

If a Tree Falls in The Forest: COVID-19, Media Choices, and Presidential Agenda Setting

Masha Krupenkin¹, Kai Zhu², Dylan Walker³, David Rothschild⁴, Duncan Watts⁵

June 8, 2020

¹Boston College

²McGill University

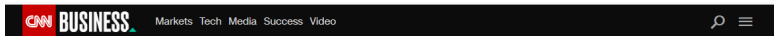
³Boston University

⁴Microsoft Research

⁵University of Pennsylvania

A recent controversy...

A recent controversy...



Broadcast networks opt out of Obama immigration speech -- except for Univision



by [Brian Stelter](#) @brianstelter

🕒 November 19, 2014: 9:51 PM ET



While ABC, NBC, and CBS will not show the President's speech, Univision viewers will be able to tune in.

Eight years ago, President George W. Bush delivered a prime time address on immigration, carried by all the big broadcast networks.



Advertisement

Newsletter

RELIABLE SOURCES

Brian Stelter's must-read
media newsletter

[Click to subscribe >](#)

5 years later...

The New York Times

40 Million Watched Trump's Prime-Time Address on TV



Media makes choices...

Media makes choices...

- ▶ Whether to run an event/speech live

Media makes choices...

- ▶ Whether to run an event/speech live
- ▶ Whether to discuss/debate issues raised by event

Media makes choices...

- ▶ Whether to run an event/speech live
- ▶ Whether to discuss/debate issues raised by event
- ▶ Whether to fact-check/debunk inaccuracies in statements by public officials

Media makes choices...

- ▶ Whether to run an event/speech live
- ▶ Whether to discuss/debate issues raised by event
- ▶ Whether to fact-check/debunk inaccuracies in statements by public officials
- ▶ How to frame controversial issues

Media makes choices...

- ▶ Whether to run an event/speech live
- ▶ Whether to discuss/debate issues raised by event
- ▶ Whether to fact-check/debunk inaccuracies in statements by public officials
- ▶ How to frame controversial issues
- ▶ Which journalists/media personalities to hire

... and choices have consequences

... and choices have consequences

- ▶ Media influences which issues people find important (Iyengar and Kinder 1987)

... and choices have consequences

- ▶ Media influences which issues people find important (Iyengar and Kinder 1987)
- ▶ Ratings of elected officials (Iyengar and Kinder 1987)

... and choices have consequences

- ▶ Media influences which issues people find important (Iyengar and Kinder 1987)
- ▶ Ratings of elected officials (Iyengar and Kinder 1987)
- ▶ Support for domestic and foreign policy (Zaller 1994)

... and choices have consequences

- ▶ Media influences which issues people find important (Iyengar and Kinder 1987)
- ▶ Ratings of elected officials (Iyengar and Kinder 1987)
- ▶ Support for domestic and foreign policy (Zaller 1994)
- ▶ Shapes real world behaviors (Lee 2002, King et al 2017)

... and choices have consequences

- ▶ Media influences which issues people find important (Iyengar and Kinder 1987)
- ▶ Ratings of elected officials (Iyengar and Kinder 1987)
- ▶ Support for domestic and foreign policy (Zaller 1994)
- ▶ Shapes real world behaviors (Lee 2002, King et al 2017)
- ▶ Influences perceptions and politics around minority groups (Abrajano and Hanjal 2015, Perry 2011, Gilens 1999, Krupenkin et al 2020)

Media and COVID-19

Media and COVID-19

- ▶ A dominant news topic due to far-reaching impact of the crisis

Media and COVID-19

- ▶ A dominant news topic due to far-reaching impact of the crisis
- ▶ Significant presidential communication - daily pressers

Media and COVID-19

- ▶ A dominant news topic due to far-reaching impact of the crisis
- ▶ Significant presidential communication - daily pressers
- ▶ Presidential pressers often run live on major networks

Media and COVID-19

- ▶ A dominant news topic due to far-reaching impact of the crisis
- ▶ Significant presidential communication - daily pressers
- ▶ Presidential pressers often run live on major networks
- ▶ **Maximum opportunity for president to influence public opinion**

Research questions:

Research questions:

1. Selection and framing effects on COVID-19 coverage by media outlet

Research questions:

1. Selection and framing effects on COVID-19 coverage by media outlet
2. Do presidential communications dictate the media agenda?

Research questions:

1. Selection and framing effects on COVID-19 coverage by media outlet
2. Do presidential communications dictate the media agenda?
3. How do presidential communications and media coverage influence public opinion?

Data and Methods

Data Roadmap

Data Roadmap

- ▶ TV News Transcripts measure media coverage of COVID-19

Data Roadmap

- ▶ TV News Transcripts measure media coverage of COVID-19
- ▶ Structural Topic Model on TV transcripts allows estimation of topics

Data Roadmap

- ▶ TV News Transcripts measure media coverage of COVID-19
- ▶ Structural Topic Model on TV transcripts allows estimation of topics
- ▶ Presser Transcripts measure presidential speech on COVID-19

Data Roadmap

- ▶ TV News Transcripts measure media coverage of COVID-19
- ▶ Structural Topic Model on TV transcripts allows estimation of topics
- ▶ Presser Transcripts measure presidential speech on COVID-19
- ▶ Bing search data allows measurement of public opinion about COVID-19

TV News Transcripts

TV News Transcripts

- ▶ Complete transcripts of national cable news, network news and local news from around 800 local TV channels across all 210 US DMAs from TVEyes database.

