What Drives Demand for Media Slant?

Marcel Garz, Gaurav Sood, Daniel F. Stone, and Justin Wallace

NYC Media Seminar
March 6, 2019
Background

Gentzkow and Shapiro (Etca, 2010): What drives media slant?

▶ (Demand or supply?)

▶ (for US newspapers in 2005)

Answer: Demand

Slant determined by reader politics, not owner's
Background

- Gentzkow and Shapiro (Etca, 2010): “What drives media slant?”
Background

- Gentzkow and Shapiro (Etca, 2010): “What drives media slant?”
- (Demand or supply?)
Background

- Gentzkow and Shapiro (Etca, 2010): “What drives media slant?”
- (Demand or supply?)
- (for US newspapers in 2005)
Gentzkow and Shapiro (Etca, 2010): “What drives media slant?”

(Demand or supply?)

(for US newspapers in 2005)

Answer: Demand
Background

- Gentzkow and Shapiro (Etca, 2010): “What drives media slant?”
  (Demand or supply?)
  (for US newspapers in 2005)
  Answer: Demand
  Slant determined by reader politics, not owner’s
GS (2010): Market forces > political forces
GS (2010): Market forces > political forces
Media consumers get the (like-minded) slant they want...
Media consumers get the (like-minded) slant they want...

- “Partisan selective exposure” is real (not a shocker)
Media consumers get the (like-minded) slant they want...

- “Partisan selective exposure” is real (not a shocker)
- Exacerbated by new media
Media consumers get the (like-minded) slant they want...

- “Partisan selective exposure” is real (not a shocker)
- Exacerbated by new media

- GS (QJE, 2011): FoxNews.com: 76% visitors conservative, 10% liberal (NYTimes.com: 30% conservative, 45% liberal)
Media consumers get the (like-minded) slant they want...

- “Partisan selective exposure” is real (not a shocker)
- Exacerbated by new media

- GS (QJE, 2011): FoxNews.com: 76% visitors conservative, 10% liberal (NYTimes.com: 30% conservative, 45% liberal)
- Pew (2014): 84% of ‘consistent conservatives’ get news from Fox News (5% from NYT)
Media consumers get the (like-minded) slant they want...

- “Partisan selective exposure” is real (not a shocker)
- Exacerbated by new media

- GS (QJE, 2011): FoxNews.com: 76% visitors conservative, 10% liberal (NYTimes.com: 30% conservative, 45% liberal)
- Pew (2014): 84% of ‘consistent conservatives’ get news from Fox News (5% from NYT)...
- 33% of ‘consistent liberals’ get news from NYT (10% from Fox)
Media consumers get the (like-minded) slant they want...

- “Partisan selective exposure” is real (not a shocker)
- Exacerbated by new media

- GS (QJE, 2011): FoxNews.com: 76% visitors conservative, 10% liberal (NYTimes.com: 30% conservative, 45% liberal)
- Pew (2014): 84% of ‘consistent conservatives’ get news from Fox News (5% from NYT)...
- 33% of ‘consistent liberals’ get news from NYT (10% from Fox)
- Flaxman, Goel, Rao (2016): “individuals typically visit ideologically similar news outlets”
Media consumers get the (like-minded) slant they want...

- “Partisan selective exposure” is real (not a shocker)
- Exacerbated by new media

- GS (QJE, 2011): FoxNews.com: 76% visitors conservative, 10% liberal (NYTimes.com: 30% conservative, 45% liberal)
- Pew (2014): 84% of ‘consistent conservatives’ get news from Fox News (5% from NYT)...
- 33% of ‘consistent liberals’ get news from NYT (10% from Fox)
- Flaxman, Goel, Rao (2016): “individuals typically visit ideologically similar news outlets”

- Still maybe echo chambers, filter bubbles etc overblown? (Guess et al, 2018)
Media consumers get the (like-minded) slant they want...

- “Partisan selective exposure” is real (not a shocker)
- Exacerbated by new media

- GS (QJE, 2011): FoxNews.com: 76% visitors conservative, 10% liberal (NYTimes.com: 30% conservative, 45% liberal)

- Pew (2014): 84% of ‘consistent conservatives’ get news from Fox News (5% from NYT)...

- 33% of ‘consistent liberals’ get news from NYT (10% from Fox)

- Flaxman, Goel, Rao (2016): “individuals typically visit ideologically similar news outlets”

- Still maybe echo chambers, filter bubbles etc overblown? (Guess et al, 2018)

- Maybe not: Eady et al, 2019: 85% of L-most quintile in bubble on Twitter; 78% of R-most quintile
But what drives demand for (like-minded) media slant?

1. Feels good = psychology (Mullainathan and Shleifer, AER, 2005) = motivated reasoning, cognitive dissonance (avoidance), ego-concerns, etc

2. Trust (Gentzkow and Shapiro, JPE, 2006)

3. Instrumental info (Chan and Suen, ReStud, 2008)

Welfare: bias is bad for (voter information) if #1, good if #3!

(Truly (privately) optimal when making a choice and info is constrained for advisor to share your `values')
But what drives demand for (like-minded) media slant?

- 3 major theories (GSS, HME, 2016)

  - Feels good = psychology (Mullainathan and Shleifer, AER, 2005) = motivated reasoning, cognitive dissonance (avoidance), ego-concerns, etc
  - Trust (Gentzkow and Shapiro, JPE, 2006)
  - Instrumental info (Chan and Suen, ReStud, 2008)

  Welfare: bias is bad for (voter information) if #1, good if #3!
  (Truly (privately) optimal when making a choice and info is constrained for advisor to share your `values')
But what drives demand for (like-minded) media slant?

- 3 major theories (GSS, HME, 2016)
- 1. Feels good = “psychology” (Mullainathan and Shleifer, AER, 2005) = motivated reasoning, cognitive dissonance (avoidance), ego-concerns, etc
But what drives demand for (like-minded) media slant?

➤ 3 major theories (GSS, HME, 2016)

➤ 1. Feels good = “psychology” (Mullainathan and Shleifer, AER, 2005) = motivated reasoning, cognitive dissonance (avoidance), ego-concerns, etc

➤ 2. Trust (Gentzkow and Shapiro, JPE, 2006)
But what drives demand for (like-minded) media slant?

- 3 major theories (GSS, HME, 2016)
- 1. Feels good = “psychology” (Mullainathan and Shleifer, AER, 2005) = motivated reasoning, cognitive dissonance (avoidance), ego-concerns, etc
- 2. Trust (Gentzkow and Shapiro, JPE, 2006)
- 3. Instrumental info (Chan and Suen, ReStud, 2008)
But what drives demand for (like-minded) media slant?

- 3 major theories (GSS, HME, 2016)
- 1. Feels good = “psychology” (Mullainathan and Shleifer, AER, 2005) = motivated reasoning, cognitive dissonance (avoidance), ego-concerns, etc
- 2. Trust (Gentzkow and Shapiro, JPE, 2006)
- 3. Instrumental info (Chan and Suen, ReStud, 2008)

Welfare: bias is bad for (voter information) if #1, good if #3!
But what drives demand for (like-minded) media slant?

- 3 major theories (GSS, HME, 2016)
- 1. Feels good = “psychology” (Mullainathan and Shleifer, AER, 2005) = motivated reasoning, cognitive dissonance (avoidance), ego-concerns, etc
- 2. Trust (Gentzkow and Shapiro, JPE, 2006)
- 3. Instrumental info (Chan and Suen, ReStud, 2008)

Welfare: bias is bad for (voter information) if #1, good if #3!

(Truly (privately) optimal when making a choice and info is constrained for advisor to share your ‘values’)}
Psych (#1) is most intuitive...
Psych (#1) is most intuitive...

- But much econ theory lit on instrumental (#3)
Psych (#1) is most intuitive...

- But much econ theory lit on instrumental (#3)
  - (e.g., Jann and Schottmuller, 2018; see paper for older cites)
Psych (#1) is most intuitive...

- But much econ theory lit on instrumental (#3)
- (e.g., Jann and Schottmuller, 2018; see paper for older cites)
- Empirical evidence limited
Psych (#1) is most intuitive...

- But much econ theory lit on instrumental (#3)
- (e.g., Jann and Schottmuller, 2018; see paper for older cites)
- Empirical evidence limited
- Our paper: first to address theories with field and real-time lab data
Empirical strategy

- Exploit a few features of online horse race news (or residential election polls/poll changes):
  - Partisan congeniality (slant) relatively clear (especially in headlines...)
  - Reported on repeatedly by major outlets across spectrum
  - Variation in congeniality over time within all outlets
  - Publicly available measure of demand (most popular lists)
Empirical strategy

- Exploit a few features of online “horse race” news (on presidential election polls/poll changes):
Empirical strategy

- Exploit a few features of online “horse race” news (on presidential election polls/poll changes):
  - 1. Partisan congeniality (slant) relatively clear (espec in headlines...)


Empirical strategy

- Exploit a few features of online “horse race” news (on presidential election polls/poll changes):
  - 1. Partisan congeniality (slant) relatively clear (espec in headlines…)
  - 2. Reported on repeatedly by major outlets across spectrum
Empirical strategy

- Exploit a few features of online “horse race” news (on presidential election polls/poll changes):
  1. Partisan congeniality (slant) relatively clear (espec in headlines…)
  2. Reported on repeatedly by major outlets across spectrum
  3. Variation in congeniality over time within all outlets
Empirical strategy

- Exploit a few features of online “horse race” news (on presidential election polls/poll changes):
  - 1. Partisan congeniality (slant) relatively clear (espec in headlines…)
  - 2. Reported on repeatedly by major outlets across spectrum
  - 3. Variation in congeniality over time within all outlets
  - 4. Publicly available measure of demand (“most popular” lists)
Empirical strategy

- Look for within-outlet-topic correlation in demand and congeniality
- Holds fixed topic, outlet = 2 major components of information
- If more congenial articles are more popular, likely due to psychology
Empirical strategy

- Look for within-outlet-topic correlation in demand and congeniality
Empirical strategy

- Look for within-outlet-topic correlation in demand and congeniality
- Holds fixed topic, outlet = 2 major components of information
Empirical strategy

- Look for within-outlet-topic correlation in demand and congeniality
- Holds fixed topic, outlet = 2 major components of information
- If more congenial articles are more popular, likely due to psychology
Issues: We are west (though hopefully also north) of A
Issues: We are west (though hopefully also north) of A

2/ In a characteristic Akerlofian style, he models econ’s research choice as finding optimum on downward sloping hardness-importance frontier (point A), then introduces social welfare function which reflects the public’s utility for an economist research (social optimum B). Gap!
Issues

Headlines vs article content

Headlines prima facie drive clicks; spot check; (illustrative) model

Variation in HR news congeniality across outlets?

Look at both across and within-variation; interpret ‘jointly’ w model

Aggregated web demand data

Complement with incentivized survey (micro-level)

‘External validity’ of horse race topic?

