Better the Devil You Know: 
An Online Field Experiment on News Consumption

Donghee Jo (Northeastern)

Viral Deception, Polarization and Networks Workshop
Nov 3, 2018
“We become so secure in our bubbles [...] (this is a) threat to our democracy.”

President Obama, in his farewell address, January 10, 2017
Political polarization: caused by selective exposure?

- A popularized, yet not empirically tested, idea:
  - Public’s self-selected exposure to like-minded media → polarization
  - Echo chambers, filter bubbles (Sunstein 2001; Pariser 2011)
Research questions

- What is the effect of deliberate media selection on polarization?
- What are the mechanisms?
This paper: online field experiment

- Mobile news curation app: South Korea (2016)
This paper: online field experiment

- Mobile news curation app: South Korea (2016)
- RCT: “Selection Group” vs. “Random Provision Group”
Focus: issue-level opinion polarization

- User-reported position on each policy issue
  - Does it become more moderate or extreme when selection is allowed?
Focus: issue-level opinion polarization

- User-reported position on each policy issue
  - Does it become more moderate or extreme when selection is allowed?
- Potentially correlated with other measures of polarization
  - Partisan alignment, affective polarization (Gentzkow 2016)
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Main takeaway: media selection $\Rightarrow$ less extremism
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• Theory: simple Bayesian model (selection $\rightarrow$ more learning)
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• Empirical building blocks
  • People update their policy views in a Bayesian manner
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• Empirical building blocks
  • People update their policy views in a Bayesian manner
  • People select their like-minded news sources
• Theory: simple Bayesian model (selection $\rightarrow$ more learning)
• Empirical building blocks
  • People update their policy views in a Bayesian manner
  • People select their like-minded news sources
• Main results (from comparison between groups)
  • Selection Group changes positions more (more “learning”);
  • Moves toward moderation
Related literature

• Role of media in political system
  • Media’s voter persuasion
  • Accountability

• Evidence on polarization and selective exposure
  • Polarization
    Abramowitz Saunders (2008), Gentzkow (2016)
  • Selective exposure
    Iyengar Hahn (2009), Gentzkow Shapiro (2011)

• Link between them
  Boxell, Gentzkow, Shapiro (2017)

• Theory on selective exposure
  • This paper: application of
    Sethi Yildiz (2016) on polarization
  • Importance of messenger
    Acemoglu et al. (2016)
  • Rational selective exposure

• Consequences of polarization
  Iyengar Westwood (2015)
Overview of talk

(I) Theory: a Bayesian model

(II) Design of online field experiment

(III) Results
   1. Position updating patterns
   2. Selection patterns
   3. Evolution of positions: comparison between groups
   4. Mechanism

(V) Conclusion
Overview of talk

(I) **Theory: a Bayesian model**

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Primitives

Agent's objective: learning about unknown true state of the world \( \theta^* \) as accurately as possible

So that she can take utility maximizing position: \( \theta^* + b \)

How: by selecting a news source and getting a signal from it

Signal has some info about true state of the world + "media bias"

\[ s_{pij} = \theta^* j + I * p_j + \epsilon_{pij} \]

Media bias: also unknown

Two news sources: F (familiar) and A (alien)

Agent has more precise idea about media bias of familiar news source
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Model’s predictions

- Position updating patterns

Math

P1: Posterior mean is affected by both prior mean and signal
P2: Affected less by signal when prior confidence is higher
P3: Affected more by signal when familiarity is higher

P4: The familiar news source is selected

Main prediction: comparison between two types of agents; selection vs. random provision

P5: If agents’ bias assessments are approximately correct, positions of “Selection Group” change more, converge more to bliss points. Furthermore, if the bliss points $\theta_i^* + b_{ij}$ are not too extreme, the positions of Selection Group gets more moderated.
Model’s predictions

- Position updating patterns
  - **P1**: *Posterior mean is affected by both prior mean and signal*
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• Position updating patterns
  
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  P2: *Affected less by signal when prior confidence is higher*
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- South Korea
  - Presidential system, two major parties
  - Level of polarization: slightly more severe than US \(^{(Source: \, CSES; \, Lupu, \, 2015)}\)
  - Level of selective exposure: similar to US
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• Spoon: iOS news curation app
  • Conducted RCT, collected data
  • Articles from wide range of media
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- Spoon: iOS news curation app
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- Sample
  - Recruit: Facebook ads
  - Age: 31, 85% consume mobile news
Experimental Design

Installation & Baseline Survey
Experimental Design

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Grace Period (1,420 users)
Five days of trial period. Random issue/article every day.
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Random Assignment to Groups (352 users)
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Issue of the day for the user is randomly selected
Selection of news source
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Selection Group
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User reads article, reports updated policy view, and evaluates article.
기 험든 정도의 세기로, 안전을 위해 시위대와의 거리에 따라 물대포 세기를 규정한 경찰 내규에도 이곳나는 것이다.

구은수 서울지방경찰청장은 경찰의 과잉진압 논란이 계속되자 이날 오전 기자간담회를 열어 백씨가 물대포에 맞아 부상을 입게 된 경위에 대한 자체 조사 내용을 공개했다. 진정무 청문
감사담당관은 이 자리에서 ‘시위대들이 빗가 5개로 경찰버스를 뒤에 집어당겨 살수를 했고
오오후 7시11분경 시위대들이 제차 집어당기리해 재살수를 했는데 백씨가 (직사한)살수에 맞아 1m 정도 뒤로 넘어갔다’고 설명했다. 당시
살수차와 백씨의 거리는 20m 정도로, 직사살수 시 2500~2800rpm의 물세기를 유지했다는 게 경찰 측 설명이다.