TV News Transcripts

- ▶ Complete transcripts of national cable news, network news and local news from around 800 local TV channels across all 210 US DMAs from TVEyes database.
- ▶ Data from 01/01/2020 - 04/30/2020

TV News Transcripts

- ▶ Complete transcripts of national cable news, network news and local news from around 800 local TV channels across all 210 US DMAs from TVEyes database.
- ▶ Data from 01/01/2020 - 04/30/2020
- ▶ Pull news "pages" that contain one of the following words/phrases:

TV News Transcripts

- ▶ Complete transcripts of national cable news, network news and local news from around 800 local TV channels across all 210 US DMAs from TVEyes database.
- ▶ Data from 01/01/2020 - 04/30/2020
- ▶ Pull news "pages" that contain one of the following words/phrases:
 - ▶ coronavirus, corona-virus, "corona virus", "wuhan virus", chinavirus, china-virus, "china virus", chinesevirus, chinese-virus, "chinese virus", SARS, MERS, covid, covid-19, epidemic, pandemic, quarantine, travelrestriction, "travel restriction", travel-restriction, flatteningthecurve, "flattening the curve", flattening-the-curve, flattenthecurve, "flatten the curve", flatten-the-curve, selfisolation, "self isolation", self-isolation, selfquarantine, "self quarantine", self-quarantine, shelterinplace, "shelter in place", shelter-in-place, socialdistancing, social-distancing, "social distancing", contacttracing, contact-tracing, "contact tracing", superspreader, "super spreader", super-spreader, ventilator, respirator, lockdown, "lock down", lock-down, "national emergency", national-emergency, nationalemergency, huanan, hubei

TV News Transcripts

TV News Transcripts

- ▶ Concatenate consecutive "pages", and keep those that have at least 2 mentions of "corona", "covid", or "virus"

TV News Transcripts

- ▶ Concatenate consecutive "pages", and keep those that have at least 2 mentions of "corona", "covid", or "virus"
 - ▶ Create documents by splitting pages into 200 word segments

TV News Transcripts

- ▶ Concatenate consecutive "pages", and keep those that have at least 2 mentions of "corona", "covid", or "virus"
 - ▶ Create documents by splitting pages into 200 word segments
- ▶ Drop all segments that contain advertising terms (eg. John Deere, Colgate, Volkswagen) and unrelated news topics (crime, weather, and traffic)

TV News Transcripts

- ▶ Concatenate consecutive "pages", and keep those that have at least 2 mentions of "corona", "covid", or "virus"
 - ▶ Create documents by splitting pages into 200 word segments
- ▶ Drop all segments that contain advertising terms (eg. John Deere, Colgate, Volkswagen) and unrelated news topics (crime, weather, and traffic)
- ▶ To prevent local news from overwhelming results, local news segments were sampled so the resulting data was 50% network/cable and 50% local news segments

TV News Transcripts

- ▶ Concatenate consecutive "pages", and keep those that have at least 2 mentions of "corona", "covid", or "virus"
 - ▶ Create documents by splitting pages into 200 word segments
- ▶ Drop all segments that contain advertising terms (eg. John Deere, Colgate, Volkswagen) and unrelated news topics (crime, weather, and traffic)
- ▶ To prevent local news from overwhelming results, local news segments were sampled so the resulting data was 50% network/cable and 50% local news segments
- ▶ Total segments: 19,670 CNN; 17,025 Fox News; 17,701 MSNBC; 79,123 Network; 133,519 local

Topic Model Info

Topic Model Info

- ▶ 100 topic Structural topic model with formula:

Topic Model Info

- ▶ 100 topic Structural topic model with formula:
 - ▶ $\text{prevalence} \sim \text{channel} + \text{date} + \text{channel}:\text{date}$

Topic Model Info

- ▶ 100 topic Structural topic model with formula:
 - ▶ $\text{prevalence} \sim \text{channel} + \text{date} + \text{channel}:\text{date}$
- ▶ Some placeholders to avoid over-dependency on local events: governor last/full names, state names, state capital names, 100 largest US city names, and county names all replaced w placeholder like GOVNAME

Topic Model Info

- ▶ 100 topic Structural topic model with formula:
 - ▶ $\text{prevalence} \sim \text{channel} + \text{date} + \text{channel}:\text{date}$
- ▶ Some placeholders to avoid over-dependency on local events: governor last/full names, state names, state capital names, 100 largest US city names, and county names all replaced w placeholder like GOVNAME
- ▶ Stopwords included: "covid", "virus", top 100 male and female first names, channel names, newscast words such as "anchor", "channel", "newsroom" in addition to standard english stopwords

Topic Model Info

- ▶ 100 topic Structural topic model with formula:
 - ▶ $\text{prevalence} \sim \text{channel} + \text{date} + \text{channel}:\text{date}$
- ▶ Some placeholders to avoid over-dependency on local events: governor last/full names, state names, state capital names, 100 largest US city names, and county names all replaced w placeholder like GOVNAME
- ▶ Stopwords included: "covid", "virus", top 100 male and female first names, channel names, newscast words such as "anchor", "channel", "newsroom" in addition to standard english stopwords
- ▶ Words of three characters or fewer were dropped

Presidential Pressers

Presidential Pressers

- ▶ Transcripts available [here](#)

Presidential Pressers

- ▶ Transcripts available [here](#)
- ▶ Used topic model estimated on news transcripts to get topics in Trump portions of pressers

Presidential Pressers

- ▶ Transcripts available [here](#)
- ▶ Used topic model estimated on news transcripts to get topics in Trump portions of pressers
 - ▶ Look at effects of top 20 topics discussed in Trump presser

Presidential Pressers

- ▶ Transcripts available [here](#)
- ▶ Used topic model estimated on news transcripts to get topics in Trump portions of pressers
 - ▶ Look at effects of top 20 topics discussed in Trump presser
- ▶ Able to link the topical context of pressers with shifts in topical content of news, as well as shifts in web search

Outcomes: Web Search Data

Outcomes: Web Search Data

- ▶ Search data is from Bing

Outcomes: Web Search Data

- ▶ Search data is from Bing
 - ▶ Bing has 5 Billion US searches/month

Outcomes: Web Search Data

- ▶ Search data is from Bing
 - ▶ Bing has 5 Billion US searches/month
 - ▶ 33% of US search market share

Outcomes: Web Search Data

- ▶ Search data is from Bing
 - ▶ Bing has 5 Billion US searches/month
 - ▶ 33% of US search market share
- ▶ Web search data allows measurement of highly temporally granular public opinion

