

# **How Partisan is Local Politics? A View from Public Meetings**

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- ▶ But, fewer constraints on the *inputs* of local governments (i.e. public deliberation)
- ▶ So, is the “politics” of local government today dominated by partisan conflicts at the national level?

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- ▶ But, we know less about, in general, **what** both officials and participants deliberate on, **how**, and if it aligns with local constituency's **partisan preferences** (Tausanovitch and Warshaw 2014).

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  - ▶ Same local issues **framed** differently in Republican- and Democrat-voting places

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Incomplete picture of *inputs*:

- ▶ We know that in large municipalities, politicians' policies and preferences align with public preferences (Tausanovitch and Warshaw 2014)
- ▶ We think there's more attention to *Redistributive* issues in big liberal cities, and *Allocational* issues in small conservative towns (Peterson 1981)

# Our Hypothesis About Local Policy-Making

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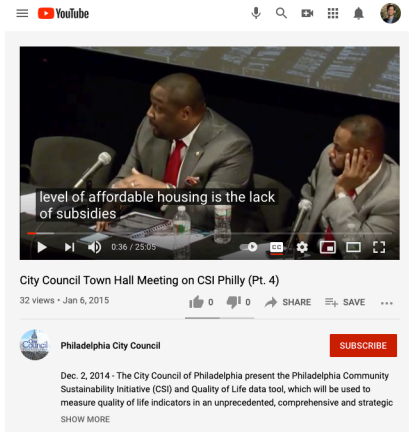
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# Our Hypothesis About Local Policy-Making

In local meetings, both the **attention paid to local issues** and how closely local political discussions **adopt national partisan language** should differ in predictable ways based on the partisan composition of municipality.



# Data Collection from YouTube



The image shows a YouTube video player interface. At the top, there is a navigation bar with the YouTube logo, a microphone icon, a search icon, a camera icon, a grid icon, a bell icon, and a profile picture icon. The video player itself shows two men in suits sitting at a table with microphones. A subtitle is displayed over the video: "level of affordable housing is the lack of subsidies". Below the video player, the title "City Council Town Hall Meeting on CSI Philly (Pt. 4)" is shown, along with "32 views · Jan 6, 2015". There are icons for likes (0), dislikes (0), share, save, and a menu icon. Below the video player, the channel name "Philadelphia City Council" is displayed with a profile picture and a red "SUBSCRIBE" button. A description follows: "Dec. 2, 2014 - The City Council of Philadelphia present the Philadelphia Community Sustainability Initiative (CSI) and Quality of Life data tool, which will be used to measure quality of life indicators in an unprecedented, comprehensive and strategic". A "SHOW MORE" link is at the bottom of the description.

URL



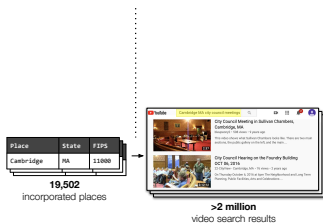
# Data Collection from YouTube

Place	State	FIPS
Cambridge	MA	11000

19,502  
incorporated places

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**Step 1:** Query for public meetings on YouTube API using census entries.



\*title or description text must contain **Place**, government body keyword (e.g. "city council"), meeting keyword (e.g. "meeting"), and **Date**

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**Step 2:** Download valid\* search results.



173,715 videos

[15:16] and make Mass Ave a safe transportation option all the way from Harvard ...

129,320 caption transcripts



173,715 metadata records

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**Step 3:** Verify videos are official public meetings from municipalities.



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**Step 4:** Parse meeting transcripts.

Speaker	Comment	FIPS	Date
Jane Doe	"My name is Jane Doe and..."	11008	Apr 4, 2019

54,688 named public comments

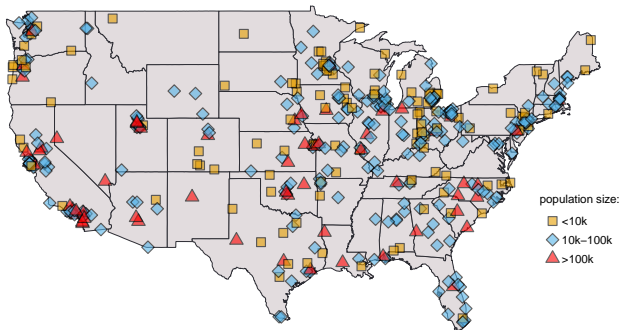
Period	FIPS	Date
"The floor is open for public comment... ... and make Mass Ave a safer transportation all the way from Harvard ... ... we now close the comment period."	11008	Apr 4, 2019