이는 ‘시위대가 20m 거리에 있는 경우
2000rpm 내외로 살수하도록 한 경찰 내규
‘사수한 물요기차’와 이건 어느 것이 다’라는게

Name of the source: known to all
기 험든 정도의 세기로, 안전을 위해 시위대와 약거에 따라 물대포 세기를 규정한 경찰 내
규에도 어긋나는 것이다.

구은수 서울지방경찰청장은 경찰과 가정전압
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'상하의 묶음기'가 아닌 느껴지는 것이다. 

Policy View

위 생각은 얼마나 확고한가요?

Confidence
기 향든 정도의 세균으로, 안전을 위해 시위대와의 거리에 따라 물대포 세균을 규정한 경찰 내규에도 이곳나는 것이다.

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이는 '시위대가 20m 거리에 있는 경우 2000rpm 내외'로 살수하도록 한 경찰 내규 '삼선·오요기적'과 아울러 어느 것이다. "

Policy View

생각 정리하기

위 생각은 얼마나 합당한가요?

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기 험든 정도의 세기로, 안전을 위해 시위대와의 거리에 따라 물대포 세기를 규정한 경찰 내규에도 어긋나는 것이다.

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이는 '시위대가 20m 거리에 있는 경우 2000rpm 내외'로 살수하도록 한 경찰 내규에 '사수히 옮기지'가 아닌 느껴지는 취지다.
Article position: crowd-sourced
Motivation to report truthfully
Overview of talk

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Experimental Design

Installation & Baseline Survey

Grace Period (1,420 users)
Five days of trial period. Random issue/article every day.

Random Assignment to Groups (352 users)

Daily Iterations
Issue of the day for the user is randomly selected

Selection of news source

<table>
<thead>
<tr>
<th>Selection Group</th>
<th>Random Provision Group</th>
</tr>
</thead>
<tbody>
<tr>
<td>Select the news source</td>
<td>Randomly selected article shown</td>
</tr>
</tbody>
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User reads article, reports updated policy view, and evaluates article.
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Selection of news source

Selection Group

Select the news source

User reads article, reports updated policy view, and evaluates article.
Position updating: consistent with Bayesian updating

P1: Posterior mean is affected by both prior mean and signal

P2: Affected less by signal when prior confidence is higher
### Posterior: affected by both prior and signal

<table>
<thead>
<tr>
<th>Subsample:</th>
<th>Given randomly selected articles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Position (pre)</td>
<td>Position (post)</td>
</tr>
<tr>
<td></td>
<td>0.660***</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
</tr>
<tr>
<td>Article position</td>
<td>0.076***</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
</tr>
</tbody>
</table>

**# of users**: 1417  
**Observations (user×issue×round)**: 7781  

Note: Prior confidence (column 2) and constant are on RHS. Round, article pool FE, and user controls are also added. Article pool FE is interacted with confidence in prior in column 2. Standard errors are clustered by user. *** p<0.01, ** p<0.05, * p<0.1
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<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td><strong>Position (pre)</strong></td>
<td>0.660*** (0.014)</td>
</tr>
<tr>
<td>Position (pre) × Confidence in prior</td>
<td>0.451*** (0.053)</td>
</tr>
<tr>
<td>Article position</td>
<td>0.076*** (0.010)</td>
</tr>
<tr>
<td>Article position × Confidence in prior</td>
<td>-0.153*** (0.054)</td>
</tr>
<tr>
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<td>Observations (user×issue×round)</td>
<td>7781</td>
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Selection Group
Select the news source

Random Provision Group
Randomly selected article shown

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Selection patterns

- Like-minded partisan media are likely to be selected

- P4: The familiar news source is selected

- Level of selective exposure: similar to level in US (Gentzkow Shapiro 2011)

- Isolation index: 0.076 - 0.143
Selection patterns

• Like-minded partisan media are likely to be selected
Selection patterns

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- *P4: The familiar news source is selected*
Selection patterns

- Like-minded partisan media are likely to be selected
- *P4: The familiar news source is selected*
- Level of selective exposure: similar to level in US *(Gentzkow Shapiro 2011)*
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1. Position updating patterns
2. Selection patterns
3. Evolution of positions: comparison between groups
4. Mechanism

(V) Conclusion
Experimental Design

- **Installation & Baseline Survey**

- **Grace Period (1,420 users)**
  Five days of trial period. Random issue/article every day.

- **Random Assignment to Groups (352 users)**

**Daily Iterations**

- Issue of the day for the user is randomly selected

- **Selection of news source**

**Selection Group**
Select the news source

**Random Provision Group**
Randomly selected article shown

User reads article, reports updated policy view, and evaluates article.
Prediction: selection $\Rightarrow$ more learning

**P5:** Positions of “Selection Group” change more, conv. more to bliss point
Media selection $\Rightarrow$ more movement (0.13 sd)

Note: # of users = 336, Observations = 1790. User controls, issue and round FE added. Standard errors are clustered by user. Vertical line indicates 95% confidence interval.
Media selection ⇒ more movement (regression)