Outcomes: Web Search Data

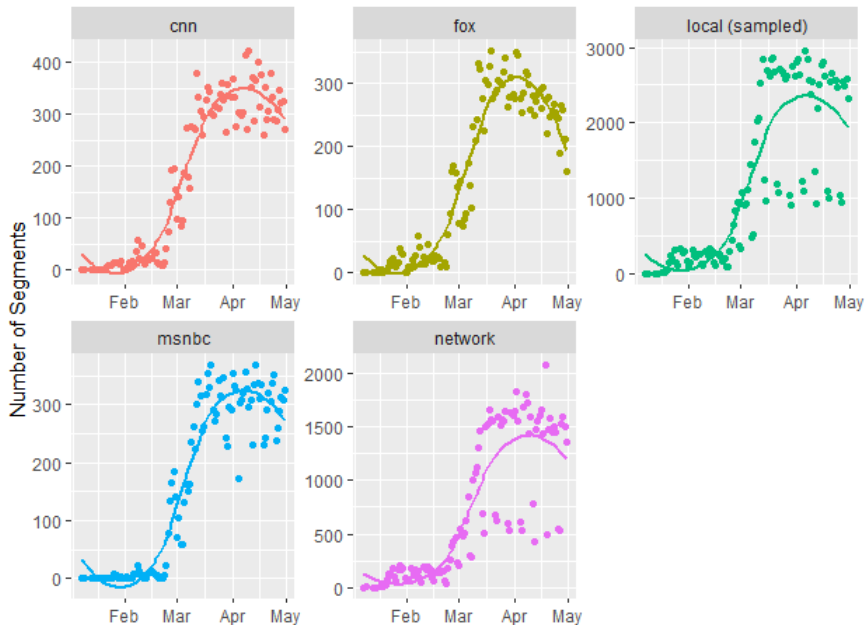
- ▶ Search data is from Bing
 - ▶ Bing has 5 Billion US searches/month
 - ▶ 33% of US search market share
- ▶ Web search data allows measurement of highly temporally granular public opinion
 - ▶ Measure responses to live events like pressers by hour, media by day

Outcomes: Web Search Data

- ▶ Search data is from Bing
 - ▶ Bing has 5 Billion US searches/month
 - ▶ 33% of US search market share
- ▶ Web search data allows measurement of highly temporally granular public opinion
 - ▶ Measure responses to live events like pressers by hour, media by day
- ▶ Use searches for words from topic model (frex, highest prob, and score) + "covid" or "corona" or "virus" to get at searches for a particular media topic

Results 1: COVID-19 Coverage by Channel

COVID-19 Segments by Channel



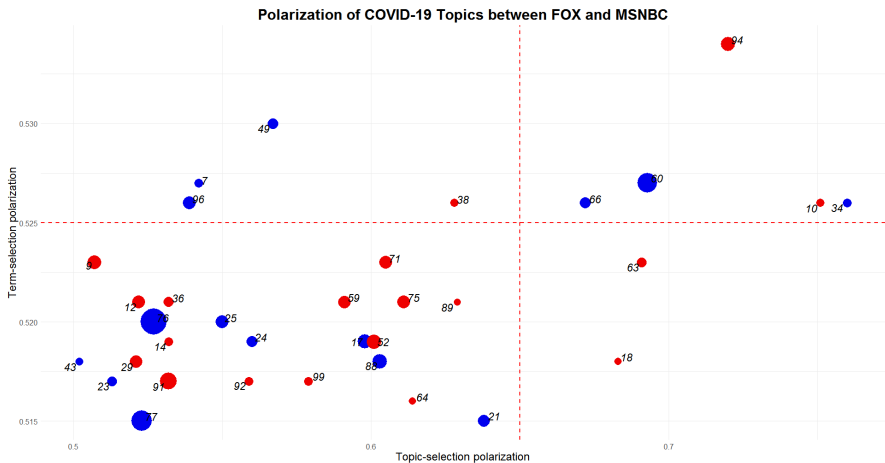
Selected Topics

Topic 10	messag, togeth, share, hero, hope, inspir, neighbor	Topic 56	thousand, corona, peopl, least, near, hundr, worldwid
Topic 12	reopen, economi, phase, open, restrict, re-open, back	Topic 58	council, rent, hotel, citi, revenu, landlord, properti
Topic 13	enemi, incred, fight, defeat, mine, horribl, sacrific	Topic 59	market, stock, price, wall, economi, investor, drop
Topic 14	restaur, busi, open, park, owner, close, custom	Topic 6	outbreak, concern, fear, spread, dead, grow, caus
Topic 15	CITYNAME, citi, mayor, area, metro, west, blasio	Topic 60	presid, trump, polit, brief, administr, press, obama
Topic 17	test, posit, result, swab, negat, site, sampl	Topic 61	stay, home, order, essenti, enforc, stay-hom, effect
Topic 18	ship, cruiss, passeng, princess, quarantin, dock, coast	Topic 63	symptom, fever, breath, cough, lung, mild, respiratori
Topic 21	governor, state, GOVNAME, feder, declar, order, announc	Topic 64	hand, wash, sanit, touch, soap, surfac, sneez
Topic 23	week, next, curv, model, peak, flatten, project	Topic 65	worker, employe, plant, healthcar, work, meat, tyson
Topic 24	mask, wear, protect, equip, face, suppli, glove	Topic 66	death, toll, grim, epicent, warn, mola, yorker
Topic 25	number, case, rate, rise, increas, unit, spike	Topic 69	unemploy, claim, file, million, benefit, appli, labor
Topic 26	counti, COUNTYNAME, local, commissi- on, depart, santa, leader	Topic 7	famili, love, friend, mother, birthday, daughter, children
Topic 27	travel, flight, airport, airlin, intern, restrict, europ	Topic 71	presid, trump, white, hous, vice, penc, american
Topic 28	doctor, offic, visit, appoint, physician, video, clinic	Topic 75	vaccin, drug, trial, treatment, research, hydroxychloroquin, studi
Topic 29	infect, antibodi, immun, asymptomat, evid, transmiss, transmit	Topic 77	fauci, american, think, countri, mitig, term, birx
Topic 30	cancel, event, postpon, year, olymp, festiv, senior	Topic 79	deal, hill, capitol, border, agreement, mex-ico, canada
Topic 31	nation, guard, militari, fema, veteran, deploy, armi	Topic 8	music, movi, film, disney, star, song, hank

