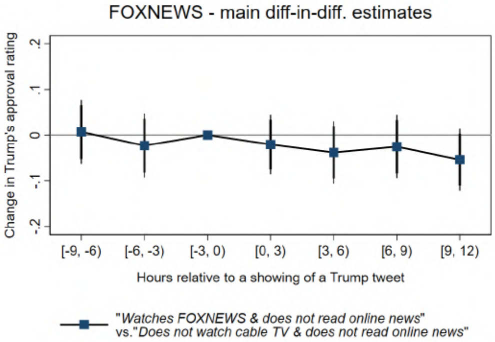
- Collapsing event-studies to pre-posts...

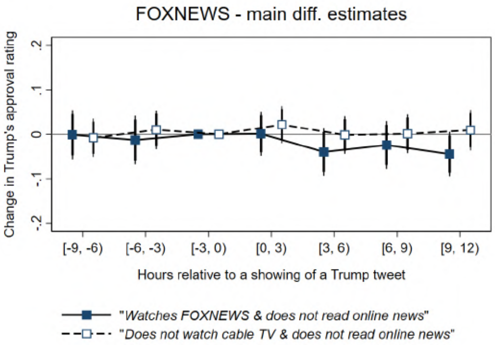
  ... **approval ratings**: $\beta_{CNN} = -.0106$ ($p = .205$), $1 - y_C = .61 \implies f_{CNN} = 1.7\%$

  ... **cand. favorability**: $\beta_{CNN} = -.0143$ ($p = .083$), $1 - y_C = .62 \implies f_{CNN} = 2.3\%$

Back

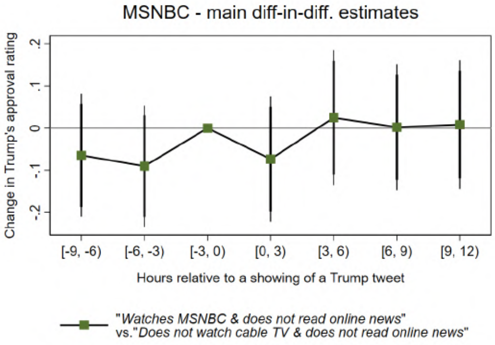
- Fox News showings did not cause Fox viewers to change their Trump views.
- Their views evolved in parallel to that of non-cable (within an event-window).

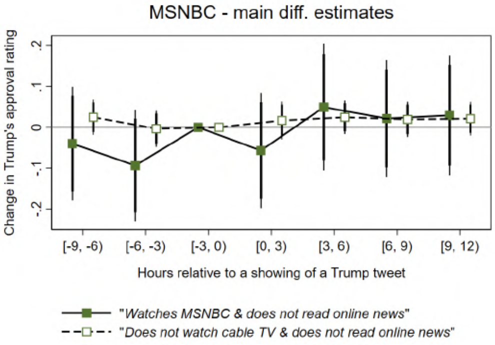




Back

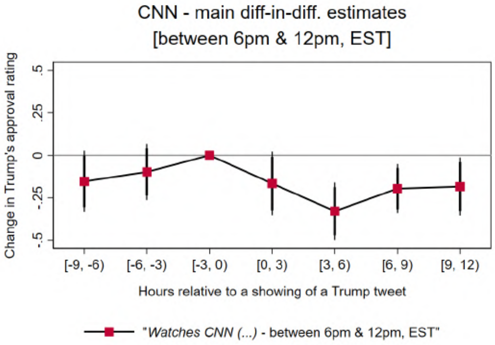
- MSNBC coverages caused no changes in how MSNBC viewers "saw" Trump.
- As with Fox News, MNSBC viewers rated Trump similarly as non-cable consumers.