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Position_post - Position_pre</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Selection Group</strong></td>
<td>0.023**</td>
<td>0.022**</td>
<td>0.022**</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.010)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.14***</td>
<td>0.19***</td>
<td>0.14***</td>
</tr>
<tr>
<td>(Omitted: Random Provision Group)</td>
<td>(0.005)</td>
<td>(0.019)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>User Controls</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Issue FE</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td># of users</td>
<td>336</td>
<td>336</td>
<td>336</td>
</tr>
<tr>
<td>Observations (user×issue)</td>
<td>1,790</td>
<td>1,790</td>
<td>1,790</td>
</tr>
</tbody>
</table>
Learning: not driven by single issue
Media selection $\Rightarrow$ less extremism

Note: # of users = 336, Observations = 1790. User controls, issue and round FE added. Initial level of extreme views is added as control. Standard errors are clustered by user. Vertical line indicates 95% confidence interval.
**Media selection ⇒ less extremism (regression)**

<table>
<thead>
<tr>
<th>Model:</th>
<th>Basic</th>
<th>First Difference (FD)</th>
<th>Lagged Dependent Variable (LDV)</th>
<th>Baseline balance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td></td>
<td>(4)</td>
</tr>
<tr>
<td>Extreme_{post}</td>
<td>Extreme_{post}^{pre}</td>
<td>Extreme_{post}</td>
<td>Extreme_{pre}</td>
<td></td>
</tr>
<tr>
<td>Sample Mean</td>
<td>0.28</td>
<td>-0.084</td>
<td>0.28</td>
<td>0.37</td>
</tr>
<tr>
<td><strong>Selection Group</strong></td>
<td>-0.066*</td>
<td>-0.074**</td>
<td>-0.069**</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.035)</td>
<td>(0.029)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>Extreme_{pre}</td>
<td></td>
<td></td>
<td>0.37***</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.38***</td>
<td>0.008</td>
<td>0.24***</td>
<td>0.37***</td>
</tr>
<tr>
<td>(Omitted: Random Provision Group)</td>
<td>(0.058)</td>
<td>(0.059)</td>
<td>(0.050)</td>
<td>(0.066)</td>
</tr>
<tr>
<td>User controls, Issue FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td># of users</td>
<td>336</td>
<td>336</td>
<td>336</td>
<td>336</td>
</tr>
<tr>
<td>Observations (user×issue)</td>
<td>1,790</td>
<td>1,790</td>
<td>1,790</td>
<td>1,790</td>
</tr>
</tbody>
</table>
Media selection $\Rightarrow$ less extremism (robust)

Proportion of extreme views

- excl: issue 1
- excl: issue 2
- excl: issue 3
- excl: issue 4
- excl: issue 5
- excl: issue 6
- excl: issue 7
- excl: issue 8
Overview of talk

(I) Theory: a Bayesian model
(II) Design of online field experiment
(III) Results
   1. Position updating patterns
   2. Selection patterns
   3. Evolution of positions: comparison between groups
   4. Mechanism

(V) Conclusion
Experimental Design

Installation & Baseline Survey

Grace Period (1,420 users)
Five days of trial period. Random issue/article every day.

Random Assignment to Groups (352 users)

Daily Iterations
Issue of the day for the user is randomly selected

Selection of news source

Selection Group
Select the news source

Random Provision Group
Randomly selected article shown

User reads article, reports updated policy view, and evaluates article.
Experimental Design

Installation & Baseline Survey

↓

Grace Period (1,420 users)

**Grace Period (1,420 users)**

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↓

Daily Iterations

Issue of the day for the user is randomly selected

↓

Selection of news source

Selection Group

Select the news source

↓

Random Provision Group

Randomly selected article shown

User reads article, reports updated policy view, and evaluates article.
### Results

<table>
<thead>
<tr>
<th>Subsample:</th>
<th>Given randomly selected articles</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td><strong>Position (post)</strong></td>
<td>0.660***</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
</tr>
<tr>
<td><strong>Position (pre) × Ideology dist. to source</strong></td>
<td>-0.029</td>
</tr>
<tr>
<td></td>
<td>(0.092)</td>
</tr>
<tr>
<td><strong>Article position</strong></td>
<td>0.076***</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
</tr>
<tr>
<td><strong>Article position × Ideology dist. to source</strong></td>
<td>-0.487***</td>
</tr>
<tr>
<td></td>
<td>(0.087)</td>
</tr>
<tr>
<td><strong># of users</strong></td>
<td>1417</td>
</tr>
<tr>
<td><strong>Observations (user × issue × round)</strong></td>
<td>7781</td>
</tr>
</tbody>
</table>

Note: Ideology dist. to source (column 2) and constant are on RHS. Round, article pool FE, and user controls are also added. Article pool FE is interacted with “ideology distance” in column 2. Standard errors are clustered by user. *** p<0.01, ** p<0.05, * p<0.1
Like-minded media → Signals taken more seriously

<table>
<thead>
<tr>
<th>Subsample:</th>
<th>Given randomly selected articles</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Position (pre)</td>
<td>0.660***</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
</tr>
<tr>
<td>Position (pre) × Ideology dist. to source</td>
<td>-0.029</td>
</tr>
<tr>
<td>Article position</td>
<td>0.076***</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
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<tr>
<td>Article position × Ideology dist. to source</td>
<td>-0.487***</td>
</tr>
<tr>
<td># of users</td>
<td>1417</td>
</tr>
<tr>
<td>Observations (user×issue×round)</td>
<td>7781</td>
</tr>
</tbody>
</table>

Note: Ideology dist. to source (column 2) and constant are on RHS. Round, article pool FE, and user controls are also added. Article pool FE is interacted with “ideology distance” in column 2. Standard errors are clustered by user. *** p<0.01, ** p<0.05, * p<0.1

P3: Affected more by signal when familiarity is higher
Experimental Design

- **Installation & Baseline Survey**

- **Grace Period (1,420 users)**
  Five days of trial period. Random issue/article every day.