Selected Topics

Topic 32	april, extend, budget, deadlin, expir, requir, june	Topic 80	world, organ, power, attack, shock, respect, protest
Topic 34	popul, communiti, black, vulner, rural, condit, dispar	Topic 82	student, univers, class, colleg, campus, spring, graduat
Topic 36	health, offici, public, depart, corona, diseases, spread	Topic 83	school, student, district, teacher, parent, educ, superintend
Topic 37	facil, resid, staff, center, inmat, prison, member	Topic 86	check, payment, deposit, stimulus, scam, account, scammer
Topic 38	china, wuhan, contain, chines, hong, kong, mainland	Topic 87	case, confirm, death, total, latest, posit, -hundr
Topic 4	game, sport, player, play, season, tournament, leagu	Topic 88	hospit, patient, ventil, care, medic, treat, capac
Topic 40	virtual, connect, zoom, meet, video, meant, technolog	Topic 89	ship, navi, comfort, sailor, captain, crui, crew
Topic 43	help, provid, support, need, resourc, communiti, care	Topic 9	senat, vote, democrat, republican, congress, pelosi, lawmak
Topic 45	place, shelter, measur, homeless, town, curfew, street	Topic 90	updat, confer, press, afternoon, daili, brief, noon
Topic 46	church, easter, sunday, pastor, servic, worship, mass	Topic 91	peopl, risk, dont, sanjay, serious, think, mortal
Topic 47	websit, inform, facebook, page, find, list, link	Topic 92	distanc, social, practic, guidelin, feet, physic, maintain
Topic 48	clean, disinfect, wipe, water, paper, surfac, bleach	Topic 93	nurs, home, survey, staf, care, senior, practition
Topic 49	itali, korea, lockdown, spain, countri, europ, iran	Topic 94	china, chine, januari, intellig, wuhan, truth, trust
Topic 5	STATENAME, state, protest, southern, across, northeast, northern	Topic 95	blood, plasma, donat, antibodi, donor, cross, recov
Topic 52	loan, money, busi, dollar, billion, small, fund	Topic 97	store, groceri, farmer, shelv, chain, shop, shopper
Topic 53	minist, prime, bori, british, london, admit, johnson	Topic 98	insur, cost, free, paid, medicar, afford, financ
Topic 55	food, meal, donat, bank, feed, pantri, volunt	Topic 99	forc, task, compani, product, manufactur, ventil, produc

Channel Polarization



Results 2: Do Pressers Influence the Media Agenda?

Media Amplification

Media Amplification

- ▶ Media often ran Trump pressers live

Media Amplification

- ▶ Media often ran Trump pressers live
- ▶ How much does the media talk about topics covered in Trump pressers during the rest of the day?

Media Amplification

- ▶ Media often ran Trump pressers live
- ▶ How much does the media talk about topics covered in Trump pressers during the rest of the day?
- ▶ Compare mean topic proportions across news segments on same date before, during, and after daily Trump presser

Media Amplification

- ▶ Media often ran Trump pressers live
- ▶ How much does the media talk about topics covered in Trump pressers during the rest of the day?
- ▶ Compare mean topic proportions across news segments on same date before, during, and after daily Trump presser
 - ▶ Before: before presser start

Media Amplification

- ▶ Media often ran Trump pressers live
- ▶ How much does the media talk about topics covered in Trump pressers during the rest of the day?
- ▶ Compare mean topic proportions across news segments on same date before, during, and after daily Trump presser
 - ▶ Before: before presser start
 - ▶ During: 0-2 hours post presser start

Media Amplification

- ▶ Media often ran Trump pressers live
- ▶ How much does the media talk about topics covered in Trump pressers during the rest of the day?
- ▶ Compare mean topic proportions across news segments on same date before, during, and after daily Trump presser
 - ▶ Before: before presser start
 - ▶ During: 0-2 hours post presser start
 - ▶ 2+ hours post presser start

Media Amplification

- ▶ Media often ran Trump pressers live
- ▶ How much does the media talk about topics covered in Trump pressers during the rest of the day?
- ▶ Compare mean topic proportions across news segments on same date before, during, and after daily Trump presser
 - ▶ Before: before presser start
 - ▶ During: 0-2 hours post presser start
 - ▶ 2+ hours post presser start
- ▶ Are pressers an exogenous shock?

Media Amplification

- ▶ Media often ran Trump pressers live
- ▶ How much does the media talk about topics covered in Trump pressers during the rest of the day?
- ▶ Compare mean topic proportions across news segments on same date before, during, and after daily Trump presser
 - ▶ Before: before presser start
 - ▶ During: 0-2 hours post presser start
 - ▶ 2+ hours post presser start
- ▶ Are pressers an exogenous shock?
 - ▶ Trump might be responding to ongoing events

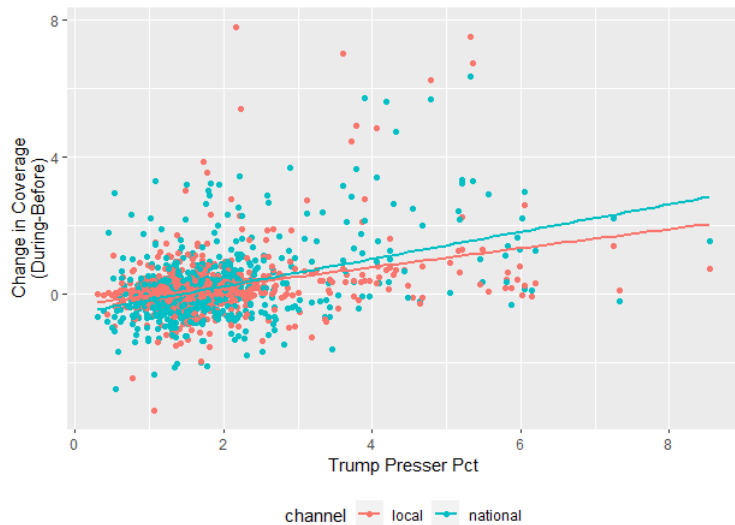
Media Amplification

- ▶ Media often ran Trump pressers live
- ▶ How much does the media talk about topics covered in Trump pressers during the rest of the day?
- ▶ Compare mean topic proportions across news segments on same date before, during, and after daily Trump presser
 - ▶ Before: before presser start
 - ▶ During: 0-2 hours post presser start
 - ▶ 2+ hours post presser start
- ▶ Are pressers an exogenous shock?
 - ▶ Trump might be responding to ongoing events
 - ▶ Robustness check: Repeat analysis only on topics where there is low correlation between news topic proportion before presser and topic proportion in presser