Survey uses related but distinct topic (debates)

MTurk; pre-registration (lack thereof); multiple testing

Ahler et al (WP 2019): no evidence of both epidemic, 25% engage in sketchy behavio...
Issues

- Headlines vs article content
Issues

- Headlines vs article content
- Headlines prima facie drive clicks; spot check; (illustrative) model
Issues

- Headlines vs article content
- Headlines prima facie drive clicks; spot check; (illustrative) model
- Variation in HR news congeniality across outlets?
Issues

- Headlines vs article content
- Headlines prima facie drive clicks; spot check; (illustrative) model
- Variation in HR news congeniality across outlets?
- Loot at both across and within-variation; interpret ‘jointly’ w model
Issues

- Headlines vs article content
- Headlines prima facie drive clicks; spot check; (illustrative) model
- Variation in HR news congeniality across outlets?
- Loot at both across and within-variation; interpret ‘jointly’ w model
- Aggregated web demand data
Issues

- Headlines vs article content
- Headlines prima facie drive clicks; spot check; (illustrative) model
- Variation in HR news congeniality across outlets?
- Loot at both across and within-variation; interpret ‘jointly’ w model
- Aggregated web demand data
- Complement with incentivized survey (micro-level)
Issues

- Headlines vs article content
- Headlines prima facie drive clicks; spot check; (illustrative) model
- Variation in HR news congeniality across outlets?
- Loot at both across and within-variation; interpret ‘jointly’ w model
- Aggregated web demand data
- Complement with incentivized survey (micro-level)
- ‘External validity’ of horse race topic?
Issues

- Headlines vs article content
- Headlines prima facie drive clicks; spot check; (illustrative) model
- Variation in HR news congeniality across outlets?
- Loot at both across and within-variation; interpret ‘jointly’ w model
- Aggregated web demand data
- Complement with incentivized survey (micro-level)
- ‘External validity’ of horse race topic?
- Survey uses related but distinct topic (debates)
Issues

- Headlines vs article content
- Headlines prima facie drive clicks; spot check; (illustrative) model
- Variation in HR news congeniality across outlets?
- Loot at both across and within-variation; interpret ‘jointly’ w model
- Aggregated web demand data
- Complement with incentivized survey (micro-level)
- ‘External validity’ of horse race topic?
- Survey uses related but distinct topic (debates)
- MTurk; pre-registration (lack thereof); multiple testing
Issues

- Headlines vs article content
- Headlines prima facie drive clicks; spot check; (illustrative) model
- Variation in HR news congeniality across outlets?
- Loot at both across and within-variation; interpret ‘jointly’ w model
- Aggregated web demand data
- Complement with incentivized survey (micro-level)
- ‘External validity’ of horse race topic?
- Survey uses related but distinct topic (debates)
- MTurk; pre-registration (lack thereof); multiple testing
- Ahler et al (WP 2019): no evidence of bot epidemic, 25% engage in sketchy behavior...
Mini lit review

Metzger et al (2015): lab study of trust vs psych, artificial news stories

Temayne (2015), Seurles et al (2016): HR slant (different outlets, no within-outlet analysis, comparison to polls)

Within-outlet-topic partisan selective engagement: Gazz et al (WP, 2019)
Mini lit review

- Metzger et al (2015): lab study of trust vs psych, artificial news stories
Mini lit review

- Metzger et al (2015): lab study of trust vs psych, artificial news stories
- Tremayne (2015), Searles et al (2016): HR slant (different outlets, no within-outlet analysis, comparison to polls)
Mini lit review

- Metzger et al (2015): lab study of trust vs psych, artificial news stories
- Tremayne (2015), Searles et al (2016): HR slant (different outlets, no within-outlet analysis, comparison to polls)
Model (modified version of MS, AER, 2005)
Model (modified version of MS, AER, 2005)

- News story $i$ from outlet $j = n_{ij} = d_i + s_j + \epsilon_i \in (-\infty, \infty)$
Model (modified version of MS, AER, 2005)

- News story $i$ from outlet $j = n_{ij} = d_i + s_j + \epsilon_i \in (-\infty, \infty)$
- $d_i =$ truth; $s_j =$ $j$’s (constant) slant; $\epsilon_i =$ noise
Model (modified version of MS, AER, 2005)

- News story $i$ from outlet $j = n_{ij} = d_i + s_j + \epsilon_i \in (-\infty, \infty)$
- $d_i =$ truth; $s_j =$ j’s (constant) slant; $\epsilon_i =$ noise

- Reader’s utility from $n_i = U_r = -\chi(s_j + \epsilon_i)^2 + \phi n_i - c_i$
Model (modified version of MS, AER, 2005)

- News story $i$ from outlet $j = n_{ij} = d_i + s_j + \epsilon_i \in (-\infty, \infty)$
- $d_i =$ truth; $s_j = j$’s (constant) slant; $\epsilon_i =$ noise

- Reader’s utility from $n_i = U_r = -\chi(s_j + \epsilon_i)^2 + \phi n_i - c_i$
- $\phi \geq 0$ is preference for congeniality (higher $n_i$ better) (psychology)
Model (modified version of MS, AER, 2005)

- News story $i$ from outlet $j = n_{ij} = d_i + s_j + \epsilon_i \in (-\infty, \infty)$
- $d_i =$ truth; $s_j =$ j’s (constant) slant; $\epsilon_i =$ noise

- Reader’s utility from $n_i = U_r = -\chi (s_j + \epsilon_i)^2 + \phi n_i - c_i$
- $\phi \geq 0$ is preference for congeniality (higher $n_i$ better) (psychology)
- $\chi \geq 0$ is preference for truth (info-seeking/trust)
Model (modified version of MS, AER, 2005)

- News story $i$ from outlet $j = n_{ij} = d_i + s_j + \epsilon_i \in (-\infty, \infty)$
- $d_i =$ truth; $s_j =$ $j$’s (constant) slant; $\epsilon_i =$ noise

- Reader’s utility from $n_i = U_r = -\chi(s_j + \epsilon_i)^2 + \phi n_i - c_i$
- $\phi \geq 0$ is preference for congeniality (higher $n_i$ better) (psychology)
- $\chi \geq 0$ is preference for truth (info-seeking/trust)
- ($c_i$ is stochastic opportunity cost rather than price)
Model (modified version of MS, AER, 2005)

- News story $i$ from outlet $j = n_{ij} = d_i + s_j + \epsilon_i \in (-\infty, \infty)$
- $d_i = \text{truth}; \ s_j = j \text{'s (constant) slant}; \ \epsilon_i = \text{noise}$

- Reader's utility from $n_i = U_r = -\chi(s_j + \epsilon_i)^2 + \phi n_i - c_i$
- $\phi \geq 0$ is preference for congeniality (higher $n_i$ better) (psychology)
- $\chi \geq 0$ is preference for truth (info-seeking/trust)
- ($c_i$ is stochastic opportunity cost rather than price)
- Quadratic cost for interior $E(U)$ maxing $s_j^* = \phi/2\chi$
Model (modified version of MS, AER, 2005)

- News story $i$ from outlet $j = n_{ij} = d_i + s_j + \epsilon_i \in (-\infty, \infty)$
- $d_i = \text{truth}; s_j = j$’s (constant) slant; $\epsilon_i = \text{noise}$

- Reader’s utility from $n_i = U_r = -\chi(s_j + \epsilon_i)^2 + \phi n_i - c_i$
- $\phi \geq 0$ is preference for congeniality (higher $n_i$ better) (psychology)
- $\chi \geq 0$ is preference for truth (info-seeking/trust)
- $(c_i \text{ is stochastic opportunity cost rather than price})$
- Quadratic cost for interior $E(U)$ maxing $s_j^* = \phi/2\chi$
- $\hat{s}_j = \text{outlet’s actual slant}$
Model (modified version of MS, AER, 2005)

- News story $i$ from outlet $j = n_{ij} = d_i + s_j + \epsilon_i \in (-\infty, \infty)$
- $d_i =$ truth; $s_j =$ $j$’s (constant) slant; $\epsilon_i =$ noise

- Reader’s utility from $n_i = U_r = -\chi(s_j + \epsilon_i)^2 + \phi n_i - c_i$
- $\phi \geq 0$ is preference for congeniality (higher $n_i$ better) (psychology)
- $\chi \geq 0$ is preference for truth (info-seeking/trust)
- ($c_i$ is stochastic opportunity cost rather than price)
- Quadratic cost for interior $E(U)$ maxing $s_j^* = \phi/2\chi$
- $\hat{s}_j =$ outlet’s actual slant
- Suppress $i$’s, $j$...
Headlines
Headlines

- Headline $h \in (-\infty, \infty)$ seen before clicking and reading
Headlines

- Headline $h \in (-\infty, \infty)$ seen before clicking and reading
- $E(n|h)$ unbiased, $E(d|h)$, $E(\epsilon|h)$ unbiased and both increasing in $h$
Model

\[ E(U_r | h) = -\chi E(\hat{s} + \epsilon | h) + \phi (E(d|h) + \hat{s} + E(\epsilon|h)) \]

The marginal effect of \( h = \frac{\partial}{\partial h} E(U_r | h) = -\chi \frac{\partial}{\partial h} E(\hat{s} + \epsilon | h) + \phi \frac{\partial}{\partial h} (E(d|h) + \hat{s} + E(\epsilon|h)) \)

Costs (error) and benefits (congeniality)

Costs increase in \( \hat{s} \) (and \( \chi \))

Benefits increase in \( \phi \)
Model

$$E(U_r|h) = -\chi E((\hat{s} + \epsilon)^2|h) + \phi (E(d|h) + \hat{s} + E(\epsilon|h)) - c$$
Model

\[ E(U_r|h) = -\chi E((\hat{s} + \epsilon)^2|h) + \phi (E(d|h) + \hat{s} + E(\epsilon|h)) - c \]

The marginal effect of \( h \) = 
\[
\frac{\partial}{\partial h} E(U_r|h) = -\chi \frac{\partial}{\partial h} E((\hat{s} + \epsilon)^2|h) + \phi \frac{\partial}{\partial h} (E(d|h) + E(\epsilon|h))
\]
Model

\[ E(U_r|h) = -\chi E((\hat{s} + \epsilon)^2|h) + \phi (E(d|h) + \hat{s} + E(\epsilon|h)) - c \]

- The marginal effect of \( h \) is
  \[ \frac{\partial}{\partial h} E(U_r|h) = -\chi \frac{\partial}{\partial h} E((\hat{s} + \epsilon)^2|h) + \phi \frac{\partial}{\partial h} (E(d|h) + E(\epsilon|h)) \]

- Costs (error) and benefits (congeniality)
$E(U_r|h) = -\chi E((\hat{s} + \epsilon)^2|h) + \phi (E(d|h) + \hat{s} + E(\epsilon|h)) - c$

The marginal effect of $h =$

$\frac{\partial}{\partial h} E(U_r|h) = -\chi \frac{\partial}{\partial h} E((\hat{s} + \epsilon)^2|h) + \phi \frac{\partial}{\partial h} (E(d|h) + E(\epsilon|h))$

Costs (error) and benefits (congeniality)

Benefits increase in $\phi$
Model

- $E(U_r|h) = -\chi E((\hat{s} + \epsilon)^2|h) + \phi (E(d|h) + \hat{s} + E(\epsilon|h)) - c$

- The marginal effect of $h = \frac{\partial}{\partial h} E(U_r|h) = -\chi \frac{\partial}{\partial h} E((\hat{s} + \epsilon)^2|h) + \phi \frac{\partial}{\partial h} (E(d|h) + E(\epsilon|h))$

- Costs (error) and benefits (congeniality)

- Benefits increase in $\phi$

- Costs increase in $\hat{s}$ (and $\chi$)
Within-outlet slant-demand relationship = \( \frac{\partial}{\partial h} E(U|r|h) \)

Greater mean slant (\( \hat{s} \)) moderates this, can even ip the sign...

Intuition: if already getting ideal (or more than ideal) slant on avg, more slant is too much.
Within-outlet slant-demand relationship = \( \frac{\partial}{\partial h} E(U_r|h) \)
Within-outlet slant-demand relationship $= \frac{\partial}{\partial h} E(U_r| h)$

Greater mean slant ($\hat{s}$) moderates this, can even flip the sign...
Within-outlet slant-demand relationship

\[ \frac{\partial}{\partial h} E(U_r | h) \]

- Greater mean slant (\( \hat{s} \)) moderates this, can even flip the sign...

- Intuition: if already getting ideal (or more than ideal) slant on avg, more slant is too much
Tentative claims
Tentative claims

- Psychology ($\phi > 0$): mean slant ($\hat{s} > 0$) and/or $\frac{\partial}{\partial h}E(U_r|h) > 0$

- Trust ($\chi > 0$) and no psych ($\phi = 0$): $\hat{s} = 0$ and $\frac{\partial}{\partial h}E(U_r|h) = 0$

- Trust and psych ($\chi > 0, \phi > 0$): $\hat{s} > 0$ and/or $\frac{\partial}{\partial h}E(U_r|h) > 0$, $= 0$, or $\hat{s} = 0$ and $\frac{\partial}{\partial h}E(U_r|h) > 0$
Tentative claims

- Psychology ($\phi > 0$): mean slant ($\hat{s} > 0$) and/or $\frac{\partial}{\partial h} E(U_r|h) > 0$
- Trust ($\chi > 0$) and no psych ($\phi = 0$): $\hat{s} = 0$ and $\frac{\partial}{\partial h} E(U_r|h) = 0$
Tentative claims

- Psychology ($\phi > 0$): mean slant ($\hat{s} > 0$) and/or $\frac{\partial}{\partial h} E(U_r|h) > 0$
- Trust ($\chi > 0$) and no psych ($\phi = 0$): $\hat{s} = 0$ and $\frac{\partial}{\partial h} E(U_r|h) = 0$
- Trust and psych ($\chi > 0$, $\phi > 0$):
Tentative claims

- Psychology ($\phi > 0$): mean slant ($\hat{s} > 0$) and/or $\frac{\partial}{\partial h} E(U_r|h) > 0$
- Trust ($\chi > 0$) and no psych ($\phi = 0$): $\hat{s} = 0$ and $\frac{\partial}{\partial h} E(U_r|h) = 0$
- Trust and psych ($\chi > 0$, $\phi > 0$):
  $\hat{s} > 0$ and $\frac{\partial}{\partial h} E(U_r|h) >, =, < 0$ or
Tentative claims

- Psychology ($\phi > 0$): mean slant ($\hat{s} > 0$) and/or $\frac{\partial}{\partial h} E(U_r|h) > 0$
- Trust ($\chi > 0$) and no psych ($\phi = 0$): $\hat{s} = 0$ and $\frac{\partial}{\partial h} E(U_r|h) = 0$
- Trust and psych ($\chi > 0$, $\phi > 0$):
  $\hat{s} > 0$ and $\frac{\partial}{\partial h} E(U_r|h) >, =, < 0$ or
  $\hat{s} = 0$ and $\frac{\partial}{\partial h} E(U_r|h) > 0$
Other factors

- What about instrumental value?
- Unlikely to explain HR slant across outlets?
- Or positive within-outlet congeniality-demand relationship?
- May be could explain a negative one?
- Truth-seekers were biased perceptions of truth? (Psychological trust?)
- Plausibly explains mean congenial slant, \( \hat{\theta} > 0 \), but not this and \( \partial E(U|\theta) > 0 \)
- Also, mean slant should decline as election approaches
- Surprise as demand driver (Frankel et al., JPE, 2012)?
- Try to check out...
- Supply-side bias?
- Keep in mind...
Other factors

▶ What about instrumental value?
Other factors

- What about instrumental value?
- Unlikely to explain HR slant across outlets?
Other factors

▶ What about instrumental value?
▶ Unlikely to explain HR slant across outlets?
▶ Or positive within-outlet congeniality-demand relationship?
Other factors

- What about instrumental value?
- Unlikely to explain HR slant across outlets?
- Or positive within-outlet congeniality-demand relationship?
- But maybe could explain a negative one?
Other factors

- What about instrumental value?
- Unlikely to explain HR slant across outlets?
- Or positive within-outlet congeniality-demand relationship?
- But maybe could explain a negative one?