- **Random Assignment to Groups (352 users)**

- **Daily Iterations**
  - Issue of the day for the user is randomly selected
  - Selection of news source

  - **Selection Group**
    Select the news source
  - **Random Provision Group**
    Randomly selected article shown

  User reads article, reports updated policy view, and evaluates article.

Pre-exposure to randomly selected news sources
Pre-exposure may lead to more selection

<table>
<thead>
<tr>
<th>Sample:</th>
<th>First selection for the issue after the grace period, Source-Name Group</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Article position - Party position of the user’s most-trusted party on the issue</td>
<td>-0.171**</td>
<td>-0.167**</td>
</tr>
<tr>
<td></td>
<td>(0.0736)</td>
<td>(0.0738)</td>
</tr>
<tr>
<td>Number of grace period exposure</td>
<td>0.0319</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0246)</td>
<td></td>
</tr>
<tr>
<td>Exposed once during grace period</td>
<td>0.0396</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0360)</td>
<td></td>
</tr>
<tr>
<td>Exposed twice during grace period</td>
<td>0.0294</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0729)</td>
<td></td>
</tr>
<tr>
<td>Exposed three times during grace period</td>
<td>0.220***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0240)</td>
<td></td>
</tr>
<tr>
<td>Choice set FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td># of users</td>
<td>84</td>
<td>84</td>
</tr>
<tr>
<td># of media selection</td>
<td>442</td>
<td>442</td>
</tr>
<tr>
<td>Observations (Choice set×choices)</td>
<td>2174</td>
<td>2174</td>
</tr>
</tbody>
</table>
### Results

**Subsample:** Random provision group after grace period, news sources with ≥ 10 evaluations

<table>
<thead>
<tr>
<th>Position (post)</th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Position (pre)</td>
<td>0.465***</td>
<td>0.475***</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>Position (pre) × # Pre-exposure</td>
<td></td>
<td>-0.041</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.030)</td>
</tr>
<tr>
<td>Article position</td>
<td>0.050**</td>
<td>0.024</td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td>(0.028)</td>
</tr>
<tr>
<td>Article position × # Pre-exposure</td>
<td></td>
<td>0.097**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.046)</td>
</tr>
<tr>
<td>News Source Position</td>
<td>-0.028</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.031)</td>
</tr>
<tr>
<td>News Source Position × # Pre-exposure</td>
<td></td>
<td>-0.105*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.055)</td>
</tr>
<tr>
<td>User FE, Article Pool FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td># of users</td>
<td>178</td>
<td>178</td>
</tr>
<tr>
<td>Observations (user×issue)</td>
<td>2830</td>
<td>2830</td>
</tr>
</tbody>
</table>
Experimental Design

Installation & Baseline Survey

Grace Period (1,420 users)
Five days of trial period. Random issue/article every day.

Random Assignment to Groups (352 users)

Daily Iterations
Issue of the day for the user is randomly selected

Selection Group
Select the news source

Random Provision Group
Randomly selected article shown

Selection Group
Select the news source

Random Provision Group, Assigned to media that they were pre-exposed to before

Random Provision Group, Assigned to media that they were not pre-exposed to before


## Pre-exposed random group: less extremism

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Position&lt;sub&gt;post&lt;/sub&gt; - Position&lt;sub&gt;pre&lt;/sub&gt;</td>
<td>0.142</td>
<td>0.275</td>
</tr>
<tr>
<td>Extreme&lt;sub&gt;post&lt;/sub&gt;</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Sample Mean</strong></td>
<td>0.0131</td>
<td>-0.0501*</td>
</tr>
<tr>
<td></td>
<td>(0.0122)</td>
<td>(0.0291)</td>
</tr>
<tr>
<td><strong>Random Provision Group, Pre-exposure</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.0223**</td>
<td>-0.0791***</td>
</tr>
<tr>
<td></td>
<td>(0.0104)</td>
<td>(0.0292)</td>
</tr>
<tr>
<td><strong>Selection Group</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant (Omitted: Random Provision, without Pre-exposure)</td>
<td>0.38***</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td>(0.058)</td>
<td>(0.059)</td>
</tr>
<tr>
<td><strong>User controls, Issue FE</strong></td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td><strong># of users</strong></td>
<td>297</td>
<td>297</td>
</tr>
<tr>
<td><strong>Observations (user×issue)</strong></td>
<td>1572</td>
<td>1572</td>
</tr>
</tbody>
</table>

Note: Issue FE, user controls, and constant are on the RHS. Extreme<sub>pre</sub> is controlled for in Column 2. Standard errors are clustered by user. *** p<0.01, ** p<0.05, * p<0.1
Other mechanisms or interpretations?