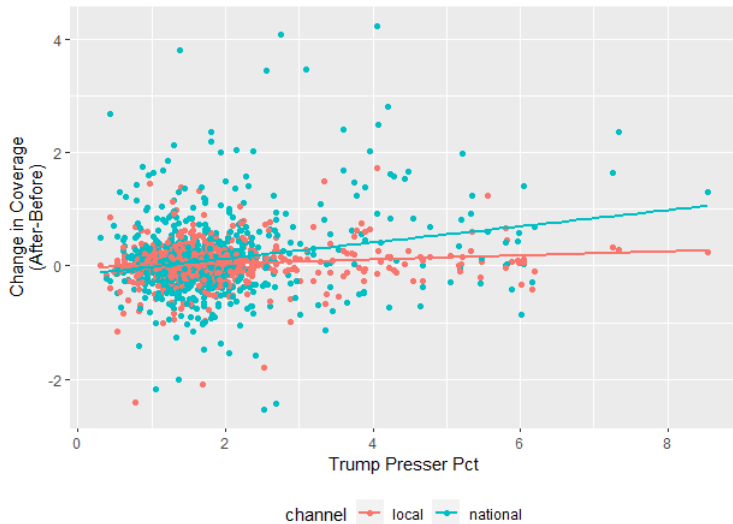
Media Amplification

- ▶ Media often ran Trump pressers live
- ▶ How much does the media talk about topics covered in Trump pressers during the rest of the day?
- ▶ Compare mean topic proportions across news segments on same date before, during, and after daily Trump presser
 - ▶ Before: before presser start
 - ▶ During: 0-2 hours post presser start
 - ▶ 2+ hours post presser start
- ▶ Are pressers an exogenous shock?
 - ▶ Trump might be responding to ongoing events
 - ▶ Robustness check: Repeat analysis only on topics where there is low correlation between news topic proportion before presser and topic proportion in presser
 - ▶ $-0.2 \leq \text{corr}(\text{Media Before, Presser}) \leq 0.2$

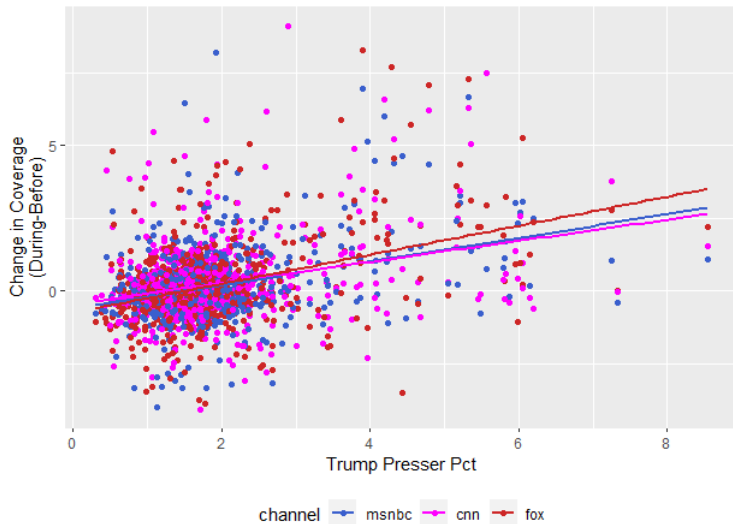
Media Amplification Local vs Cable (During)



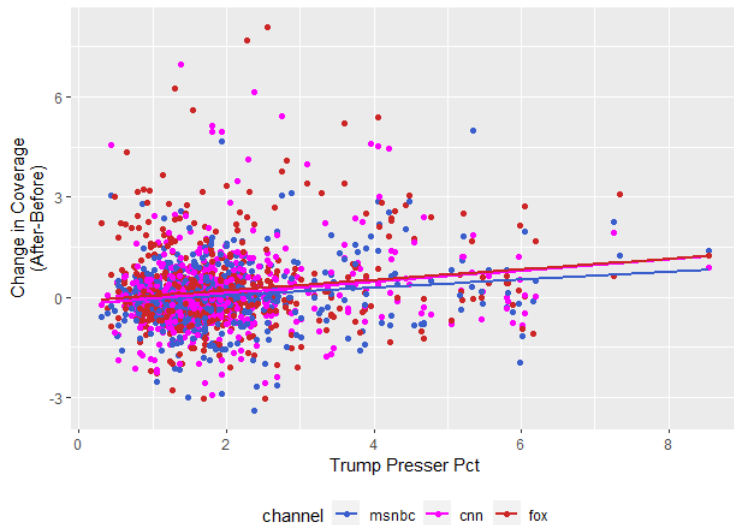
Media Amplification Local vs Cable (After)



Media Amplification by Channel (During)



Media Amplification by Channel (After)



Media Amplification (Cable)

Media Amplification (Cable)

- ▶ Topic X proportion by hour \sim Presser Topic X + time + date
+ Presser Topic X:time + Topic FE + Topic FE:time

Media Amplification (Cable)

- ▶ Topic X proportion by hour \sim Presser Topic X + time + date
+ Presser Topic X:time + Topic FE + Topic FE:time
- ▶ SE Clustered by date

Media Amplification (Cable)

- ▶ Topic X proportion by hour \sim Presser Topic X + time + date + Presser Topic X:time + Topic FE + Topic FE:time
- ▶ SE Clustered by date