18,302 public comment periods

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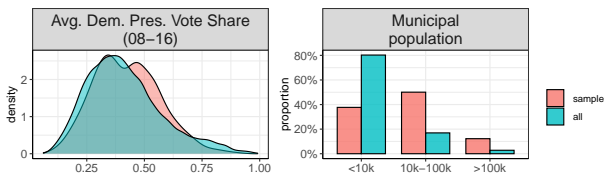


# Sample Characteristics: Geographic Distribution



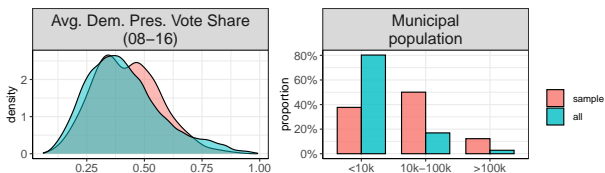
39,941 meetings across 1,222 municipalities in 47 states

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To account for skews, weight all places by inverse model-based sample propensity scores  $\widehat{w}_i^{-1}$  for each municipality  $i$ :

$$w_i = \text{logit}^{-1} \left( \beta_1 s_{j[i]} + \beta_2 p_i + \beta_3 r_i + \beta_3 v_i \right)$$

where  $s_{j[i]}$  is a state indicator,  $p_i$  is municipal population,  $r_i$  is average municipal revenue per person 2015 government,  $v_i$  is average Pres. vote share (2008-2016), and  $w_i$  is an indicator for inclusion in our sample.

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- ▶ **No regional accent effects, but slight mistranscriptions of ethnic minorities' comments.**

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**We split each meeting into public portion and officials portions  $\rightsquigarrow$  exploring individual commenters in future work**

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To avoid model dependence:

- ▶ Topic model with alternative  $K$
- ▶ Topic model with alternative arena categorization
- ▶ Topics re-weighted at place-level by IPW weights
- ▶ Keyword-based topic model from Census of Gov'ts local issues

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## Public commenter in Philadelphia, PA:

"Some of the concern is in the 1800's we may not have known who was lynched for their land but in 2014 I know that the house down the street land belonged to Miss Mary [so] if we're going to be [sustainable](#) and [we] are in this initiative ... [equality](#). We have to have families actually get dollars with our public money, we need to make sure the [African American](#) people are receiving those dollars which is not necessarily as fair and [equitable](#) right now."

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## Elected official in Fairhope, AL:

"It is extremely naive for anyone to think that there would not be heavy abuse of the restrictions on purchase and consumption of alcohol contained in the draft ordinance turning the entire downtown area into an open bar; [it] would not seem to contribute to maintaining the character of our charming town ... beach communities work hard to attract swarms of drinkers, you know, adult and underage they don't care to promote **economic growth** in their towns ... Fairhope is not a beach community. Fairhope prides itself as being a **family**-friendly town. It's difficult for me to understand how allowing alcohol to be openly consumed on the city streets 24/7 would contribute to a **family**-friendly environment"

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- ▶ We have measures of differential Republican usage  $\gamma_j$  of  $j = 1, \dots, 1000$  most partisan phrases in Congress from 2009-2016 (e.g. “climate change”, “raise taxes”, “Jesus Christ”) (Gentzkow, Shapiro, and Taddy 2019)

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$$w_{ij} \sim \text{Pois}(\lambda_{ij}),$$

$$\lambda_{ij} = \exp(\alpha_j + \underbrace{\beta_i}_{\text{municipality's partisan intensity}} + \underbrace{\psi_i}_{\text{municipality's partisan slant}} \gamma_j).$$

## Measurement: Partisan Expression

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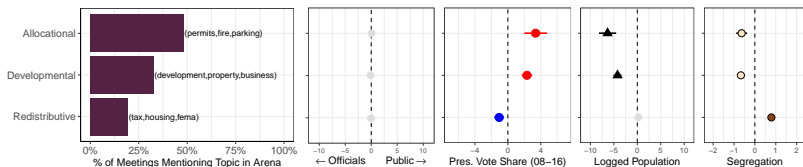
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- ▶ Estimate using Expectation Maximization algorithm
- ▶ Fit again for public-only ( $\beta_i^{\text{public}}, \psi^{\text{public}}$ ) and officials-only ( $\beta_i^{\text{officials}}, \psi^{\text{officials}}$ )