- Selection leads to better article quality?
- Selection leads to exposure to more moderate sources?
- Angry reaction?
- Party identification / sourting?
- Other counterfactual?
Overview of talk

(I) Theory: a Bayesian model

(II) Design of online field experiment

(III) Results

1. Position updating patterns
2. Selection patterns
3. Evolution of positions: comparison between groups
4. Mechanism

(V) Conclusion
Conclusion

- Deliberate media selection $\Rightarrow \downarrow$ polarization
- Mechanism: selection of more informative sources $\Rightarrow$ more learning
Conclusion

- Deliberate media selection ⇒ ↓ polarization
- Mechanism: selection of more informative sources ⇒ more learning
- Policy implication: under right conditions, making information about the messenger (the news source) salient can be better for news consumers’ learning
  - Can choose articles that are likely to be more informative
  - Easier to adjust for media biases
Deliberate media selection \(\Rightarrow\) ↓ polarization

Mechanism: selection of more informative sources \(\Rightarrow\) more learning

Policy implication: under right conditions, making information about the messenger (the news source) salient can be better for news consumers’ learning

- Can choose articles that are likely to be more informative
- Easier to adjust for media biases

Then why current trend in polarization? \(\Rightarrow\) future research
Thank you
Is polarization truly rising?

- Politicians
  - Roll call voting: Poole and Rosenthal (1991), McCarthy et al. (2016)
  - Language: Jensen et al. (2012), Gentzkow and Shapiro (2016)

- Public
  - Partisan homogeneity: Baldassar and Gelman (2008), Gentzkow (2016)
Consequences of polarization

Conventional remedy: balanced exposure

The New York Times

POLITICS

Right and Left: Partisan Writing You Shouldn’t Miss

By ANNA DUBENKO  JUNE 12, 2017

From the Left

A view of downtown Los Angeles last month. Melissa Lyttle for The New York Times

- Ann Friedman in The Baffler:
  "The hard truth about liberal secession fantasies is that California is not a place where progressive policies enable everyone to become successful. It's a place to which people move to enjoy their success when they've beaten the odds elsewhere."

From the Right

The former FBI director James B. Comey testified on Capitol Hill last week. J. Scott Applewhite/AP

- Andrew C. McCarthy in National Review:
  "I now believe President Donald Trump fired Federal Bureau of Investigation director James Comey because he believes Comey intentionally misled the public into believing Trump was under investigation by the FBI."
### Balance: first article