	<i>Dependent variable:</i>	
	all topics (1)	topics $\text{abs}(\text{corr}) \leq 0.2$ (2)
Presser Proportion	0.139*** (0.034)	-0.001 (0.020)
timeAfter	-0.052 (0.075)	-0.034 (0.045)
timeDuring	-0.098 (0.163)	-0.092 (0.119)
Presser Proportion:timeAfter	0.063** (0.029)	0.061** (0.029)
Presser Proportion:timeDuring	0.103 (0.064)	0.130 (0.090)
date	0.005*** (0.001)	0.003*** (0.001)
topic FE	X	X
topic x time FE	X	X
Constant	1.738*** (0.076)	0.393*** (0.034)

Note:

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Takeway

Takeway

- ▶ Clear amplification of pressers in media

Takeway

- ▶ Clear amplification of pressers in media
 - ▶ In the "during" period, many channels run pressers live

Takeway

- ▶ Clear amplification of pressers in media
 - ▶ In the "during" period, many channels run pressers live
 - ▶ Amplification in the "after" period about one half the strength as in the "during" period

Takeway

- ▶ Clear amplification of pressers in media
 - ▶ In the "during" period, many channels run pressers live
 - ▶ Amplification in the "after" period about one half the strength as in the "during" period
- ▶ Cable and local equally likely to run live presser, but cable more likely to have post-presser agenda influenced

Takeway

- ▶ Clear amplification of pressers in media
 - ▶ In the "during" period, many channels run pressers live
 - ▶ Amplification in the "after" period about one half the strength as in the "during" period
- ▶ Cable and local equally likely to run live presser, but cable more likely to have post-presser agenda influenced
- ▶ There are no differences in amplification between cable channels

Results 3: What drives public opinion?

Effects of Pressers and Media?

Effects of Pressers and Media?

1. Do searches for topic X follow media coverage of topic X?

Effects of Pressers and Media?

1. Do searches for topic X follow media coverage of topic X?
 - ▶ On days when media talks more about topic X, are there more searches for topic X?

Effects of Pressers and Media?

1. Do searches for topic X follow media coverage of topic X?
 - ▶ On days when media talks more about topic X, are there more searches for topic X?
2. Can we see a causal effect of pressers on search?

Effects of Pressers and Media?

1. Do searches for topic X follow media coverage of topic X?
 - ▶ On days when media talks more about topic X, are there more searches for topic X?
2. Can we see a causal effect of pressers on search?
 - ▶ Is there an increase in searches for a topic during Trump's presser where the topic is mentioned?

Effects of Pressers and Media?

1. Do searches for topic X follow media coverage of topic X?
 - ▶ On days when media talks more about topic X, are there more searches for topic X?
2. Can we see a causal effect of pressers on search?
 - ▶ Is there an increase in searches for a topic during Trump's presser where the topic is mentioned?
 - ▶ Days when Trump did not talk about topic X in his presser serve as counterfactuals for when he did

Do searches for topic X follow media coverage of topic X?

Do searches for topic X follow media coverage of topic X?

- $\text{Binomial}(\text{Searches for Topic X}, \text{Searches for Corona}) \sim \text{Daily Mean Topic X Proportion} + \text{date} + \text{day of week} + \text{topic FE} + \text{topic:date}$

Do searches for topic X follow media coverage of topic X?

- ▶ $\text{Binomial}(\text{Searches for Topic X}, \text{Searches for Corona}) \sim \text{Daily Mean Topic X Proportion} + \text{date} + \text{day of week} + \text{topic FE} + \text{topic:date}$
- ▶ SE Clustered by date

Do searches for topic X follow media coverage of topic X?

- ▶ $\text{Binomial}(\text{Searches for Topic X}, \text{Searches for Corona}) \sim \text{Daily Mean Topic X Proportion} + \text{date} + \text{day of week} + \text{topic FE} + \text{topic:date}$
- ▶ SE Clustered by date
- ▶ National news only

Do searches for topic X follow media coverage of topic X?

- ▶ Binomial(Searches for Topic X, Searches for Corona) \sim Daily Mean Topic X Proportion + date + day of week + topic FE + topic:date
- ▶ SE Clustered by date
- ▶ National news only

	<i>Dependent variable:</i>	
	All Tops (1)	Select Tops (2)
Media Topic Proportion	19.669*** (2.416)	22.322*** (3.163)
Date	0.011*** (0.004)	-0.0002 (0.004)
Day of week FE	X	X
topic FE	X	X
topic x Date	X	X
Constant	-212.585*** (71.390)	-1.298 (78.144)

Note:

*p<0.1; **p<0.05; ***p<0.01

Pressers

Pressers

- ▶ Hourly searches for Topic X during the presser + one hour before

Pressers

- ▶ Hourly searches for Topic X during the presser + one hour before
- ▶ $\text{Binomial}(\text{Searches for Topic X}, \text{Searches for Corona}) \sim$
Presser Topic X Proportion + time + Presser X
Proportion:time + date + day of week + topic FE

Pressers

- ▶ Hourly searches for Topic X during the presser + one hour before
- ▶ $\text{Binomial}(\text{Searches for Topic X}, \text{Searches for Corona}) \sim$
Presser Topic X Proportion + time + Presser X
Proportion:time + date + day of week + topic FE
- ▶ SE Clustered by date

Pressers

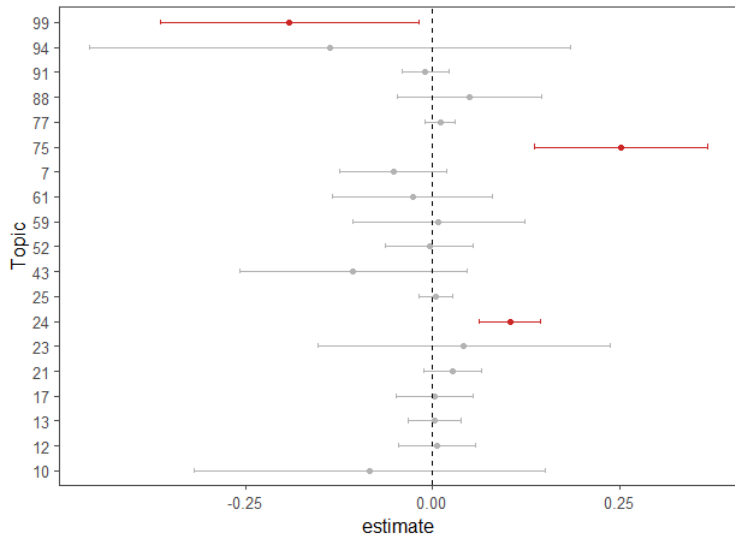
- ▶ Hourly searches for Topic X during the presser + one hour before
- ▶ Binomial(Searches for Topic X, Searches for Corona) ~ Presser Topic X Proportion + time + Presser X Proportion:time + date + day of week + topic FE
- ▶ SE Clustered by date