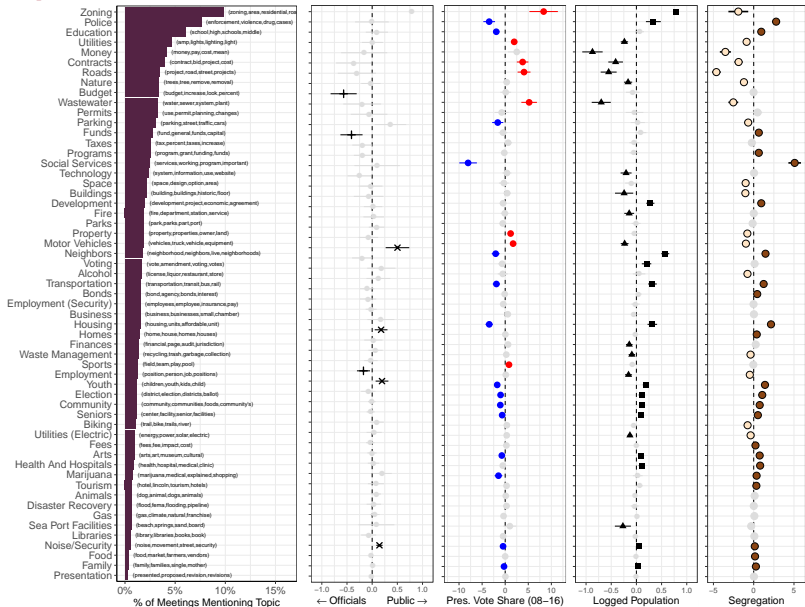
# Findings



# Small, But Robust Differences in Issue Attention



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Motivation

Expectations

Data

Measurement

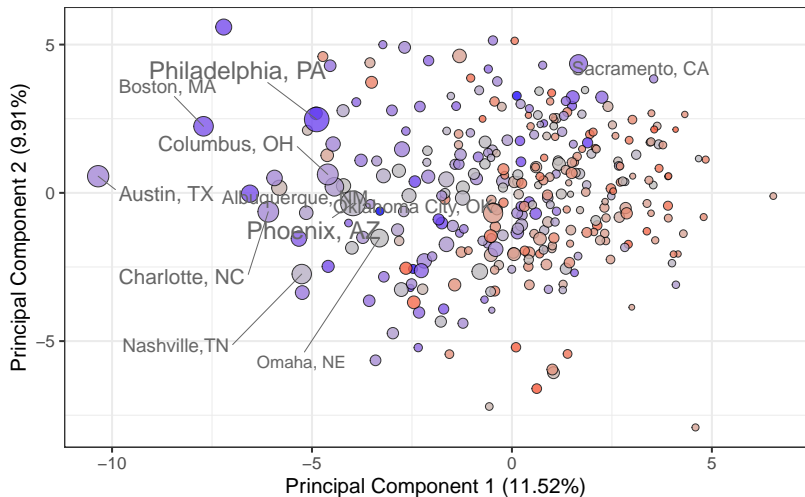
Findings

Conclusion

References

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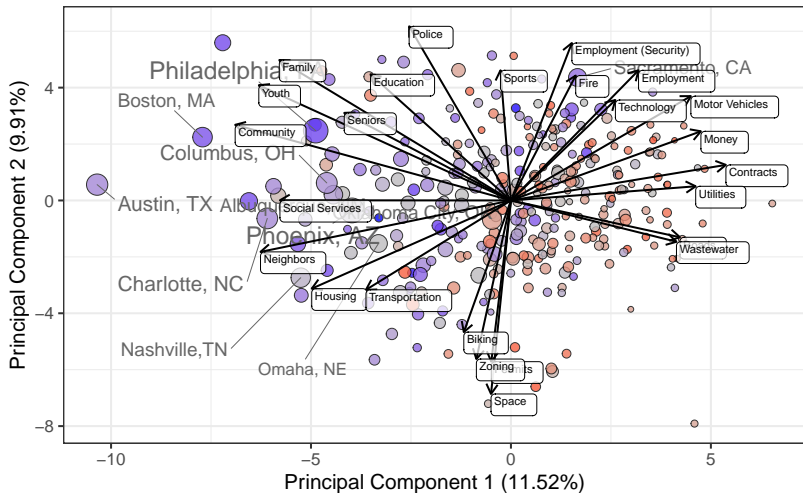
“Summaries” of issue attention correlates with partisan composition