<table>
<thead>
<tr>
<th></th>
<th>(1) Age</th>
<th>(2) Gender (1=f, 2=m)</th>
<th>(3) Political knowledge score: [0,5]</th>
<th>(4) Trust on Democrat [-1,1] scale</th>
<th>(5) Trust on Saenuri (Korean Republican) [-1,1] scale</th>
<th>(6) Initial belief^2 [0,5] scale</th>
<th>(7) Initial knowledge on issue</th>
<th>(8) # of forms of media used to get political information</th>
</tr>
</thead>
<tbody>
<tr>
<td>Position of first article</td>
<td>0.0992</td>
<td>-0.00320</td>
<td>0.0567</td>
<td>0.0347</td>
<td>-0.000975</td>
<td>-0.0110</td>
<td>-0.0259</td>
<td>0.000745</td>
</tr>
<tr>
<td>(0.305)</td>
<td>(0.0199)</td>
<td>(0.0692)</td>
<td>(0.0225)</td>
<td>(0.0178)</td>
<td>(0.0167)</td>
<td>(0.0506)</td>
<td>(0.0423)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>30.92***</td>
<td>1.613***</td>
<td>2.754***</td>
<td>0.111***</td>
<td>-0.723***</td>
<td>0.519***</td>
<td>3.356***</td>
<td>1.899***</td>
</tr>
<tr>
<td>(0.252)</td>
<td>(0.0168)</td>
<td>(0.0573)</td>
<td>(0.0185)</td>
<td>(0.0139)</td>
<td>(0.00969)</td>
<td>(0.0327)</td>
<td>(0.0361)</td>
<td></td>
</tr>
<tr>
<td># of users</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations (user × issue)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1420</td>
<td>3,906</td>
</tr>
<tr>
<td>Subsample:</td>
<td>Users who finished the grace period</td>
<td></td>
<td>User × issue combination w/ at least one article read after grace period</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>30.82</td>
<td>-0.276</td>
<td>31.28</td>
<td>0.198</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[7.42]</td>
<td>[0.895]</td>
<td>[7.54]</td>
<td>[1.104]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td>1.64</td>
<td>0.038</td>
<td>1.64</td>
<td>0.065</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1=f, 2=m)</td>
<td>[.48]</td>
<td>[.059]</td>
<td>[.48]</td>
<td>[.067]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Political knowledge</td>
<td>2.86</td>
<td>-0.183</td>
<td>2.97</td>
<td>-0.156</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Score [0,5] scale</td>
<td>[1.64]</td>
<td>[.205]</td>
<td>[1.63]</td>
<td>[.226]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time spent on news</td>
<td>190.7</td>
<td>121.6*</td>
<td>202.9</td>
<td>137.9</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>media last week (min)</td>
<td>[386]</td>
<td>[70.98]</td>
<td>[439.1]</td>
<td>[96.35]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spent time on ground wave TV news</td>
<td>0.39</td>
<td>0.022</td>
<td>0.39</td>
<td>0.072</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[.49]</td>
<td>[.061]</td>
<td>[.49]</td>
<td>[.07]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spent time on cable TV news</td>
<td>0.32</td>
<td>.101*</td>
<td>0.33</td>
<td>0.086</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[.47]</td>
<td>[.059]</td>
<td>[.47]</td>
<td>[.068]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spent time on internet News portal service</td>
<td>0.8</td>
<td>0.04</td>
<td>0.81</td>
<td>0.023</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spent time on a newspaper website</td>
<td>0.28</td>
<td>0.015</td>
<td>0.29</td>
<td>-0.01</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spent time on reading newspaper news</td>
<td>0.15</td>
<td>-0.068</td>
<td>0.15</td>
<td>-0.036</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trust on liberal party [-1,1] scale</td>
<td>0.13</td>
<td>0.068</td>
<td>0.15</td>
<td>0.001</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[.54]</td>
<td>[.066]</td>
<td>[.54]</td>
<td>[.076]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trust on conserv. party [-1,1] scale Retention</td>
<td>-0.74</td>
<td>0.038</td>
<td>-0.77</td>
<td>0.076</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[.4]</td>
<td>[.052]</td>
<td>[.38]</td>
<td>[.058]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
| | Retention | 0.61 | 0.038 | | [
<p>| | | [.49] | [.042] | |
| # Users | 352 | 352 | 322 | 322 |
| Observations (user × issue) | 2816 | 2816 | 1711 | 1711 |</p>
<table>
<thead>
<tr>
<th>Subsample:</th>
<th>Users who finished the grace period</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td></td>
<td>Attrition dummy</td>
</tr>
<tr>
<td>Random Provision Group</td>
<td>0.0380 (0.0422)</td>
</tr>
<tr>
<td>Extreme</td>
<td>-0.0194 (0.0828)</td>
</tr>
<tr>
<td></td>
<td>Position - Party Position</td>
</tr>
<tr>
<td>Confidence</td>
<td>-0.0179 (0.0626)</td>
</tr>
<tr>
<td>Age</td>
<td>-0.00424 (0.00275)</td>
</tr>
<tr>
<td>Gender</td>
<td>0.0411 (0.0424)</td>
</tr>
<tr>
<td>(1=f, 2=m)</td>
<td></td>
</tr>
<tr>
<td>Political knowledge</td>
<td>-0.0180 (0.0122)</td>
</tr>
<tr>
<td>Score [0,5] scale</td>
<td></td>
</tr>
<tr>
<td>Time spent on news media last week (min)</td>
<td>-2.95e-05 (3.27e-05)</td>
</tr>
<tr>
<td>Trust on liberal party [-1,1] scale</td>
<td>0.00606 (0.0432)</td>
</tr>
<tr>
<td>Trust on conserv. party [-1,1] scale</td>
<td>0.0290 (0.0526)</td>
</tr>
<tr>
<td>Trust on progress. party [-1,1] scale</td>
<td>-0.0571 (0.0442)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.371*** (0.0346)</td>
</tr>
<tr>
<td>p-value for F-stat</td>
<td>0.505</td>
</tr>
<tr>
<td># Users</td>
<td>352</td>
</tr>
<tr>
<td>Observations (user x issue)</td>
<td>2,816</td>
</tr>
<tr>
<td>Subsample:</td>
<td>Sample for random provision of articles</td>
</tr>
<tr>
<td>------------------------------------------------</td>
<td>----------------------------------------</td>
</tr>
<tr>
<td></td>
<td>Observations (1)</td>
</tr>
<tr>
<td>Gender (1=f, 2=m)</td>
<td>1420</td>
</tr>
<tr>
<td>Age</td>
<td>1420</td>
</tr>
<tr>
<td>Political Knowledge Score ([0,5] scale)</td>
<td>1420</td>
</tr>
<tr>
<td>Trust in Democratic Party ([ -1,1] scale)</td>
<td>1420</td>
</tr>
<tr>
<td>Trust in Saenuri party ([-1,1] scale)</td>
<td>1420</td>
</tr>
<tr>
<td>Trust in Justice party ([-1,1] scale)</td>
<td>1420</td>
</tr>
<tr>
<td>Whether spent time on any TV news</td>
<td>1420</td>
</tr>
<tr>
<td>Whether spent time on ground wave TV news</td>
<td>1420</td>
</tr>
<tr>
<td>Whether spent time on cable TV news</td>
<td>1420</td>
</tr>
<tr>
<td>Whether spent time on any Internet news</td>
<td>1420</td>
</tr>
<tr>
<td>Whether spent time on Internet news portal service</td>
<td>1420</td>
</tr>
<tr>
<td>Whether spent time on a newspaper website</td>
<td>1420</td>
</tr>
<tr>
<td>Whether spent time on reading paper news</td>
<td>1420</td>
</tr>
<tr>
<td>Time spent on news media last week (minutes)</td>
<td>1420</td>
</tr>
</tbody>
</table>
Full design

Daily Iterations

Issue of the day for the user is randomly selected

Selection of news source

<table>
<thead>
<tr>
<th>G1</th>
<th>G2</th>
<th>G3</th>
<th>G4</th>
<th>G5</th>
<th>G6</th>
<th>G7</th>
</tr>
</thead>
<tbody>
<tr>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

Selection Group (93)

Random Provision Group (217)
Randomly selected article shown

User reads article, updates policy view, and evaluates article.
Distribution of article position
Issue list

- Foreign policy toward North Korea
- Providing free lunch to every elementary school student
- Single nationalized history textbook
- Cash support to unemployed youth
- Who should pay (central vs. regional government) for free early education for ages 3-5
- Minimum wage
- Law governing legislative process (minority protection vs. faster process)
- Flexible labor market vs. job security
Cardinality examples

- Foreign policy toward North Korea
  - **North Korea is our enemy; we should be aggressive in all aspects**
  - Supporting North Korea can be considered, but only after steps for denuclearization are taken
  - Both sides have their points; I am neutral
  - Communication and collaboration first, but aggression is also necessary
  - **We should put all our effort on communication and collaboration**