	<i>Dependent variable:</i>
timeDuring	0.003 (0.025)
Presser Proportion	0.003 (0.026)
timeDuring:Presser Proportion	0.004 (0.009)
Date	0.005*** (0.001)
Topic FE	X
Day of week FE	X
Constant	-93.888*** (22.062)

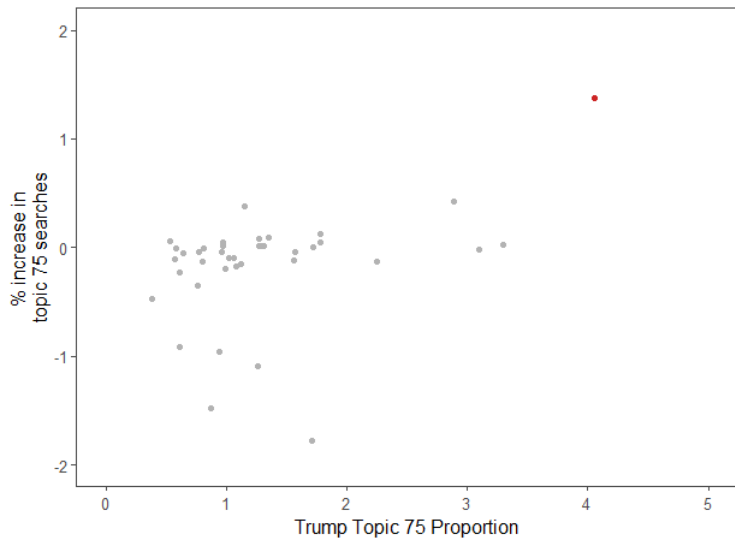
Note:

*p<0.1; **p<0.05; ***p<0.01

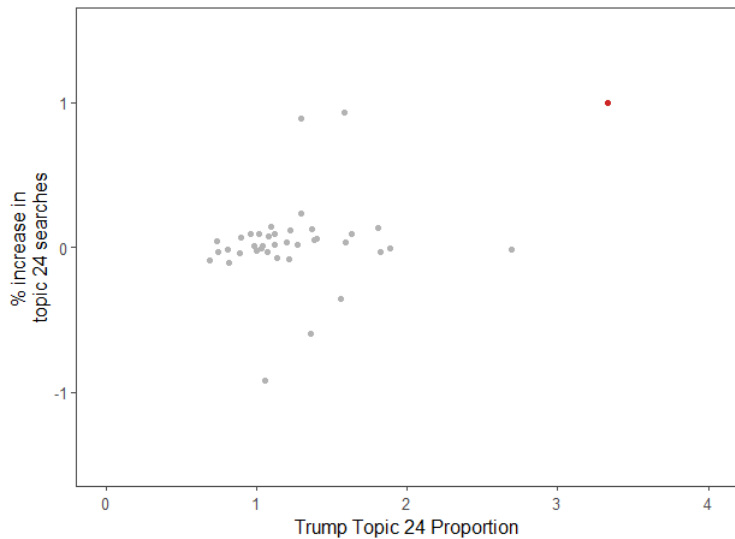
Are there individual topics where Trump has an effect?



Are the Effects Consistent? (Topic 75)



Are the Effects Consistent? (Topic 24)



Takeway

Takeway

- ▶ No causal effect of pressers

Takeway

- ▶ No causal effect of pressers
 - ▶ Rarely, an effect (first mention of hydroxychloroquine), but highly inconsistent

Takeway

- ▶ No causal effect of pressers
 - ▶ Rarely, an effect (first mention of hydroxychloroquine), but highly inconsistent
- ▶ Clear association between media coverage and search

Takeway

- ▶ No causal effect of pressers
 - ▶ Rarely, an effect (first mention of hydroxychloroquine), but highly inconsistent
- ▶ Clear association between media coverage and search
- ▶ Suggests that media coverage, not pressers, is most important

Conclusion

Media makes choices

Media makes choices

- ▶ How to frame COVID-19 Coverage

Media makes choices

- ▶ How to frame COVID-19 Coverage
 - ▶ Fox News much more likely to focus on China blame

Media makes choices

- ▶ How to frame COVID-19 Coverage
 - ▶ Fox News much more likely to focus on China blame
 - ▶ MSNBC on Trump Admin

Media makes choices

- ▶ How to frame COVID-19 Coverage
 - ▶ Fox News much more likely to focus on China blame
 - ▶ MSNBC on Trump Admin
- ▶ How to interact with pressers

Media makes choices

- ▶ How to frame COVID-19 Coverage
 - ▶ Fox News much more likely to focus on China blame
 - ▶ MSNBC on Trump Admin
- ▶ How to interact with pressers
 - ▶ Stronger agenda setting effect for cable vs local news

Media makes choices

- ▶ How to frame COVID-19 Coverage
 - ▶ Fox News much more likely to focus on China blame
 - ▶ MSNBC on Trump Admin
- ▶ How to interact with pressers
 - ▶ Stronger agenda setting effect for cable vs local news
- ▶ Agenda setting of media choices

Media makes choices

- ▶ How to frame COVID-19 Coverage
 - ▶ Fox News much more likely to focus on China blame
 - ▶ MSNBC on Trump Admin
- ▶ How to interact with pressers
 - ▶ Stronger agenda setting effect for cable vs local news
- ▶ Agenda setting of media choices
 - ▶ No causal effect of pressers on search

Media makes choices

- ▶ How to frame COVID-19 Coverage
 - ▶ Fox News much more likely to focus on China blame
 - ▶ MSNBC on Trump Admin
- ▶ How to interact with pressers
 - ▶ Stronger agenda setting effect for cable vs local news
- ▶ Agenda setting of media choices
 - ▶ No causal effect of pressers on search
 - ▶ Clear relationship between news coverage and search

Appendix

Objectivity?