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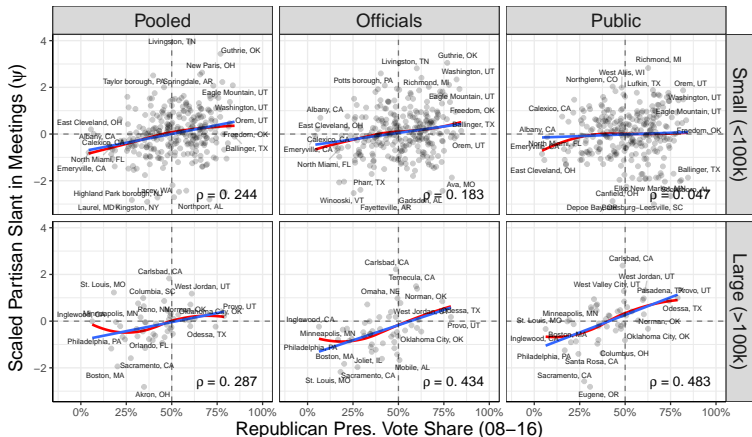
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top 25 variables with highest  $\sqrt{PC1^2 + PC2^2}$

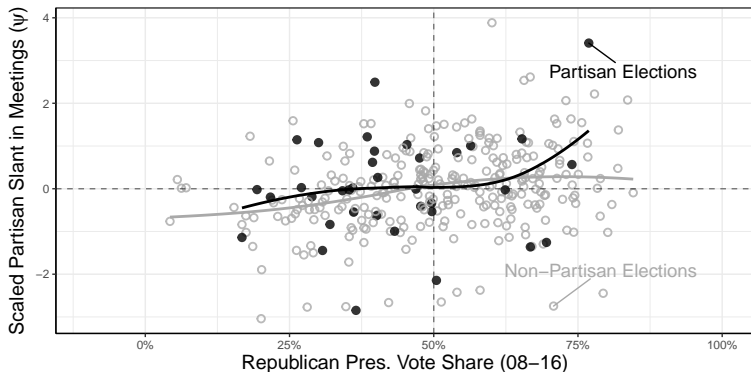


# How Municipalities Deliberate Aligns with How They Vote

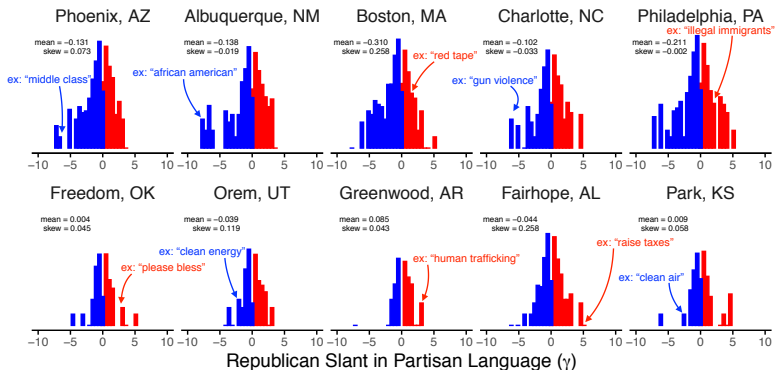
# How Municipalities Deliberate Aligns with How They Vote



# ...And No Difference Between "Formally" Partisan and Non-Partisan Municipalities



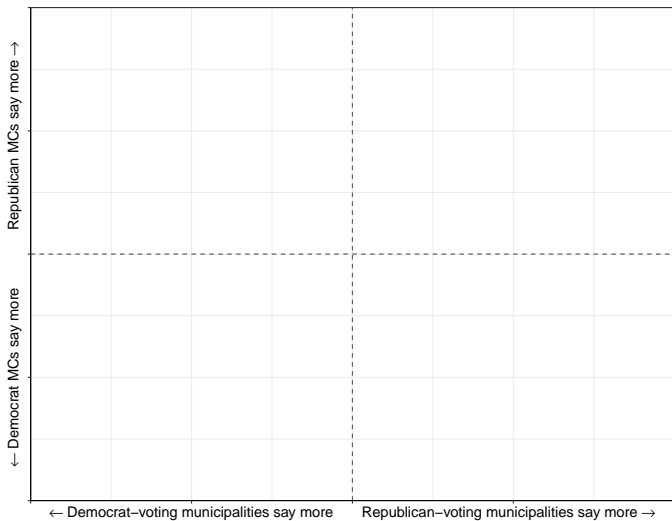
# Distribution of Partisan Expression *Within* Municipalities is Asymmetric, But Not Polarized