- Truth-seekers with biased perceptions of truth? (Psychological trust?)
Other factors

- What about instrumental value?
- Unlikely to explain HR slant across outlets?
- Or positive within-outlet congeniality-demand relationship?
- But maybe could explain a negative one?

- Truth-seekers w biased perceptions of truth? (Psychological trust?)
- Plausibly explains mean congenial slant, $\hat{s} > 0$, but not this and $\frac{\partial}{\partial h} E(U_r|h) > 0$
Other factors

- What about instrumental value?
- Unlikely to explain HR slant across outlets?
- Or positive within-outlet congeniality-demand relationship?
- But maybe could explain a negative one?

- Truth-seekers w biased perceptions of truth? (Psychological trust?)
- Plausibly explains mean congenial slant, $\hat{s} > 0$, but not this and $\frac{\partial}{\partial h} E(U_r|h) > 0$
- Also, mean slant should decline as election approaches
Other factors

▶ What about instrumental value?
▶ Unlikely to explain HR slant across outlets?
▶ Or positive within-outlet congeniality-demand relationship?
▶ But maybe could explain a negative one?

▶ Truth-seekers w biased perceptions of truth? (Psychological trust?)
▶ Plausibly explains mean congenial slant, \( \hat{s} > 0 \), but not this and \( \frac{\partial}{\partial h} E(U_r|h) > 0 \)
▶ Also, mean slant should decline as election approaches

▶ Surprise as demand driver (Frankel et al, JPE, 2012)?
Other factors

- What about instrumental value?
- Unlikely to explain HR slant across outlets?
- Or positive within-outlet congeniality-demand relationship?
- But maybe could explain a negative one?

- Truth-seekers w biased perceptions of truth? (Psychological trust?)
- Plausibly explains mean congenial slant, $\hat{s} > 0$, but not this and $\frac{\partial}{\partial h} E(U_r|h) > 0$
- Also, mean slant should decline as election approaches

- Surprise as demand driver (Frankel et al, JPE, 2012)?
- Try to check out...
Other factors

- What about instrumental value?
- Unlikely to explain HR slant across outlets?
- Or positive within-outlet congeniality-demand relationship?
- But maybe could explain a negative one?

- Truth-seekers w biased perceptions of truth? (Psychological trust?)
- Plausibly explains mean congenial slant, \( \hat{s} > 0 \), but not this and
  \( \frac{\partial}{\partial h} E(U_r|h) > 0 \)
- Also, mean slant should decline as election approaches

- Surprise as demand driver (Frankel et al, JPE, 2012)?
- Try to check out...

- Supply-side bias?
Other factors

▶ What about instrumental value?
▶ Unlikely to explain HR slant across outlets?
▶ Or positive within-outlet congeniality-demand relationship?
▶ But maybe could explain a negative one?

▶ Truth-seekers w biased perceptions of truth? (Psychological trust?)
▶ Plausibly explains mean congenial slant, \( \hat{s} > 0 \), but not this and
  \[ \frac{\partial}{\partial h} E(U_r|h) > 0 \]
▶ Also, mean slant should decline as election approaches

▶ Surprise as demand driver (Frankel et al, JPE, 2012)?
▶ Try to check out...

▶ Supply-side bias?
▶ Keep in mind…
Summary

If an outlet is systematically congenial, and positive within-outlet congeniality-demand: likely due to psychology.

Systematically congenial outlets could be due to psychology and/or trust but not instrumental.

If an outlet is systematically congenial, and negative within-outlet congeniality-demand: likely due to trust, may be instrumental.
Summary

- If an outlet is systematically congenial, and positive within-outlet congeniality-demand: likely due to psychology.
Summary

- If an outlet is systematically congenial, and positive within-outlet congeniality-demand: likely due to **psychology**

- Systematically congenial outlets could be due to **psychology** and/or **trust** but not instrumental
Summary

- If an outlet is systematically congenial, and positive within-outlet congeniality-demand: likely due to **psychology**

- Systematically congenial outlets could be due to **psychology** and/or **trust** but not instrumental

- If an outlet is systematically congenial, and negative within-outlet congeniality-demand: likely due to **trust**, maybe **instrumental**
Horse race (HR) news data
Horse race (HR) news data

- 6 web outlets (2 L/2 N/2 R) that report “most viewed” stories
Horse race (HR) news data

- 6 web outlets (2 L/2 N/2 R) that report “most viewed” stories
- Last 2 pres elections

- 2016 (∼July 1 - election day):
  - Scraped three times a day:
    - Google News, Yahoo News
    - Fox News, Wall Street Journal

- 2012 (∼July 1 - election day):
  - Use snapshots stored by web.archive.org
  - New York Times, Huntington Post
  - USA Today, Yahoo News
  - Fox News, Wall Street Journal
Horse race (HR) news data

- 6 web outlets (2 L/2 N/2 R) that report “most viewed” stories
- Last 2 pres elections

- 2016 (≈ July 1 - election day):
  - Scrape three times a day:
    Google News, Yahoo News
    Fox News, Wall Street Journal
Horse race (HR) news data

- 6 web outlets (2 L/2 N/2 R) that report “most viewed” stories
- Last 2 pres elections

- 2016 (~ July 1 - election day):
  - Scrape three times a day:
    - Google News, Yahoo News
    - Fox News, Wall Street Journal

- 2012 (~ July 1 - election day):
  - Use snapshots stored by web.archive.org
  - New York Times, Huffington Post
    - USA Today, Yahoo News
    - Fox News, Wall Street Journal
Identifying HR stories and measuring *slant*
Identifying HR stories and measuring *slant*

1. Broad headlines keyword-based search ("poll", "lead" etc)
Identifying HR stories and measuring *slant*

1. Broad headlines keyword-based search ("poll", "lead" etc)
2. Just headlines b/c: drive clicks; simplicity; spot-check similar article content
Identifying HR stories and measuring *slant*

1. Broad headlines keyword-based search ("poll", "lead" etc)
2. Just headlines b/c: drive clicks; simplicity; spot-check similar article content
3. Exclude opinion pieces
Identifying HR stories and measuring *slant*

1. Broad headlines keyword-based search ("poll", "lead" etc)
2. Just headlines b/c: drive clicks; simplicity; spot-check similar article content
3. Exclude opinion pieces
4. 2,025 headlines
Identifying HR stories and measuring \textit{slant}

1. Broad headlines keyword-based search ("poll", "lead" etc)
2. Just headlines b/c: drive clicks; simplicity; spot-check similar article content
3. Exclude opinion pieces
4. 2,025 headlines
5. Rate \textquote{slant} of each by 3 master MTurkers w 5 pt scale:
   \begin{itemize}
   \item \textquote{Very good news for Dem's chances (bad for R's)} = -1
   \item \textquote{Good news for D} = -0.5
   \item \textquote{Neutral} = 0
   \item \textquote{Good news for R's chances} = 0.5
   \item \textquote{Very good news for R} = 1
   \item \textquote{Ambiguous HR news}
   \item \textquote{Not HR news}
   \end{itemize}
Identifying HR stories and measuring *slant*

1. Broad headlines keyword-based search (“poll”, “lead” etc)
2. Just headlines b/c: drive clicks; simplicity; spot-check similar article content
3. Exclude opinion pieces
4. 2,025 headlines
5. Rate ‘slant’ of each by 3 master MTurkers w 5 pt scale:
   - Very good news for Dem’s chances (bad for R’s) = -1
   - Good news for D = -0.5
Identifying HR stories and measuring *slant*

1. Broad headlines keyword-based search ("poll", "lead" etc)
2. Just headlines b/c: drive clicks; simplicity; spot-check similar article content
3. Exclude opinion pieces
4. 2,025 headlines
5. Rate ‘slant’ of each by 3 master MTurkers w 5 pt scale:
   - Very good news for Dem’s chances (bad for R’s) = -1
   - Good news for D = -0.5
   - Neutral = 0
Identifying HR stories and measuring *slant*

1. Broad headlines keyword-based search ("poll", "lead" etc)
2. Just headlines b/c: drive clicks; simplicity; spot-check similar article content
3. Exclude opinion pieces
4. 2,025 headlines
5. Rate ‘slant’ of each by 3 master MTurkers w 5 pt scale:
   - Very good news for Dem’s chances (bad for R’s) = -1
   - Good news for D = -0.5
   - Neutral = 0
   - Good news for R’s chances = 0.5
   - Very good news for R = 1
Identifying HR stories and measuring *slant*

1. Broad headlines keyword-based search (“poll”, “lead” etc)
2. Just headlines b/c: drive clicks; simplicity; spot-check similar article content
3. Exclude opinion pieces
4. 2,025 headlines
5. Rate ‘slant’ of each by 3 master MTurkers w 5 pt scale:
   - Very good news for Dem’s chances (bad for R’s) = -1
   - Good news for D = -0.5
   - Neutral = 0
   - Good news for R’s chances = 0.5
   - Very good news for R = 1
   - Ambiguous HR news
   - Not HR news
Measuring slant

- Regular spot-checks; strong incentives for effort/quality; validation
- Results similar but much noisier with strict text-based measures
- Still: data quantity-quality trade-off
- Used different measures for robustness

Slant 1 = most inclusive of ambiguous/irrelevant headlines
Slant 2 = medium
Slant 3 = least inclusive
Measuring slant

- Regular spot-checks; strong incentives for effort/quality; validation

SLANT 1 = most inclusive of ambiguous/irrelevant headlines
SLANT 2 = medium
SLANT 3 = least inclusive
Measuring slant

- Regular spot-checks; strong incentives for effort/quality; validation
- Results similar but much noisier with strict text-based measures
Measuring slant

- Regular spot-checks; strong incentives for effort/quality; validation
- Results similar but much noisier with strict text-based measures
- Still: data quantity-quality trade-off
Measuring slant

- Regular spot-checks; strong incentives for effort/quality; validation
- Results similar but much noisier with strict text-based measures
- Still: data quantity-quality trade-off
- Use different measures for robustness
Measuring slant

- Regular spot-checks; strong incentives for effort/quality; validation
- Results similar but much noisier with strict text-based measures
- Still: data quantity-quality trade-off
- Use different measures for robustness

\[ Slant_1 \quad = \quad \text{most inclusive of ambiguous/irrelevant headlines} \]
\[ Slant_2 \quad = \quad \text{medium} \]
\[ Slant_3 \quad = \quad \text{least inclusive} \]
Examples
Examples

▶ “amid last minute push in va clinton holds 6 point lead in latest poll”
Examples

- “amid last minute push in va clinton holds 6 point lead in latest poll”
- $Slant_i = -1$ for $i = 1, 2, 3$
Examples

- “amid last minute push in va clinton holds 6 point lead in latest poll”
- $Slant_i = -1$ for $i = 1, 2, 3$
- “polls trump and clinton virtually tied in key swing states”
Examples

- “amid last minute push in va clinton holds 6 point lead in latest poll”
- $Slant_i = -1$ for $i = 1, 2, 3$
- “polls trump and clinton virtually tied in key swing states”
- $Slant_1 = Slant_2 = 0$;
Examples

- “amid last minute push in va clinton holds 6 point lead in latest poll”
- $\text{Slant}_i = -1$ for $i = 1, 2, 3$
- “polls trump and clinton virtually tied in key swing states”
- $\text{Slant}_1 = \text{Slant}_2 = 0; \text{Slant}_3 = .
Examples

- “amid last minute push in va clinton holds 6 point lead in latest poll”
- $Slant_i = -1$ for $i = 1, 2, 3$

- “polls trump and clinton virtually tied in key swing states”
- $Slant_1 = Slant_2 = 0; Slant_3 = 0$

- “obama: if clinton wins Florida she will win the election”
Examples

- “amid last minute push in va clinton holds 6 point lead in latest poll”
- $Slant_i = -1$ for $i = 1, 2, 3$

- “polls trump and clinton virtually tied in key swing states”
- $Slant_1 = Slant_2 = 0$; $Slant_3 =$ .