Objectivity?

- ▶ Newsworthiness - number of plane crashes vs successful landings

Objectivity?

- ▶ Newsworthiness - number of plane crashes vs successful landings
- ▶ Market pressures - "Lewinsky quotient" (Zaller 1999)

Objectivity?

- ▶ Newsworthiness - number of plane crashes vs successful landings
- ▶ Market pressures - "Lewinsky quotient" (Zaller 1999)
- ▶ Political pressures - accusations of bias (Facebook)

Objectivity?

- ▶ Newsworthiness - number of plane crashes vs successful landings
- ▶ Market pressures - "Lewinsky quotient" (Zaller 1999)
- ▶ Political pressures - accusations of bias (Facebook)
- ▶ Corporate ownership (Sinclair, Amazon)

Objectivity?

- ▶ Newsworthiness - number of plane crashes vs successful landings
- ▶ Market pressures - "Lewinsky quotient" (Zaller 1999)
- ▶ Political pressures - accusations of bias (Facebook)
- ▶ Corporate ownership (Sinclair, Amazon)
- ▶ Platforming/deplatforming (Tom Cotton op ed)

Objectivity?

- ▶ Newsworthiness - number of plane crashes vs successful landings
- ▶ Market pressures - "Lewinsky quotient" (Zaller 1999)
- ▶ Political pressures - accusations of bias (Facebook)
- ▶ Corporate ownership (Sinclair, Amazon)
- ▶ Platforming/deplatforming (Tom Cotton op ed)
- ▶ Broader debates over role of journalism

Are presidential communications always newsworthy?

Are presidential communications always newsworthy?

- ▶ Even if they are inaccurate?

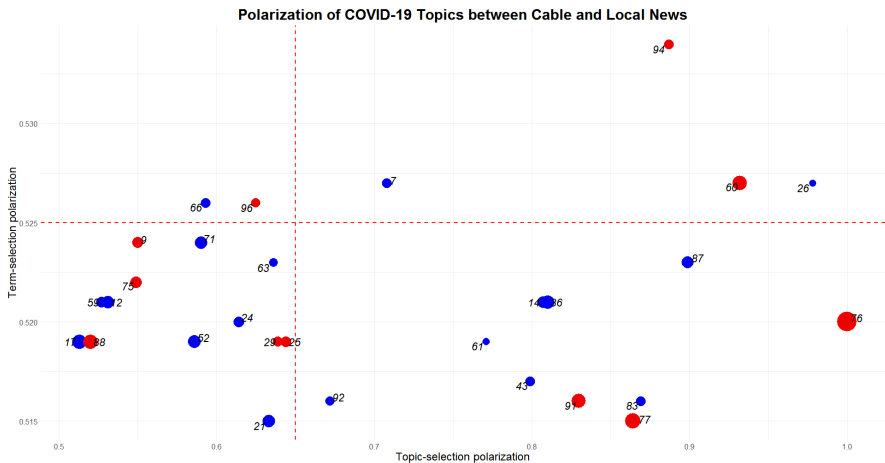
Are presidential communications always newsworthy?

- ▶ Even if they are inaccurate?
- ▶ Even if they are dangerous or incite violence?

Are presidential communications always newsworthy?

- ▶ Even if they are inaccurate?
- ▶ Even if they are dangerous or incite violence?
- ▶ Who makes the call?

Local vs National News



Term Selection Polarization

We apply the estimator of phrase polarization from Gentzkow et al. (2019). Polarization is defined as the expected posterior probability that an observer with a neutral prior would assign to a TV segment's true source (e.g. FOX or MSNBC) after observing a single token drawn at random from the TV segment. If there is no difference in term usage between the two sources, this probability should be 0.5, i.e, our guess is at best as good as random.

The estimator consistently estimates polarization under the assumption that a segment's tokens are drawn from a multinomial logit model. It can be thought of as weighted averages of token-level features, where the features are weighted by the distribution of token use for channels and then the channel-level averages are averaged across all tokens.

$$\pi^{LO} = \frac{1}{2} \left(\frac{1}{|D|} \sum_{i \in D} \hat{\mathbf{q}}_i \cdot \hat{\boldsymbol{\rho}}_{-i} + \frac{1}{|R|} \sum_{i \in R} \hat{\mathbf{q}}_i \cdot (1 - \hat{\boldsymbol{\rho}}_{-i}) \right)$$

Where $\mathbf{q}_i = \mathbf{c}_i / m_i$ is the vector of empirical token frequencies for segment i , with \mathbf{c}_i being the vector of token counts for segment i and m_i is the sum of token counts for segment i ; and $\boldsymbol{\rho}_D / (\boldsymbol{\rho}_D + \boldsymbol{\rho}_R)$ is a vector of empirical posterior probabilities.

When applying this measure to a group of documents about a given topic, this polarization estimator measures how different channels talk about the same topic differently. Therefore, it gives us an intuitive measure of how media are “framing” or “spinning” in its coverage.

Topic Selection Polarization

We also define a simple measure of polarization of topic selection level, i.e. how skew is a given topic is distributed across channels based on topic proportion estimated by our structural topic model. This gives us a measure of what the media choose to talk about.

Let d index the document and T index the topic. Each document has a vector of weights for each topic that sum to 1. We can speak of $w_{T,d}$ which is the weight of topic T for a particular document d . For each topic, we can calculate two numbers that correspond to the probability of a document that is about topic T being sourced from MSNBC or FOX, respectively:

$$P(MSNBC|T) = \frac{\sum_{d \in MSNBC} w_{T,d}}{\sum_d w_{T,d}}$$

$$P(FOX|T) = \frac{\sum_{d \in FOX} w_{T,d}}{\sum_d w_{T,d}}$$

Clearly, $P(MSNBC|T) + P(FOX|T) = 1$

The topic selection polarization of a given topic can be defined as:

$$\rho_T^{Topic} = \max(P(MSNBC|T), P(FOX|T))$$

Do Channels Disagree about Pressers?