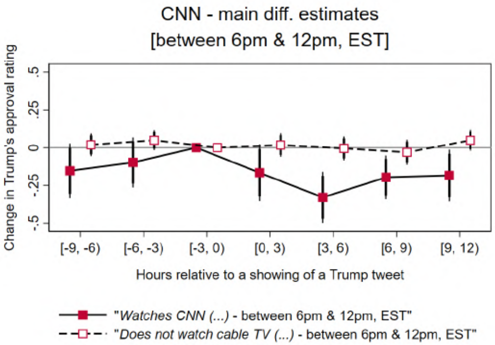




Back

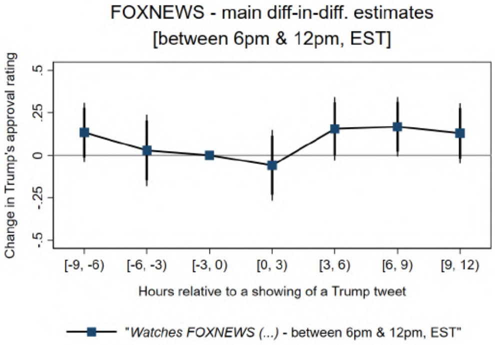
- CNN results are driven exclusively by prime-time showings of Trump tweets.
- Again, driven by changes in how CNN viewers rated Trump (vs. non-cable).

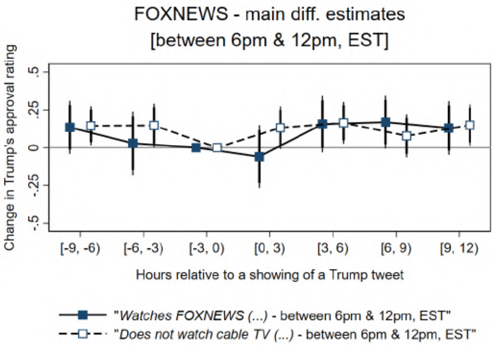




Back

- Fox News prime-time showings instead cause an improvement in Trump ratings.
- Result is driven by showings "unrelated" to news cycle (note: not shown here).

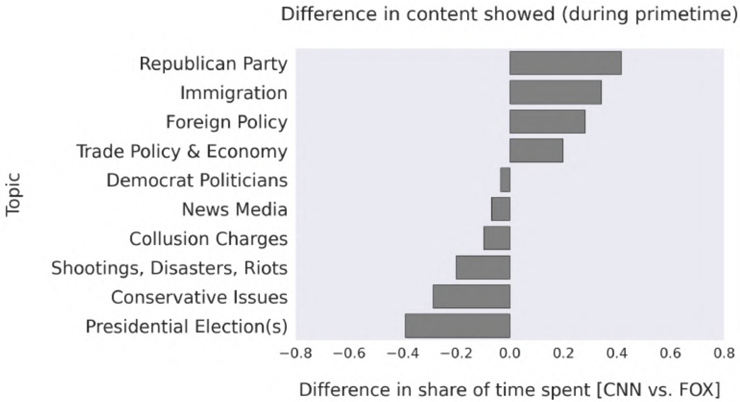




Filtering effect

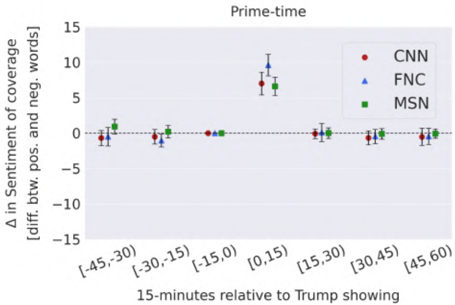
Back

- CNN chose to cover immigration and Republican Party related topics more.
- Fox News focused more on conservative and "anti-election" type of statements.

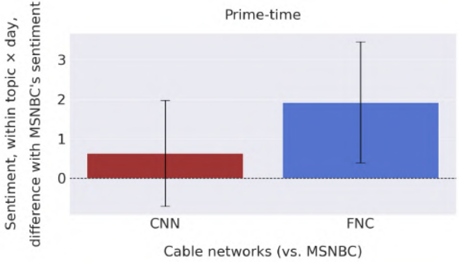


Back

- On average, Fox News *seems* to use more positive language than CNN.



- Same *suggestive* pattern when fixing content of tweet covered in a day.



Back

Figure: Fox News broadcast of a Trump Truth Social post – September 1, 2022.