- “obama: if clinton wins Florida she will win the election”
- $Slant_1 = -0.5;$
Examples

- “amid last minute push in va clinton holds 6 point lead in latest poll”
- $Slant_i = -1$ for $i = 1, 2, 3$

- “polls trump and clinton virtually tied in key swing states”
- $Slant_1 = Slant_2 = 0; Slant_3 = \cdot$

- “obama: if clinton wins Florida she will win the election”
- $Slant_1 = -0.5; Slant_2 = Slant_3 = \cdot$
**Figure:** Mean $Slant_i$ and poll average relative to election day in 2012

Note: Positive values of $Slant$ denote better chances of winning for the Republican candidate, whereas negative values indicate better chances for the Democratic candidate.
Figure: Mean $Slant_i$ and poll average relative to election day in 2012

Note: Positive values of $Slant$ denote better chances of winning for the Republican candidate, whereas negative values indicate better chances for the Democratic candidate.
Figure: Mean $Slant_i$ and poll average relative to election day in 2016
Figure: Mean $Slant_i$ and poll average relative to election day in 2016

Note: Positive values of $Slant$ denote better chances of winning for the Republican candidate, whereas negative values indicate better chances for the Democratic candidate.
### 2012 sample sizes

<table>
<thead>
<tr>
<th>Outlet</th>
<th>Type</th>
<th>$Slant_1$</th>
<th>$Slant_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fox</strong></td>
<td>Other</td>
<td>38</td>
<td>23</td>
</tr>
<tr>
<td></td>
<td>Most viewed</td>
<td>25</td>
<td>22</td>
</tr>
<tr>
<td><strong>WSJ</strong></td>
<td>Other</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>Most viewed</td>
<td>7</td>
<td>7</td>
</tr>
<tr>
<td><strong>USAToday</strong></td>
<td>Other</td>
<td>13</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>Most viewed</td>
<td>19</td>
<td>16</td>
</tr>
<tr>
<td><strong>Yahoo</strong></td>
<td>Other</td>
<td>76</td>
<td>31</td>
</tr>
<tr>
<td></td>
<td>Most viewed</td>
<td>30</td>
<td>22</td>
</tr>
<tr>
<td><strong>NYT</strong></td>
<td>Other</td>
<td>59</td>
<td>42</td>
</tr>
<tr>
<td></td>
<td>Most viewed</td>
<td>21</td>
<td>14</td>
</tr>
<tr>
<td><strong>HuffPost</strong></td>
<td>Other</td>
<td>119</td>
<td>76</td>
</tr>
<tr>
<td></td>
<td>Most viewed</td>
<td>12</td>
<td>10</td>
</tr>
<tr>
<td>Outlet</td>
<td>Type</td>
<td>( Slant_1 )</td>
<td>( Slant_3 )</td>
</tr>
<tr>
<td>-----------</td>
<td>------------</td>
<td>---------------</td>
<td>---------------</td>
</tr>
<tr>
<td>Fox</td>
<td>Other</td>
<td>23</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>Most viewed</td>
<td>47</td>
<td>25</td>
</tr>
<tr>
<td>WSJ</td>
<td>Other</td>
<td>12</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>Most viewed</td>
<td>11</td>
<td>9</td>
</tr>
<tr>
<td>Google</td>
<td>Other</td>
<td>270</td>
<td>161</td>
</tr>
<tr>
<td></td>
<td>Most viewed</td>
<td>46</td>
<td>26</td>
</tr>
<tr>
<td>Yahoo</td>
<td>Other</td>
<td>85</td>
<td>39</td>
</tr>
<tr>
<td></td>
<td>Most viewed</td>
<td>8</td>
<td>6</td>
</tr>
<tr>
<td>NYT</td>
<td>Other</td>
<td>33</td>
<td>21</td>
</tr>
<tr>
<td></td>
<td>Most viewed</td>
<td>22</td>
<td>11</td>
</tr>
<tr>
<td>WashPost</td>
<td>Other</td>
<td>96</td>
<td>45</td>
</tr>
<tr>
<td></td>
<td>Most viewed</td>
<td>43</td>
<td>24</td>
</tr>
</tbody>
</table>
Across-outlet Analysis

1. Intensive margin: how much does slant vary across outlets (given ‘true news’ and given outlet reports HR news)?

   Using story-level data set:
   \[ \text{regress } \text{Slant}_i \text{ on outlet } \text{FEs, day } \text{FEs, and poll controls} \]

2. Extensive margin: does ‘true slant’ affect # HR stories reported?

   Using outlet-daily time series:
   \[ \text{regress } \# \text{HR stories on } \text{Slant}_i \text{ of other outlets same day or on current polls that day} \]
Across-outlet Analysis

1. Intensive margin: how much does slant vary across outlets (given ‘true news’ and given outlet reports HR news)?

Using story-level data set:

- regress Slant\(i\) on outlet FEs, day FEs, and poll controls

2. Extensive margin: does ‘true slant’ affect # HR stories reported?

Using outlet-daily time series:

- regress # HR stories on Slant\(i\) of other outlets same day or on current polls that day
Across-outlet Analysis

1. Intensive margin: how much does slant vary across outlets (given ‘true news’ and given outlet reports HR news)?

Using story-level data set:
1. Intensive margin: how much does slant vary across outlets (given ‘true news’ and given outlet reports HR news)?

- Using story-level data set:
  - regress $Slant_i$ on outlet FEs, day FEs, and poll controls
Across-outlet Analysis

1. Intensive margin: how much does slant vary across outlets (given ‘true news’ and given outlet reports HR news)?

   Using story-level data set:

   regress $Slant_i$ on outlet FEs, day FEs, and poll controls

2. Extensive margin: does ‘true slant’ affect # HR stories reported?
Across-outlet Analysis

1. Intensive margin: how much does slant vary across outlets (given ‘true news’ and given outlet reports HR news)?
   - Using story-level data set:
     - regress $Slant_i$ on outlet FEs, day FEs, and poll controls

2. Extensive margin: does ‘true slant’ affect # HR stories reported?
   - Using outlet-daily time series:
Across-outlet Analysis

1. Intensive margin: how much does slant vary across outlets (given ‘true news’ and given outlet reports HR news)?

Using story-level data set:

- regress $Slant_i$ on outlet FE, day FE, and poll controls

2. Extensive margin: does ‘true slant’ affect # HR stories reported?

Using outlet-daily time series:

- regress # HR stories on $Slant_i$ of other outlets same day or
Across-outlet Analysis

1. Intensive margin: how much does slant vary across outlets (given ‘true news’ and given outlet reports HR news)?

Using story-level data set:

- regress $Slant_i$ on outlet FEs, day FEs, and poll controls

2. Extensive margin: does ‘true slant’ affect # HR stories reported?

Using outlet-daily time series:

- regress # HR stories on $Slant_i$ of other outlets same day or on current polls that day
1. 2012 Slant across outlets, intensive margin
1. 2012 Slant across outlets, intensive margin

- LHS = \( Slant_i = S_i \in [-1, 1] \), -1 = pro-D
1. 2012 Slant across outlets, intensive margin

- LHS = \( Slant_i = S_i \in [-1, 1] \), -1 = pro-D
- RHS = outlet FEs (Yahoo omitted), day FEs, poll controls

<table>
<thead>
<tr>
<th></th>
<th>WSJ</th>
<th>USA Today</th>
<th>NYT</th>
<th>Hupost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fox</td>
<td>0.327**</td>
<td>0.440***</td>
<td>0.671***</td>
<td></td>
</tr>
<tr>
<td>(0.134)</td>
<td>(0.132)</td>
<td>(0.189)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>WSJ</td>
<td>-0.392*</td>
<td>-0.276</td>
<td>0.016</td>
<td></td>
</tr>
<tr>
<td>(0.223)</td>
<td>(0.207)</td>
<td>(0.330)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>USA Today</td>
<td>-0.185</td>
<td>-0.067</td>
<td>0.039</td>
<td></td>
</tr>
<tr>
<td>(0.192)</td>
<td>(0.198)</td>
<td>(0.236)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NYT</td>
<td>-0.258*</td>
<td>-0.141</td>
<td>-0.098</td>
<td></td>
</tr>
<tr>
<td>(0.134)</td>
<td>(0.143)</td>
<td>(0.221)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hupost</td>
<td>-0.444***</td>
<td>-0.262**</td>
<td>-0.146</td>
<td></td>
</tr>
<tr>
<td>(0.110)</td>
<td>(0.120)</td>
<td>(0.182)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: OLS estimates, using story-level data. Standard errors are clustered by the first date the story was available. *, **, *** denote 10%, 5%, 1% significance.
1. 2012 Slant across outlets, intensive margin

- LHS = Slant\(_i\) = S\(_i\) \(\in [-1, 1]\), -1 = pro-D
- RHS = outlet FEs (Yahoo omitted), day FEs, poll controls
- Headline-level data set

<table>
<thead>
<tr>
<th></th>
<th>Fox</th>
<th>WSJ</th>
<th>USA Today</th>
<th>NYT</th>
<th>HuffPost</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.327</td>
<td>0.440</td>
<td>0.671***</td>
<td>-0.392*</td>
<td>-0.276</td>
</tr>
<tr>
<td></td>
<td>(0.134)</td>
<td>(0.132)</td>
<td>(0.189)</td>
<td>(0.223)</td>
<td>(0.207)</td>
</tr>
<tr>
<td></td>
<td>-0.392*</td>
<td>-0.276</td>
<td>0.016</td>
<td>-0.185</td>
<td>-0.067</td>
</tr>
<tr>
<td></td>
<td>(0.192)</td>
<td>(0.198)</td>
<td>(0.236)</td>
<td>(0.192)</td>
<td>(0.198)</td>
</tr>
<tr>
<td></td>
<td>-0.258*</td>
<td>-0.141</td>
<td>-0.098</td>
<td>-0.258*</td>
<td>-0.141</td>
</tr>
<tr>
<td></td>
<td>(0.134)</td>
<td>(0.143)</td>
<td>(0.221)</td>
<td>(0.134)</td>
<td>(0.143)</td>
</tr>
<tr>
<td></td>
<td>-0.444***</td>
<td>-0.262**</td>
<td>-0.146</td>
<td>-0.444***</td>
<td>-0.262**</td>
</tr>
<tr>
<td></td>
<td>(0.110)</td>
<td>(0.120)</td>
<td>(0.182)</td>
<td>(0.110)</td>
<td>(0.120)</td>
</tr>
</tbody>
</table>

Note: OLS estimates, using story-level data. Standard errors are clustered by the first date the story was available. *, **, *** denote 10%, 5%, 1% significance.
1. 2012 Slant across outlets, intensive margin

- LHS = Slant\(_i\) = \(S_i \in [-1, 1]\), -1 = pro-D
- RHS = outlet FEs (Yahoo omitted), day FEs, poll controls
- Headline-level data set

<table>
<thead>
<tr>
<th></th>
<th>(S_1)</th>
<th>(S_2)</th>
<th>(S_3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fox</td>
<td>0.327**</td>
<td>0.440***</td>
<td>0.671***</td>
</tr>
<tr>
<td></td>
<td>(0.134)</td>
<td>(0.132)</td>
<td>(0.189)</td>
</tr>
<tr>
<td>WSJ</td>
<td>-0.392*</td>
<td>-0.276</td>
<td>0.016</td>
</tr>
<tr>
<td></td>
<td>(0.223)</td>
<td>(0.207)</td>
<td>(0.330)</td>
</tr>
<tr>
<td>USA Today</td>
<td>-0.185</td>
<td>-0.067</td>
<td>0.039</td>
</tr>
<tr>
<td></td>
<td>(0.192)</td>
<td>(0.198)</td>
<td>(0.236)</td>
</tr>
<tr>
<td>NYT</td>
<td>-0.258*</td>
<td>-0.141</td>
<td>-0.098</td>
</tr>
<tr>
<td></td>
<td>(0.134)</td>
<td>(0.143)</td>
<td>(0.221)</td>
</tr>
<tr>
<td>HuffPost</td>
<td>-0.444***</td>
<td>-0.262**</td>
<td>-0.146</td>
</tr>
<tr>
<td></td>
<td>(0.110)</td>
<td>(0.120)</td>
<td>(0.182)</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.393</td>
<td>0.372</td>
<td>0.472</td>
</tr>
<tr>
<td>N</td>
<td>400</td>
<td>363</td>
<td>267</td>
</tr>
</tbody>
</table>