- Providing free lunch to every elementary school student
  - It is a populist policy to provide free lunch to every student, and it doesn’t help the society at all
  - This policy is a waste of budget, and it is enough to improve the current policy of targeted support
  - Both sides have their points; I am neutral
  - If feasible, it is desirable to provide free lunch to as many students as possible
  - It should be implemented right away; it is the right of students to get free lunch, and it is a part of education
Cardinality examples

- Foreign policy toward North Korea
  - North Korea is our enemy; we should be aggressive in all aspects
  - Supporting North Korea can be considered, but only after steps for denuclearization are taken
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  - It is a populist policy to provide free lunch to every student, and it doesn’t help the society at all
  - This policy is a waste of budget, and it is enough to improve the current policy of targeted support
  - Both sides have their points; I am neutral
  - If feasible, it is desirable to provide free lunch to as many students as possible
  - It should be implemented right away; it is the right of students to get free lunch, and it is a part of education
## Media selection of Selection Group

<table>
<thead>
<tr>
<th>Subsample:</th>
<th>Selection Group</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Dependent Variable:</td>
</tr>
<tr>
<td></td>
<td>Article position (proxy for selected news source’s expected position)</td>
</tr>
</tbody>
</table>

Position (pre)

User’s party position

# of users

Observations

Note: Round, issue, article pool FE, user controls, and constant are on the RHS. Standard errors are clustered by user. *** p<0.01, ** p<0.05, * p<0.1
### Media selection of Selection Group

<table>
<thead>
<tr>
<th>Subsample:</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Dependent Variable:</td>
</tr>
<tr>
<td></td>
<td>Article position (proxy for selected news source’s expected position)</td>
</tr>
</tbody>
</table>

**Position (pre)**

**User’s party position**

**# of users**

**Observations**

- Party position: average baseline positions on the issue of users who share the same most trusted party at the baseline

Note: Round, issue, article pool FE, user controls, and constant are on the RHS. Standard errors are clustered by user. *** p<0.01, ** p<0.05, * p<0.1
Readers select their partisan media

<table>
<thead>
<tr>
<th>Subsample:</th>
<th>Selection Group</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Dependent Variable:</td>
</tr>
<tr>
<td></td>
<td>Article position (proxy for selected news source’s expected position)</td>
</tr>
<tr>
<td>Position (pre)</td>
<td>0.011</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
</tr>
<tr>
<td>User’s party position</td>
<td>0.257***</td>
</tr>
<tr>
<td></td>
<td>(0.057)</td>
</tr>
<tr>
<td># of users</td>
<td>84</td>
</tr>
<tr>
<td>Observations</td>
<td>1448</td>
</tr>
</tbody>
</table>

Note: Round, issue, article pool FE, user controls, and constant are on the RHS. Standard errors are clustered by user. *** p<0.01, ** p<0.05, * p<0.1
Readers select their partisan media

**P4: The familiar news source is selected**

<table>
<thead>
<tr>
<th>Subsample:</th>
<th>Selection Group</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Dependent Variable:</td>
</tr>
<tr>
<td></td>
<td>Article position (proxy for selected news source’s expected position)</td>
</tr>
<tr>
<td>Position (pre)</td>
<td>0.011</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
</tr>
<tr>
<td>User’s party position</td>
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</tr>
<tr>
<td></td>
<td>(0.057)</td>
</tr>
<tr>
<td># of users</td>
<td>84</td>
</tr>
<tr>
<td>Observations</td>
<td>1448</td>
</tr>
</tbody>
</table>

Note: Round, issue, article pool FE, user controls, and constant are on the RHS. Standard errors are clustered by user. *** p<0.01, ** p<0.05, * p<0.1
Readers select their partisan media

**P4: The familiar news source is selected**

<table>
<thead>
<tr>
<th>Subsample:</th>
<th>Selection Group</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variable:</strong></td>
<td><strong>Article position (proxy for selected news source’s expected position)</strong></td>
</tr>
<tr>
<td>Position (pre)</td>
<td>0.011</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
</tr>
<tr>
<td>User’s party position</td>
<td>0.257***</td>
</tr>
<tr>
<td></td>
<td>(0.057)</td>
</tr>
<tr>
<td># of users</td>
<td>84</td>
</tr>
<tr>
<td>Observations</td>
<td>1448</td>
</tr>
</tbody>
</table>

Note: Round, issue, article pool FE, user controls, and constant are on the RHS. Standard errors are clustered by user. *** p<0.01, ** p<0.05, * p<0.1

- **Isolation index: 0.076 - 0.143;**
- Similar to US ([Gentzkow and Shapiro, 2011](#))
**P4: The familiar news source is selected**

<table>
<thead>
<tr>
<th>Subsample:</th>
<th>Random articles (placebo)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Dependent Variable:</td>
</tr>
<tr>
<td></td>
<td>Article position (proxy for selected news source’s expected position)</td>
</tr>
<tr>
<td>Position (pre)</td>
<td>-0.003 (0.010)</td>
</tr>
<tr>
<td>User’s party position</td>
<td>0.022 (0.023)</td>
</tr>
<tr>
<td># of users</td>
<td>1305</td>
</tr>
<tr>
<td>Observations</td>
<td>7348</td>
</tr>
</tbody>
</table>

Note: Round, issue, article pool FE, user controls, and constant are on the RHS. Standard errors are clustered by user. *** p<0.01, ** p<0.05, * p<0.1

- **Isolation index:** 0.076 - 0.143;
- Similar to US *(Gentzkow and Shapiro, 2011)*
Learning: economic significance?