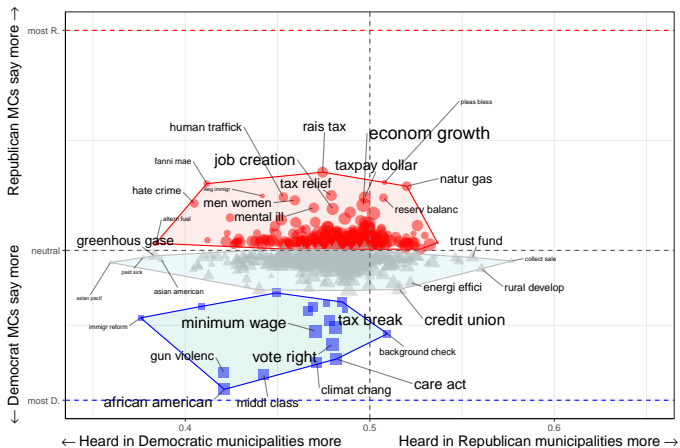


# Partisan Language is Heard in Liberal Places, Omitted in Conservative Places

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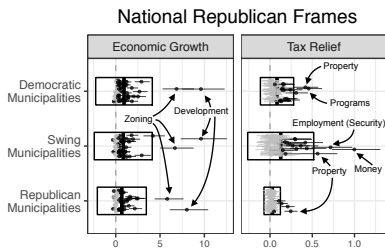
Estimate heterogeneities in mentions of four national partisan frames (**economic growth**, **tax relief**, **racial minorities**, **climate change**) in context of local topics:

$$\log(\text{FrameMentions}_{it}) = \beta_{it}\text{Topic}_{it} + \beta_0\text{NumTopicMentions}_{it} + \beta_1 \log(\text{NumMeetings}_i) + \beta_2\text{Demog}_i$$

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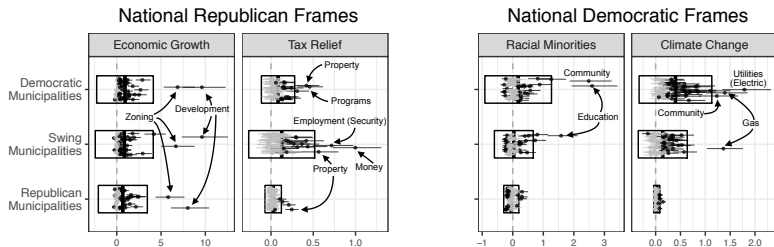
Predicted Increase in Usages of Frame in Context of Individual Issue

(Reference topic is Alcohol)

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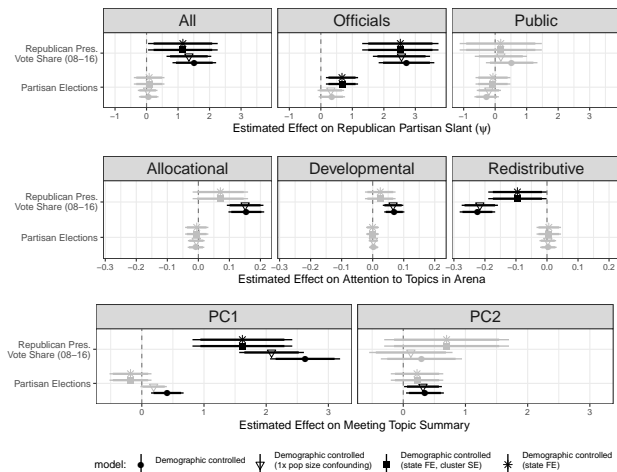


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# Summary of Model-Adjusted Effects

All effects persist after adjusting for population size, diversity, segregation, and state:



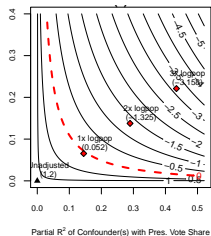
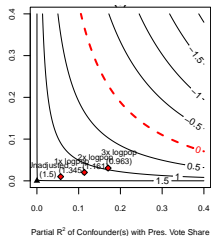
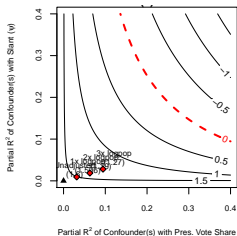


# Sensitivity Analyses: Slant Alignment Result

How much omitted variable bias (relative to the the effect of log population size) would be needed to destroy or reverse alignment result?

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# A More Nuanced View about Partisan Polarization

How strongly a town voted for Trump tells you about its' local politics.

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**How strongly a town voted for Trump tells you about its' local politics.**

- ▶ But, differences in overall issue attention across place are pretty small
- ▶ Distribution of partisan slant is nearly identical across places
- ▶ Tail of liberal language in **liberal** cities drives differences in *average* slant
- ▶ Asymmetric *omission* of partisan language and frames (e.g., climate change, racial minorities) from **conservative** places

# Concluding Thoughts

No Democratic or Republican way to pick up garbage

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No Democratic or Republican way to pick up garbage  $\rightsquigarrow$  but, in local politics, how often it's discussed (relative to other issues) and whether climate change and racial equity considerations are made is influenced by partisanship.



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