Note: OLS estimates, using story-level data. Standard errors are clustered by the first date the story was available. *, **, *** denote 10%, 5%, 1% significance.
1. 2016 Slant across outlets

<table>
<thead>
<tr>
<th>Outlet</th>
<th>2016 Slant</th>
<th>2017 Slant</th>
<th>2018 Slant</th>
</tr>
</thead>
<tbody>
<tr>
<td>WSJ</td>
<td>-0.265</td>
<td>-0.379***</td>
<td>0.083</td>
</tr>
<tr>
<td>Google</td>
<td>0.055</td>
<td>0.119</td>
<td>0.431**</td>
</tr>
<tr>
<td>NYT</td>
<td>-0.322**</td>
<td>-0.131</td>
<td>0.048</td>
</tr>
<tr>
<td>WP</td>
<td>-0.109</td>
<td>0.001</td>
<td>0.194</td>
</tr>
<tr>
<td>R²</td>
<td>0.236</td>
<td>0.308</td>
<td>0.405</td>
</tr>
<tr>
<td>N</td>
<td>696</td>
<td>501</td>
<td>381</td>
</tr>
</tbody>
</table>

Note: OLS estimates, using story-level data. Standard errors are clustered by the first date the story was available. *, **, *** denote 10%, 5%, 1% significance.
1. 2016 Slant across outlets

- LHS = $Slant_i = S_i \in [-1, 1]$
1. 2016 Slant across outlets

- LHS = $Slant_i = S_i \in [-1, 1]$
- RHS = outlet FEs (Yahoo omitted), day FEs, poll controls
1. 2016 Slant across outlets

- LHS = $Slant_i = S_i \in [-1, 1]$
- RHS = outlet FEs (Yahoo omitted), day FEs, poll controls

<table>
<thead>
<tr>
<th>Outlet</th>
<th>$S_1$</th>
<th>$S_2$</th>
<th>$S_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fox</td>
<td>0.328*</td>
<td>0.389*</td>
<td>0.712***</td>
</tr>
<tr>
<td></td>
<td>(0.173)</td>
<td>(0.219)</td>
<td>(0.248)</td>
</tr>
<tr>
<td>WSJ</td>
<td>-0.265</td>
<td>-0.379*</td>
<td>0.083</td>
</tr>
<tr>
<td></td>
<td>(0.202)</td>
<td>(0.228)</td>
<td>(0.280)</td>
</tr>
<tr>
<td>Google</td>
<td>0.055</td>
<td>0.119</td>
<td>0.431**</td>
</tr>
<tr>
<td></td>
<td>(0.134)</td>
<td>(0.160)</td>
<td>(0.178)</td>
</tr>
<tr>
<td>NYT</td>
<td>-0.322**</td>
<td>-0.131</td>
<td>0.048</td>
</tr>
<tr>
<td></td>
<td>(0.157)</td>
<td>(0.200)</td>
<td>(0.204)</td>
</tr>
<tr>
<td>WashPost</td>
<td>-0.109</td>
<td>0.001</td>
<td>0.194</td>
</tr>
<tr>
<td></td>
<td>(0.148)</td>
<td>(0.170)</td>
<td>(0.193)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.236</td>
<td>0.308</td>
<td>0.405</td>
</tr>
<tr>
<td>$N$</td>
<td>696</td>
<td>501</td>
<td>381</td>
</tr>
</tbody>
</table>

Note: OLS estimates, using story-level data. Standard errors are clustered by the first date the story was available. *, **, *** denote 10%, 5%, 1% significance.
2. 2012 # HR stories per day by outlet (ext margin)
2. 2012 # HR stories per day by outlet (ext margin)

- Outlet-level daily time series

<table>
<thead>
<tr>
<th>Outlet</th>
<th>Poll avg (Rep - Dem)</th>
<th>(Robust std. errors)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fox</td>
<td>-0.447***</td>
<td>(0.156)</td>
</tr>
<tr>
<td>WSJ</td>
<td>-0.040</td>
<td>(0.083)</td>
</tr>
<tr>
<td>NYT</td>
<td>-0.006</td>
<td>(0.090)</td>
</tr>
<tr>
<td>HotPost</td>
<td>0.186*</td>
<td>(0.103)</td>
</tr>
</tbody>
</table>

Note: Poisson estimates, robust standard errors.
2. 2012 # HR stories per day by outlet (ext margin)

- Outlet-level daily time series
- (Not headline-level b/c need obs with 0 HR stories reported)
2. 2012 # HR stories per day by outlet (ext margin)

- Outlet-level daily time series
- (Not headline-level b/c need obs with 0 HR stories reported)
- LHS = # HR stories

<table>
<thead>
<tr>
<th>Outlet</th>
<th>Fox WSJ NYT Hupost</th>
<th>Poll avg (Rep-Dem)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>0.186 -0.447*** -0.040 -0.006</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.103) (0.156) (0.083) (0.090)</td>
</tr>
</tbody>
</table>

Note: Poisson estimates, robust std errors.
2. 2012 # HR stories per day by outlet (ext margin)

- Outlet-level daily time series
- (Not headline-level b/c need obs with 0 HR stories reported)
- LHS = # HR stories
- RHS = 1) Polls (Rep - Dem) or 2) other outlets’ slant
2. 2012 # HR stories per day by outlet (ext margin)

- Outlet-level daily time series
- (Not headline-level b/c need obs with 0 HR stories reported)
- LHS = # HR stories
- RHS = 1) Polls (Rep - Dem) or 2) other outlets’ slant
- Control for # stories reported by other outlets
2. 2012 # HR stories per day by outlet (ext margin)

- Outlet-level daily time series
- (Not headline-level b/c need obs with 0 HR stories reported)
- LHS = # HR stories
- RHS = 1) Polls (Rep - Dem) or 2) other outlets’ slant
- Control for # stories reported by other outlets

<table>
<thead>
<tr>
<th>Outlet</th>
<th>Fox</th>
<th>WSJ</th>
<th>NYT</th>
<th>HoP</th>
<th>Post</th>
</tr>
</thead>
<tbody>
<tr>
<td>Polls</td>
<td>0.186*</td>
<td>-0.447***</td>
<td>-0.040</td>
<td>-0.006</td>
<td></td>
</tr>
<tr>
<td>(Std. Err.)</td>
<td>(0.103)</td>
<td>(0.156)</td>
<td>(0.083)</td>
<td>(0.090)</td>
<td></td>
</tr>
</tbody>
</table>

Note: Poisson estimates, robust std errors.
2. 2012 # HR stories per day by outlet (ext margin)

- Outlet-level daily time series
- (Not headline-level b/c need obs with 0 HR stories reported)
- LHS = # HR stories
- RHS = 1) Polls (Rep - Dem) or 2) other outlets’ slant
- Control for # stories reported by other outlets

<table>
<thead>
<tr>
<th>Poll avg (Rep - Dem)</th>
<th>Fox</th>
<th>WSJ</th>
<th>NYT</th>
<th>HuffPost</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.186*</td>
<td>-0.447***</td>
<td>-0.040</td>
<td>-0.006</td>
</tr>
<tr>
<td>(0.103)</td>
<td>(0.156)</td>
<td>(0.083)</td>
<td>(0.090)</td>
<td></td>
</tr>
</tbody>
</table>

Note: Poisson estimates, robust std errors.
2. 2016 # HR stories per day by outlet

<table>
<thead>
<tr>
<th>Outlet</th>
<th>Poll Avg (Rep - Dem)</th>
<th>Std Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fox</td>
<td>0.091 (-0.341**)</td>
<td>0.102</td>
</tr>
<tr>
<td>WSJ</td>
<td>-0.128</td>
<td>0.162</td>
</tr>
<tr>
<td>NYT</td>
<td>0.076</td>
<td>0.136</td>
</tr>
</tbody>
</table>

Note: Poisson estimates, robust standard errors.
2. 2016 # HR stories per day by outlet

- Outlet-level daily time series

<table>
<thead>
<tr>
<th>Outlet</th>
<th>Polled Avg (Rep-Dem)</th>
<th>Std Error</th>
<th>Polled Avg (Rep-Dem)</th>
<th>Std Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fox</td>
<td>0.091</td>
<td>0.102</td>
<td>WSJ</td>
<td>-0.341</td>
</tr>
<tr>
<td>NYT</td>
<td>-0.128</td>
<td>0.136</td>
<td>Washington Post</td>
<td>0.076</td>
</tr>
</tbody>
</table>

Note: Poisson estimates, robust standard errors.
2. 2016 # HR stories per day by outlet

- Outlet-level daily time series
- LHS = # HR stories
2. 2016 # HR stories per day by outlet

- Outlet-level daily time series
- LHS = # HR stories
- RHS = 1) Polls (Rep - Dem) or 2) other outlets’ slant

Note: Poisson estimates, robust standard errors.
2. 2016 # HR stories per day by outlet

- Outlet-level daily time series
- LHS = # HR stories
- RHS = 1) Polls (Rep - Dem) or 2) other outlets’ slant
- Control for # stories reported by other outlets

<table>
<thead>
<tr>
<th>Poll avg (Rep - Dem)</th>
<th>Fox</th>
<th>WSJ</th>
<th>NYT</th>
<th>WashPost</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.091</td>
<td>(-0.102)</td>
<td>-0.341*</td>
<td>-0.128</td>
<td>0.076</td>
</tr>
<tr>
<td>(0.136)</td>
<td>(0.162)</td>
<td>(0.090)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Poisson estimates, robust standard errors.
2. 2016 # HR stories per day by outlet

- Outlet-level daily time series
- LHS = # HR stories
- RHS = 1) Polls (Rep - Dem) or 2) other outlets’ slant
- Control for # stories reported by other outlets

<table>
<thead>
<tr>
<th>Poll avg (Rep - Dem)</th>
<th>Fox</th>
<th>WSJ</th>
<th>NYT</th>
<th>WashPost</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.091</td>
<td>-0.341**</td>
<td>-0.128</td>
<td>0.076</td>
</tr>
<tr>
<td></td>
<td>(0.102)</td>
<td>(0.162)</td>
<td>(0.136)</td>
<td>(0.090)</td>
</tr>
</tbody>
</table>

Note: Poisson estimates, robust std errors.
So-
So-

- Fox reporting slanted right of other outlets both years, given day/polls (int. margin)
So-

- Fox reporting slanted right of other outlets both years, given day/polls (int. margin)
- Huff Post left of others; NYT left of others in 2016 only
So-

- Fox reporting slanted right of other outlets both years, given day/polls (int. margin)
- Huff Post left of others; NYT left of others in 2016 only
- Psych or trust
- Fox reporting slanted right of other outlets both years, given day/polls (int. margin)
- Huff Post left of others; NYT left of others in 2016 only
- Psych or trust
- No evidence of decline in slant as election approaches (favors psych)
So-

- Fox reporting slanted right of other outlets both years, given day/polls (int. margin)
- Huff Post left of others; NYT left of others in 2016 only
- Psych or trust
- No evidence of decline in slant as election approaches (favors psych)
- WSJ more likely to report HR news when polls lean left (both yrs) (!) (supply-side bias? instrumental value?)
Within-outlet behavior
Within-outlet behavior

- First check within-outlet slant variation correlation with ‘true news’
Within-outlet behavior

- First check within-outlet slant variation correlation with ‘true news’
- Then within-outlet slant-demand relationship
### 1. 2012 within-outlet slant vs polls

**LHS:** Slant

**RHS:** Poll differences (Rep votes - D votes) = Poll, 1 week change

<table>
<thead>
<tr>
<th>Outlet</th>
<th>Poll Coefficient</th>
<th>Poll Standard Error</th>
<th>Poll Change Coefficient</th>
<th>Poll Change Standard Error</th>
<th>R²</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fox</td>
<td>0.243***</td>
<td>0.068</td>
<td>0.103</td>
<td>0.074</td>
<td>0.251</td>
<td>61</td>
</tr>
<tr>
<td>WSJ</td>
<td>0.101</td>
<td>0.109</td>
<td>0.290*</td>
<td>0.165</td>
<td>0.204</td>
<td>12</td>
</tr>
<tr>
<td>USA</td>
<td>0.177***</td>
<td>0.047</td>
<td>0.172*</td>
<td>0.091</td>
<td>0.154</td>
<td>98</td>
</tr>
<tr>
<td>NYT</td>
<td>0.355**</td>
<td>0.149</td>
<td>0.231*</td>
<td>0.131</td>
<td>0.261</td>
<td>30</td>
</tr>
<tr>
<td>H reboot</td>
<td>-0.039</td>
<td>0.056</td>
<td>0.447***</td>
<td>0.051</td>
<td>0.358</td>
<td>76</td>
</tr>
<tr>
<td>USA Post</td>
<td>0.099***</td>
<td>0.030</td>
<td>0.287***</td>
<td>0.058</td>
<td>0.220</td>
<td>123</td>
</tr>
</tbody>
</table>

Note: OLS estimates, bootstrap standard errors.
1. 2012 within-outlet slant vs polls

- Headline-level data sets, split by outlet

<table>
<thead>
<tr>
<th>Outlet</th>
<th>Poll Coefficient</th>
<th>Poll Change Coefficient</th>
<th>R^2</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fox</td>
<td>0.243***</td>
<td>0.103</td>
<td>0.251</td>
<td>61</td>
</tr>
<tr>
<td>WSJ</td>
<td>0.101</td>
<td>0.290*</td>
<td>0.204</td>
<td>12</td>
</tr>
<tr>
<td>Y USA</td>
<td>0.177***</td>
<td>0.172*</td>
<td>0.154</td>
<td>98</td>
</tr>
<tr>
<td>NYT</td>
<td>0.355**</td>
<td>0.231*</td>
<td>0.261</td>
<td>30</td>
</tr>
<tr>
<td>HP post</td>
<td>-0.039</td>
<td>0.447***</td>
<td>0.358</td>
<td>76</td>
</tr>
<tr>
<td>∆ Poll</td>
<td>0.099***</td>
<td>0.287***</td>
<td>0.220</td>
<td>123</td>
</tr>
</tbody>
</table>

Note: OLS estimates, bootstrap standard errors.
1. 2012 within-outlet slant vs polls

- Headline-level data sets, split by outlet
- LHS = Slant_i

Note: OLS estimates, bootstrap std errors.
1. 2012 within-outlet slant vs polls

- Headline-level data sets, split by outlet
- LHS = \( Slant_i \)
- RHS = Poll diff levels (Rep votes - D votes) = Poll,

\[
\begin{array}{cccccc}
\text{Fox} & \text{WSJ} & \text{NYT} & \text{HuffPost} & \text{Poll} & \text{Poll change} \\
0.243*** & 0.101 & 0.177*** & 0.355** & -0.039 & 0.099*** \\
(0.068) & (0.109) & (0.047) & (0.149) & (0.056) & (0.030) \\
\text{Poll change} & 0.103 & 0.290* & 0.172* & 0.231* & 0.447*** & 0.287*** \\
(0.074) & (0.165) & (0.091) & (0.131) & (0.051) & (0.058) \\
\text{R}^2 & 0.251 & 0.204 & 0.154 & 0.261 & 0.358 & 0.220 \\
N & 61 & 12 & 98 & 30 & 76 & 123 \\
\end{array}
\]

Note: OLS estimates, bootstrap std errors.
1. 2012 within-outlet slant vs polls

- Headline-level data sets, split by outlet
- LHS = $Slant_i$
- RHS = Poll diff levels (Rep votes - D votes) = Poll, 1 week change ($\Delta$ Poll)

<table>
<thead>
<tr>
<th>Outlet</th>
<th>Poll Slope</th>
<th>Poll Intercept</th>
<th>Poll Diff Slope</th>
<th>Poll Diff Intercept</th>
<th>R²</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fox</td>
<td>0.243***</td>
<td>0.101</td>
<td>0.103</td>
<td>0.290*</td>
<td>0.251</td>
<td>61</td>
</tr>
<tr>
<td>WSJ</td>
<td>0.177***</td>
<td>0.099***</td>
<td>0.172*</td>
<td>0.287***</td>
<td>0.204</td>
<td>12</td>
</tr>
<tr>
<td>USA</td>
<td>0.355**</td>
<td>-0.039</td>
<td>0.231*</td>
<td>0.447***</td>
<td>0.154</td>
<td>98</td>
</tr>
<tr>
<td>NYT</td>
<td>-0.039</td>
<td>0.099***</td>
<td>0.231*</td>
<td>0.447***</td>
<td>0.358</td>
<td>30</td>
</tr>
<tr>
<td>HPop</td>
<td>0.099***</td>
<td>-0.039</td>
<td>0.231*</td>
<td>0.447***</td>
<td>0.220</td>
<td>76</td>
</tr>
</tbody>
</table>

Note: OLS estimates, bootstrap standard errors.
1. 2012 within-outlet slant vs polls

- Headline-level data sets, split by outlet
- LHS = $Slant_i$
- RHS = Poll diff levels (Rep votes - D votes) = Poll, 1 week change ($\Delta$ Poll)
- coefficients > 0: poll slant $\rightarrow$ reporting slant (this is ‘good’!)
1. 2012 within-outlet slant vs polls

- Headline-level data sets, split by outlet
- LHS = \textit{Slant}_i
- RHS = Poll diff levels (Rep votes - D votes) = Poll, 1 week change (\(\Delta\) Poll)
- coefficients > 0: poll slant \(\rightarrow\) reporting slant (this is ‘good’!)

<table>
<thead>
<tr>
<th></th>
<th>Fox</th>
<th>WSJ</th>
<th>Y</th>
<th>USA</th>
<th>NYT</th>
<th>HPost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poll</td>
<td>0.243***</td>
<td>0.101</td>
<td>0.177***</td>
<td>0.355**</td>
<td>-0.039</td>
<td>0.099***</td>
</tr>
<tr>
<td></td>
<td>(0.068)</td>
<td>(0.109)</td>
<td>(0.047)</td>
<td>(0.149)</td>
<td>(0.056)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>(\Delta) Poll</td>
<td>0.103</td>
<td>0.290*</td>
<td>0.172*</td>
<td>0.231*</td>
<td>0.447***</td>
<td>0.287***</td>
</tr>
<tr>
<td></td>
<td>(0.074)</td>
<td>(0.165)</td>
<td>(0.091)</td>
<td>(0.131)</td>
<td>(0.051)</td>
<td>(0.058)</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.251</td>
<td>0.204</td>
<td>0.154</td>
<td>0.261</td>
<td>0.358</td>
<td>0.220</td>
</tr>
<tr>
<td>N</td>
<td>61</td>
<td>12</td>
<td>98</td>
<td>30</td>
<td>76</td>
<td>123</td>
</tr>
</tbody>
</table>

Note: OLS estimates, bootstrap std errors.
2. 2016 within-outlet slant vs polls

<table>
<thead>
<tr>
<th>Outlet/Headline Data Sets</th>
<th>LHS: Slant (i)</th>
<th>RHS: Polls - 1 week change ((\Delta \text{Poll}))</th>
<th>Coefficient (b)</th>
<th>Polls (\rightarrow) Slant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fox WSJ YG NYT WP</td>
<td>0.070</td>
<td>0.041</td>
<td>0.220***</td>
<td>0.267***</td>
</tr>
<tr>
<td></td>
<td>(0.070)</td>
<td>(0.093)</td>
<td>(0.053)</td>
<td>(0.032)</td>
</tr>
<tr>
<td></td>
<td>0.180**</td>
<td>-0.029</td>
<td>0.097**</td>
<td>0.038</td>
</tr>
<tr>
<td></td>
<td>(0.085)</td>
<td>(0.180)</td>
<td>(0.047)</td>
<td>(0.035)</td>
</tr>
</tbody>
</table>

- \(R^2\) 0.089 - 0.092 0.211 0.205 0.118 0.100
- N 70 23 93 316 55 139

Note: OLS estimates, bootstrap std errors.
2. 2016 within-outlet slant vs polls

- Outlet-headline data sets
2. 2016 within-outlet slant vs polls

- Outlet-headline data sets
- LHS = \( Slant_i \)

<table>
<thead>
<tr>
<th>Outlet/Headline</th>
<th>Fox</th>
<th>WSJ</th>
<th>YG</th>
<th>NYT</th>
<th>WPi</th>
<th>Post</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poll</td>
<td>0.070</td>
<td>0.041</td>
<td>0.220***</td>
<td>0.267***</td>
<td>0.197***</td>
<td>0.210***</td>
</tr>
<tr>
<td>( \Delta ) Poll</td>
<td>0.180**</td>
<td>-0.029</td>
<td>0.097**</td>
<td>0.038</td>
<td>-0.032</td>
<td>-0.049</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.089</td>
<td>-0.092</td>
<td>0.211</td>
<td>0.205</td>
<td>0.118</td>
<td>0.100</td>
</tr>
<tr>
<td>N</td>
<td>70</td>
<td>23</td>
<td>93</td>
<td>316</td>
<td>55</td>
<td>139</td>
</tr>
</tbody>
</table>

Note: OLS estimates, bootstrap std errors.
2. 2016 within-outlet slant vs polls

- Outlet-headline data sets
- LHS = $Slant_i$
- RHS = Poll diff levels (R-D) = Poll, 1 week change ($\Delta$ Poll)
2. 2016 within-outlet slant vs polls

- Outlet-headline data sets
- LHS = \textit{Slant}_i
- RHS = Poll diff levels (R-D) = Poll, 1 week change (\Delta \text{Poll})
- coefficients > 0: polls $\rightarrow$ slant
2. 2016 within-outlet slant vs polls

- Outlet-headline data sets
- LHS = $Slant_i$
- RHS = Poll diff levels (R-D) = Poll, 1 week change ($\Delta$ Poll)
- coefficients $> 0$: polls $\rightarrow$ slant

<table>
<thead>
<tr>
<th></th>
<th>Fox</th>
<th>WSJ</th>
<th>Y</th>
<th>G</th>
<th>NYT</th>
<th>WPost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poll</td>
<td>0.070</td>
<td>0.041</td>
<td>0.220***</td>
<td>0.267***</td>
<td>0.197***</td>
<td>0.210***</td>
</tr>
<tr>
<td></td>
<td>(0.070)</td>
<td>(0.093)</td>
<td>(0.053)</td>
<td>(0.032)</td>
<td>(0.071)</td>
<td>(0.046)</td>
</tr>
<tr>
<td>$\Delta$ Poll</td>
<td>0.180**</td>
<td>-0.029</td>
<td>0.097**</td>
<td>0.038</td>
<td>-0.032</td>
<td>-0.049</td>
</tr>
<tr>
<td></td>
<td>(0.085)</td>
<td>(0.180)</td>
<td>(0.047)</td>
<td>(0.035)</td>
<td>(0.078)</td>
<td>(0.058)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.089</td>
<td>-0.092</td>
<td>0.211</td>
<td>0.205</td>
<td>0.118</td>
<td>0.100</td>
</tr>
<tr>
<td>N</td>
<td>70</td>
<td>23</td>
<td>93</td>
<td>316</td>
<td>55</td>
<td>139</td>
</tr>
</tbody>
</table>

Note: OLS estimates, bootstrap std errors.
So-

`Slant` in polls levels and/or display slant for all outlets

- Only for: Fox in 2016 (ok), NYT in 2012 (!?)

- $R^2$: highest for NYT in 2012; partisan outlets similar in 2016

- Slant isn't arbitrary (though may be becoming more so)
So-

- ‘Slant’ in poll levels and/or diffs predict slant for all outlets
So-

- ‘Slant’ in poll levels and/or diffs predict slant for all outlets
- Diffs only for: Fox in 2016 (ok),
So-

- ‘Slant’ in poll levels and/or diffs predict slant for all outlets
- Diffs only for: Fox in 2016 (ok), NYT in 2012 (!?)
So-

- ‘Slant’ in poll levels and/or diffs predict slant for all outlets
- Diffs only for: Fox in 2016 (ok), NYT in 2012 (?!)
- $R^2$: highest for NYT in 2012;
So-

- ‘Slant’ in poll levels and/or diffs predict slant for all outlets
- Diffs only for: Fox in 2016 (ok), NYT in 2012 (?!)
- $R^2$: highest for NYT in 2012; partisan outlets similar in 2016
So-

- ‘Slant’ in poll levels and/or diffs predict slant for all outlets
- Diffs only for: Fox in 2016 (ok), NYT in 2012 (?!)
- $R^2$: highest for NYT in 2012; partisan outlets similar in 2016
- Slant isn’t arbitrary (though maybe becoming more so)
2. 2012 within-outlet slant vs demand

<table>
<thead>
<tr>
<th>Story Level</th>
<th>MV (S1)</th>
<th>MV (S3)</th>
<th>Fox ( \times S_i )</th>
<th>WSJ ( \times S_i )</th>
<th>USA Today ( \times S_i )</th>
<th>Yahoo ( \times S_i )</th>
<th>NYT ( \times S_i )</th>
<th>Hupost ( \times S_i )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.170**</td>
<td>0.116</td>
<td>-0.010</td>
<td>0.001</td>
<td>-0.106</td>
<td>-0.088</td>
<td>-0.013</td>
<td>0.026</td>
</tr>
<tr>
<td></td>
<td>(0.083)</td>
<td>(0.135)</td>
<td>(0.202)</td>
<td>(0.186)</td>
<td>(0.088)</td>
<td>(0.111)</td>
<td>(0.072)</td>
<td>(0.087)</td>
</tr>
<tr>
<td>R^2</td>
<td>0.379</td>
<td>0.353</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: OLS estimates, clustered standard errors.
2. 2012 within-outlet slant vs demand

- Story-level data set; LHS = “most viewed” dummy (MV)
2. 2012 within-outlet slant vs demand

- Story-level data set; LHS = “most viewed” dummy (MV)
- RHS = outlet FEs, day FEs, outlet FE-$Slant_i$ interactions
2. 2012 within-outlet slant vs demand

- Story-level data set; LHS = “most viewed” dummy (MV)
- RHS = outlet FEs, day FEs, outlet FE-Slant<i>_i_ interactions

<table>
<thead>
<tr>
<th></th>
<th>MV (S&lt;sub&gt;1&lt;/sub&gt;)</th>
<th>MV (S&lt;sub&gt;3&lt;/sub&gt;)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fox × S&lt;sub&gt;i&lt;/sub&gt;</td>
<td>0.170**</td>
<td>0.116</td>
</tr>
<tr>
<td></td>
<td>(0.083)</td>
<td>(0.135)</td>
</tr>
<tr>
<td>WSJ × S&lt;sub&gt;i&lt;/sub&gt;</td>
<td>-0.010</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.202)</td>
<td>(0.186)</td>
</tr>
<tr>
<td>USA Today × S&lt;sub&gt;i&lt;/sub&gt;</td>
<td>-0.106</td>
<td>-0.088</td>
</tr>
<tr>
<td></td>
<td>(0.088)</td>
<td>(0.111)</td>
</tr>
<tr>
<td>Yahoo × S&lt;sub&gt;i&lt;/sub&gt;</td>
<td>-0.043</td>
<td>-0.027</td>
</tr>
<tr>
<td></td>
<td>(0.043)</td>
<td>(0.064)</td>
</tr>
<tr>
<td>NYT × S&lt;sub&gt;i&lt;/sub&gt;</td>
<td>-0.013</td>
<td>0.026</td>
</tr>
<tr>
<td></td>
<td>(0.072)</td>
<td>(0.087)</td>
</tr>
<tr>
<td>HuffPost × S&lt;sub&gt;i&lt;/sub&gt;</td>
<td>0.010</td>
<td>0.021</td>
</tr>
<tr>
<td></td>
<td>(0.048)</td>
<td>(0.068)</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.379</td>
<td>0.353</td>
</tr>
<tr>
<td>(N)</td>
<td>425</td>
<td>277</td>
</tr>
</tbody>
</table>

Note: OLS estimates, clustered std errors.
1. 2016 within-outlet slant vs demand

<table>
<thead>
<tr>
<th></th>
<th>MV ($S_1$)</th>
<th>MV ($S_3$)</th>
<th>Fox $\times S_i$</th>
<th>WSJ $\times S_i$</th>
<th>Yahoo $\times S_i$</th>
<th>Google $\times S_i$</th>
<th>NYT $\times S_i$</th>
<th>WashPost $\times S_i$</th>
<th>$R^2$</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0.131*</td>
<td>-0.179*</td>
<td>-0.043</td>
<td>0.389</td>
<td>-0.021</td>
<td>0.016</td>
<td>0.193*</td>
<td>-0.043</td>
<td>0.286</td>
<td>381</td>
</tr>
<tr>
<td></td>
<td>(0.069)</td>
<td>(0.094)</td>
<td>(0.244)</td>
<td>(0.293)</td>
<td>(0.087)</td>
<td>(0.029)</td>
<td>(0.111)</td>
<td>(0.056)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: OLS estimates, clustered standard errors.
1. 2016 within-outlet slant vs demand

- Story-level data set; LHS = “most viewed” dummy (MV)
1. 2016 within-outlet slant vs demand

- Story-level data set; LHS = “most viewed” dummy (MV)
- RHS = outlet FEs, day FEs, outlet FE-\(Slant_i\) interactions

Note: OLS estimates, clustered std errors.
1. 2016 within-outlet slant vs demand

- Story-level data set; LHS = “most viewed” dummy (MV)
- RHS = outlet FEs, day FEs, outlet FE-Slant\(_i\) interactions

<table>
<thead>
<tr>
<th></th>
<th>MV (S(_1))</th>
<th>MV (S(_3))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fox (\times S_i)</td>
<td>-0.131*</td>
<td>-0.179*</td>
</tr>
<tr>
<td></td>
<td>(0.069)</td>
<td>(0.094)</td>
</tr>
<tr>
<td>WSJ (\times S_i)</td>
<td>-0.043</td>
<td>0.389</td>
</tr>
<tr>
<td></td>
<td>(0.244)</td>
<td>(0.293)</td>
</tr>
<tr>
<td>Yahoo (\times S_i)</td>
<td>-0.021</td>
<td>0.089</td>
</tr>
<tr>
<td></td>
<td>(0.087)</td>
<td>(0.141)</td>
</tr>
<tr>
<td>Google (\times S_i)</td>
<td>0.016</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.032)</td>
</tr>
<tr>
<td>NYT (\times S_i)</td>
<td>0.193*</td>
<td>0.511</td>
</tr>
<tr>
<td></td>
<td>(0.111)</td>
<td>(0.324)</td>
</tr>
<tr>
<td>WashPost (\times S_i)</td>
<td>-0.043</td>
<td>0.019</td>
</tr>
<tr>
<td></td>
<td>(0.056)</td>
<td>(0.082)</td>
</tr>
<tr>
<td>(R)</td>
<td>0.286</td>
<td>0.371</td>
</tr>
<tr>
<td>(N)</td>
<td>696</td>
<td>381</td>
</tr>
</tbody>
</table>

Note: OLS estimates, clustered std errors.
So-
So-

- More congenial news more popular for Fox in 2012 (ok)
So-

- More congenial news more popular for Fox in 2012 (ok)
- Less popular for Fox in 2016 and for NYT in 2016 (??)
More congenial news more popular for Fox in 2012 (ok)
Less popular for Fox in 2016 and for NYT in 2016 (??)
Maybe less congenial headlines more trusted...
Other issues
Other issues

- Surprise?
Other issues

- Surprise?
- Conditional on current polls, other outlet slants: no
Other issues

- Surprise?
- Conditional on current polls, other outlet slants: no
- But maybe could/should do more here (look at within-outlet changes or closeness)
Other issues
Other issues

- What about total traffic to website? (Could influence Top 10)

**Figure:** Google Trends data (day 0 = election day)

Note: Curves are kernel-weighted smoothed local polynomials with 95% confidence intervals. “NYT” = Google searches for “new york times”; “Fox” = Google searches for “fox...
Micro-data
Micro-data

- Issue w/web data: who’s clicking?
Micro-data

- Issue w/web data: who’s clicking?
- Are ‘uncongenial’ clicks coming from other side?
Micro-data

- Issue w/web data: who’s clicking?
- Are ‘uncongenial’ clicks coming from other side?
- Incentivized MTurk surveys AM after 2016 US presidential debates
Micro-data

- Issue w/web data: who’s clicking?
- Are ‘uncongenial’ clicks coming from other side?
- Incentivized MTurk surveys AM after 2016 US presidential debates
- Related issue w/known timing of stories and varying congeniality
Micro-data

- Issue w/web data: who’s clicking?
- Are ‘uncongenial’ clicks coming from other side?
- Incentivized MTurk surveys AM after 2016 US presidential debates
- Related issue w/known timing of stories and varying congeniality
- NYT and Fox agreed Clinton won first;
Micro-data

- Issue w/web data: who’s clicking?
- Are ‘uncongenial’ clicks coming from other side?
- Incentivized MTurk surveys AM after 2016 US presidential debates
- Related issue w/known timing of stories and varying congeniality
- NYT and Fox agreed Clinton won first;
- Pence (R) won second;
Micro-data

- Issue w/web data: who’s clicking?
- Are ‘uncongenial’ clicks coming from other side?
- Incentivized MTurk surveys AM after 2016 US presidential debates
- Related issue w/known timing of stories and varying congeniality
- NYT and Fox agreed Clinton won first;
- Pence (R) won second;
- mixed verdict on third (Fox: Trump won; NYT: ambiguous)
Micro-data

- Issue w/web data: who’s clicking?
- Are ‘uncongenial’ clicks coming from other side?
- Incentivized MTurk surveys AM after 2016 US presidential debates
- Related issue w/known timing of stories and varying congeniality
- NYT and Fox agreed Clinton won first;
- Pence (R) won second;
- mixed verdict on third (Fox: Trump won; NYT: ambiguous)
- 638 responses across 3 surveys (346 Dem./177 Rep./115 Ind.) (736 dropped 98 incorrect answers)
Survey structure

- Respondents given incentive to read 1 of 4 real and timely articles based on headline:
  - New York Times verdict on debate
  - Fox News verdict on debate
  - Yahoo News on non-debate political topic
  - Yahoo News on non-political topic
- Told they'd get extra payment if knowledge question answered correctly
- And questions for each article same difficulty
- So people uninterested in politics endogenously opt-out of political topics
- And people interested in politics are not already informed
Survey structure

- Respondents given incentive to read 1 of 4 real and timely (~10AM) articles based on headline:
  - New York Times verdict on debate
  - Fox News verdict on debate
  - Yahoo News on non-debate political topic
  - Yahoo News on non-political topic
Survey structure

- Respondents given incentive to read 1 of 4 real and timely (~10AM) articles based on headline:
  - New York Times verdict on debate
  - Fox News verdict on debate
  - Yahoo News on non-debate political topic
  - Yahoo News on non-political topic

- Told they’d get extra payment if knowledge question answered correctly
Survey structure

- Respondents given incentive to read 1 of 4 real and timely (~10AM) articles based on headline:
  - New York Times verdict on debate
  - Fox News verdict on debate
  - Yahoo News on non-debate political topic
  - Yahoo News on non-political topic
- Told they’d get extra payment if knowledge question answered correctly
- And questions for each article same difficulty
Survey structure

- Respondents given incentive to read 1 of 4 real and timely (~10AM) articles based on headline:
  - New York Times verdict on debate
  - Fox News verdict on debate
  - Yahoo News on non-debate political topic
  - Yahoo News on non-political topic

- Told they’d get extra payment if knowledge question answered correctly

- And questions for each article same difficulty

- So people uninterested in politics endogenously opt-out of political topics
Survey structure

- Respondents given incentive to read 1 of 4 real and timely (~10AM) articles based on headline:
  - New York Times verdict on debate
  - Fox News verdict on debate
  - Yahoo News on non-debate political topic
  - Yahoo News on non-political topic

- Told they’d get extra payment if knowledge question answered correctly

- And questions for each article same difficulty

- So people uninterested in politics endogenously opt-out of political topics

- And people interested in politics are not already informed
Instrumental value?
Instrumental value?

- Debate news does plausibly contain info on quality of candidate
Instrumental value?

- Debate news does plausibly contain info on quality of candidate.
- So could have instrumental value (make you change who you support).
Instrumental value?

- Debate news does plausibly contain info on quality of candidate
- So could have instrumental value (make you change who you support)
- But more likely for *uncongenial* news
Figure: News choices of Dems by debate (blue=NYT, red=Fox, gray=other)
Surveys: Results

Figure: News choices of Dems and Independents by debate (blue=NYT, red=Fox, gray=other)
Surveys: Results

Figure: News choices by debate

![Bar chart showing news choices by debate for Democrats, Independents, and Republicans. The chart compares different news sources: NYT, Other News, and Fox, across three debates with various congeniality levels.](chart.png)
Surveys: Regressions

- Regress choice of NYT (Fox) (NYT or Fox) on:
  - Survey, party (D, R, I/other), survey-party FEs (+ other covars)
  - I/other group provides relatively clean control
- If D (R) more likely to click NYT (Fox) when more congenial:
  - Psychological
- If D (R) more likely to click Fox (NYT) when more congenial:
  - Psychological or trust
- If D (R) more likely to click NYT or Fox when uncongenial:
  - Instrumental (may be trust)
Surveys: Regressions

- Regress choice of NYT (Fox) (NYT or Fox) on:
  - Survey, party (D, R, I/other), survey-party FE (+ other covars)
  - I/other group provides relatively clean control
  - If D (R) more likely to click NYT (Fox) when more congenial:
    - psych
  - If D (R) more likely to click Fox (NYT) when more congenial:
    - psych or trust
  - If D (R) more likely to click NYT or Fox when uncongenial:
    - instrumental (may be trust)
Surveys: Regressions

- Regress choice of NYT (Fox) (NYT or Fox) on:
  - Survey, party (D, R, I/other), survey-party FEs (+ other covars)
Surveys: Regressions

- Regress choice of NYT (Fox) (NYT or Fox) on:
- Survey, party (D, R, I/other), survey-party FEs (+ other covars)
- I/other group provides relatively clean control
Surveys: Regressions

- Regress choice of NYT (Fox) (NYT or Fox) on:
- Survey, party (D, R, I/other), survey-party FEs (+ other covars)
- I/other group provides relatively clean control
- If D (R) more likely to click NYT (Fox) when more congenial: psych
Surveys: Regressions

- Regress choice of NYT (Fox) (NYT or Fox) on:

- Survey, party (D, R, I/other), survey-party FEs (+ other covars)

- I/other group provides relatively clean control

- If D (R) more likely to click NYT (Fox) when more congenial: **psych**

- If D (R) more likely to click Fox (NYT) when more congenial: **psych or trust**
Surveys: Regressions

- Regress choice of NYT (Fox) (NYT or Fox) on:
  - Survey, party (D, R, I/other), survey-party FEs (+ other covars)
  - I/other group provides relatively clean control
- If D (R) more likely to click NYT (Fox) when more congenial: **psych**
- If D (R) more likely to click Fox (NYT) when more congenial: **psych** or **trust**
- If D (R) more likely to click NYT or Fox when uncongenial: **instrumental** (maybe **trust**)
## Survey experiment: Regressions

**Table:** LHS = dummy for choose NYT, Fox, or either

<table>
<thead>
<tr>
<th></th>
<th>NYT</th>
<th>Fox</th>
<th>NYT + Fox</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Debate 2 × Clinton supporter (uncong.)</strong></td>
<td>0.040</td>
<td>-0.275***</td>
<td>-0.235**</td>
</tr>
<tr>
<td></td>
<td>(0.094)</td>
<td>(0.075)</td>
<td>(0.106)</td>
</tr>
<tr>
<td><strong>Debate 3 × Clinton supporter (ambig.)</strong></td>
<td>0.139</td>
<td>-0.276***</td>
<td>-0.137</td>
</tr>
<tr>
<td></td>
<td>(0.097)</td>
<td>(0.095)</td>
<td>(0.117)</td>
</tr>
<tr>
<td><strong>Debate 2 × Trump supporter (cong.)</strong></td>
<td>0.056</td>
<td>0.194*</td>
<td>0.250**</td>
</tr>
<tr>
<td></td>
<td>(0.101)</td>
<td>(0.103)</td>
<td>(0.122)</td>
</tr>
<tr>
<td><strong>Debate 3 × Trump supporter (cong.)</strong></td>
<td>-0.052</td>
<td>0.181</td>
<td>0.129</td>
</tr>
<tr>
<td></td>
<td>(0.099)</td>
<td>(0.117)</td>
<td>(0.132)</td>
</tr>
<tr>
<td><strong>Adj. $R^2$</strong></td>
<td>0.080</td>
<td>0.121</td>
<td>0.090</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>637</td>
<td>637</td>
<td>637</td>
</tr>
</tbody>
</table>

Note: All models are estimated using OLS with robust standard errors and include survey, education, gender, age, and party identity (Democrat, lean Democrat, Republican, lean Republican, independent) fixed effects. The reference category is debate 1, which resulted in congenial news for Democrats/Clinton supporters and uncongenial news for Republicans/Trump supporters. *, **, *** denote 10%, 5%, 1% significance.
Some congeniality effects...
Some congeniality effects...

- Congeniality increases D demand for Fox news (psych or trust)
Some congeniality effects...

- Congeniality increases D demand for Fox news (psych or trust)
- Congeniality doesn’t affect D demand for NYT news
Some congeniality effects...

- Congeniality increases D demand for Fox news (psych or trust)
- Congeniality doesn’t affect D demand for NYT news
- Congeniality weakly increases R demand for Fox news (psych)
Some congeniality effects...

- Congeniality increases D demand for Fox news (psych or trust)
- Congeniality doesn’t affect D demand for NYT news
- Congeniality weakly increases R demand for Fox news (psych)
- Congeniality doesn’t affect R demand for NYT news
Some congeniality effects...

- Congeniality increases D demand for Fox news (psych or trust)
- Congeniality doesn’t affect D demand for NYT news
- Congeniality weakly increases R demand for Fox news (psych)
- Congeniality doesn’t affect R demand for NYT news
- Consistent w negative congeniality-demand effects for Fox 2016 driven by Ds (but still implausible?)
Some congeniality effects...

- Congeniality increases D demand for Fox news (psych or trust)
- Congeniality doesn’t affect D demand for NYT news
- Congeniality weakly increases R demand for Fox news (psych)
- Congeniality doesn’t affect R demand for NYT news
- Consistent w negative congeniality-demand effects for Fox 2016 driven by Ds (but still implausible?)
- Not consistent w negative congeniality-demand effects for NYT 2016 driven by Rs
Some congeniality effects...

- Congeniality increases D demand for Fox news (psych or trust)
- Congeniality doesn’t affect D demand for NYT news
- Congeniality weakly increases R demand for Fox news (psych)
- Congeniality doesn’t affect R demand for NYT news
- Consistent w negative congeniality-demand effects for Fox 2016 driven by Ds (but still implausible?)
- Not consistent w negative congeniality-demand effects for NYT 2016 driven by Rs

- Regardless: many on both sides willing to get uncongenial news from trusted source (consistent with weak within-outlet HR effects)
Some congeniality effects...

- Congeniality increases D demand for Fox news (psych or trust)
- Congeniality doesn’t affect D demand for NYT news
- Congeniality weakly increases R demand for Fox news (psych)
- Congeniality doesn’t affect R demand for NYT news
- Consistent w negative congeniality-demand effects for Fox 2016 driven by Ds (but still implausible?)
- Not consistent w negative congeniality-demand effects for NYT 2016 driven by Rs

- Regardless: many on both sides willing to get uncongenial news from trusted source (consistent with weak within-outlet HR effects)
- And no evidence of increased interest in uncongenial news (consistent with HR results in general)
(What about debate article slant across/within outlets?)

**Table:** # links on presidential debates the morning following each debate

<table>
<thead>
<tr>
<th>Debate</th>
<th>#1</th>
<th>#2 (VP)</th>
<th>#3</th>
<th>#4</th>
<th>#1</th>
<th>#2 (VP)</th>
<th>#3</th>
<th>#4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fox</td>
<td>12</td>
<td>7</td>
<td>12</td>
<td>13</td>
<td>24</td>
<td>25</td>
<td>31</td>
<td>17</td>
</tr>
<tr>
<td>NYT</td>
<td>20</td>
<td>19</td>
<td>21</td>
<td>19</td>
<td>23</td>
<td>14</td>
<td>23</td>
<td>25</td>
</tr>
</tbody>
</table>

Note: The counts are based on web.archive.org snapshots of nytimes.com and foxnews.com at approximately 10:00 AM the morning following each debate.
Wrapping up
Wrapping up

- News is skewed congenially for several outlet-yrs, across topics, even for relatively objective topic like HR
Wrapping up

- News is skewed congenially for several outlet-yrs, across topics, even for relatively objective topic like HR
- But within-outlets, congeniality varies over time and is correlated w ‘reality’...
Wrapping up

- News is skewed congenially for several outlet-yrs, across topics, even for relatively objective topic like HR
- But within-outlets, congeniality varies over time and is correlated with ‘reality’...
  and more congenial news is usually not more popular, sometimes less
Wrapping up

- News is skewed congenially for several outlet-yrs, across topics, even for relatively objective topic like HR
- But within-outlets, congeniality varies over time and is correlated with ‘reality’...
  and more congenial news is usually not more popular, sometimes less
- Evidence of psychology and trust forces (psych stronger for Rs, 2012 top 10 and survey results)
Wrapping up

- News is skewed congenially for several outlet-yrs, across topics, even for relatively objective topic like HR
- But within-outlets, congeniality varies over time and is correlated with ‘reality’…
  and more congenial news is usually not more popular, sometimes less
- Evidence of psychology and trust forces (psych stronger for Rs, 2012 top 10 and survey results)
- Limited evidence of instrumental info-driven demand for slant (except maybe WSJ)
Wrapping up

- News is skewed congenially for several outlet-yrs, across topics, even for relatively objective topic like HR

- But within-outlets, congeniality varies over time and is correlated with ‘reality’… and more congenial news is usually not more popular, sometimes less

- Evidence of psychology and trust forces (psych stronger for Rs, 2012 top 10 and survey results)

- Limited evidence of instrumental info-driven demand for slant (except maybe WSJ)

- Interpretation: Consumers like congenial news but must be grounded in reality
Wrapping up

- News is skewed congenially for several outlet-yrs, across topics, even for relatively objective topic like HR
- But within-outlets, congeniality varies over time and is correlated w ‘reality’...
  and more congenial news is usually not more popular, sometimes less
- Evidence of psychology and trust forces (psych stronger for Rs, 2012 top 10 and survey results)
- Limited evidence of instrumental info-driven demand for slant (except maybe WSJ)
- Interpretation: Consumers like congenial news but must be grounded in reality
- Suggests psych-trust feedback loop:
Wrapping up

- News is skewed congenially for several outlet-yrs, across topics, even for relatively objective topic like HR
- But within-outlets, congeniality varies over time and is correlated with ‘reality’...
  and more congenial news is usually not more popular, sometimes less
- Evidence of psychology and trust forces (psych stronger for Rs, 2012 top 10 and survey results)
- Limited evidence of instrumental info-driven demand for slant (except maybe WSJ)
- Interpretation: Consumers like congenial news but must be grounded in reality
- Suggests psych-trust feedback loop:
- Psych value requires trust; trust depends on psych...
Wrapping up

- News is skewed congenially for several outlet-yrs, across topics, even for relatively objective topic like HR
- But within-outlets, congeniality varies over time and is correlated with ‘reality’...
  and more congenial news is usually not more popular, sometimes less
- Evidence of psychology and trust forces (psych stronger for Rs, 2012 top 10 and survey results)
- Limited evidence of instrumental info-driven demand for slant (except maybe WSJ)
- Interpretation: Consumers like congenial news but must be grounded in reality
- Suggests psych-trust feedback loop:
  - Psych value requires trust; trust depends on psych...
- And trust importance may help explain affective polarization...
Other concluding remarks

Context matters more than you’d think (as always?):
NYT and Fox both very different in 2012 vs 2016 for same topic
So repeated nature of HR news likely matters...
(results likely different for other topics)
Dislants on factual issue (HR) implies objective bias
Could cause distrust of validity of election results
Whether due to psycho or trust - results support need for policies/something to mitigate exposure to biased partisan news...
That’s all - thanks!
Other concluding remarks

- Context matters more than you’d think (as always?):
Other concluding remarks

- Context matters more than you’d think (as always?):
- NYT and Fox both very different in 2012 vs 2016 for same topic
Other concluding remarks

- Context matters more than you’d think (as always?):
- NYT and Fox both very different in 2012 vs 2016 for same topic
- So repeated nature of HR news likely matters...
Other concluding remarks

- Context matters more than you’d think (as always?):
- NYT and Fox both very different in 2012 vs 2016 for same topic
- So repeated nature of HR news likely matters...
- (results likely different for other topics)
Other concluding remarks

- Context matters more than you’d think (as always?):
- NYT and Fox both very different in 2012 vs 2016 for same topic
- So repeated nature of HR news likely matters...
- (results likely different for other topics)

- Diff slants on factual issue (HR) implies objective bias
Other concluding remarks

- Context matters more than you’d think (as always?):
- NYT and Fox both very different in 2012 vs 2016 for same topic
- So repeated nature of HR news likely matters...
- (results likely different for other topics)

- Diff slants on factual issue (HR) implies objective bias
- Could cause distrust of validity of election results
Other concluding remarks

- Context matters more than you’d think (as always?):
- NYT and Fox both very different in 2012 vs 2016 for same topic
- So repeated nature of HR news likely matters…
- (results likely different for other topics)
- Diff slants on factual issue (HR) implies objective bias
- Could cause distrust of validity of election results
- Whether due to psych or trust - results support need for policies/something to mitigate exposure to biased partisan news…
Other concluding remarks

- Context matters more than you’d think (as always?):
- NYT and Fox both very different in 2012 vs 2016 for same topic
- So repeated nature of HR news likely matters...
- (results likely different for other topics)

- Diff slants on factual issue (HR) implies objective bias
- Could cause distrust of validity of election results
- Whether due to psych or trust - results support need for policies/something to mitigate exposure to biased partisan news...

- That’s all - thanks!