North Korea is our enemy; we should be aggressive in every front

We should put all our effort on communication and collaboration
## Article quality by group

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Residualized article quality</td>
<td></td>
</tr>
<tr>
<td>Sample Mean</td>
<td></td>
<td>0.005</td>
</tr>
<tr>
<td>Sample S.D.</td>
<td></td>
<td>0.529</td>
</tr>
<tr>
<td>Selection Group</td>
<td>-0.034</td>
<td>0.013</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.026)</td>
</tr>
<tr>
<td>Constant (omitted: Random Provision)</td>
<td>0.018</td>
<td>-0.083</td>
</tr>
<tr>
<td></td>
<td>(0.058)</td>
<td>(0.052)</td>
</tr>
<tr>
<td>Sample restriction: article quality evaluation ≥ 10</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td># of users</td>
<td>332</td>
<td>302</td>
</tr>
<tr>
<td>Observations (user×issue)</td>
<td>1456</td>
<td>872</td>
</tr>
</tbody>
</table>

Note: I pooled the article qualities and residualize by regressing the quality on |supporting party’s position – article position| and |baseline position on the issue – article position| to deal with subjective evaluation that is affected by pre-existing view about the issue and about the political parties.
## Article characteristics by group

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Article extremism</td>
<td>Article extremism</td>
<td>Article Position</td>
<td>Article Position</td>
</tr>
<tr>
<td></td>
<td>(relative)</td>
<td>(absolute)</td>
<td>– Position (pre)</td>
<td>– Party Position</td>
</tr>
<tr>
<td>Sample Mean</td>
<td>-0.293</td>
<td>0.175</td>
<td>0.316</td>
<td>0.279</td>
</tr>
<tr>
<td>Selection Group</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.004</td>
<td>-0.001</td>
<td>0.003</td>
<td>-0.023*</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.006)</td>
<td>(0.014)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Constant (omitted: Random Provision)</td>
<td>-0.287***</td>
<td>0.175***</td>
<td>0.312***</td>
<td>0.285***</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.009)</td>
<td>(0.008)</td>
<td>(0.007)</td>
</tr>
<tr>
<td># of users</td>
<td>336</td>
<td>336</td>
<td>336</td>
<td>316</td>
</tr>
<tr>
<td>Observations (user×issue)</td>
<td>1,772</td>
<td>1,772</td>
<td>1,772</td>
<td>1,664</td>
</tr>
</tbody>
</table>

Note: Article pool FE, user controls, and constant are on the RHS. Standard errors are clustered by user. *** p<0.01, ** p<0.05, * p<0.1.
Article extremism (relative) = sign(Position (pre) – 0.5) × (Article Position - Position (pre))
Article extremism (absolute) = sign(Article Position – 0.5)
<table>
<thead>
<tr>
<th>Subsample:</th>
<th>Random Provision Group, User × issue combination w/ at least one article read after grace period, Time spent &lt; 10 minutes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model:</td>
<td>Linear Regression</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Time spent</td>
<td></td>
</tr>
<tr>
<td>Sample Mean</td>
<td>2.353</td>
</tr>
<tr>
<td>Sample Median</td>
<td>1.800</td>
</tr>
<tr>
<td>Sample S.D.</td>
<td>1.823</td>
</tr>
<tr>
<td></td>
<td>Article position – Position of the user’s most trusted party</td>
</tr>
<tr>
<td># of political words</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Article position – Position of the user’s most trusted party</td>
</tr>
<tr>
<td>User controls, Issue FE</td>
<td>Y</td>
</tr>
<tr>
<td># of users</td>
<td>188</td>
</tr>
<tr>
<td>Observations (user×issue)</td>
<td>858</td>
</tr>
</tbody>
</table>
No evidence of party sorting

Note: # of users = 336, Observations = 1790. User controls, issue and round FE added. |Position(pre) – Party Position| is added as control. Standard errors are clustered by user. Vertical line indicates 95% confidence interval.
Histogram by party

(a) Prior of opposition supporters by group

(b) Posterior of opposition supporters by group

(c) Prior of incumbent supporters by group

(d) Posterior of incumbent supporters by group

Legend:
- Selection Group
- Random Provision Group
- SG, density
- RPG, density
### 1990 counterfactual: similar results

#### Subsample:
User × issue combination w/ at least one article read after grace (excluding Random Provision Group that are exposed to less well-known sources)

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample Mean</td>
<td>0.140</td>
<td>0.284</td>
</tr>
<tr>
<td>Sample S.D.</td>
<td>0.167</td>
<td>0.451</td>
</tr>
<tr>
<td>Selection Group</td>
<td>0.0160</td>
<td>-0.0769**</td>
</tr>
<tr>
<td></td>
<td>(0.0120)</td>
<td>(0.0324)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.168***</td>
<td>0.184**</td>
</tr>
<tr>
<td></td>
<td>(0.0259)</td>
<td>(0.0769)</td>
</tr>
<tr>
<td>Omitted Group: Random Provision Group, exposed to historically well-known sources</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Control: Extreme\text{pre}</td>
<td></td>
<td>Y</td>
</tr>
<tr>
<td>User controls, Issue FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td># of users</td>
<td>289</td>
<td>289</td>
</tr>
<tr>
<td>Observations (user×issue)</td>
<td>993</td>
<td>993</td>
</tr>
</tbody>
</table>
Primitives

News source $p$ sends a signal to $i$ on issue $j$:

$$s_{pij} = \theta_j^* + I_{pj}^* + \epsilon_{pij}$$
Primitives

News source $p$ sends a signal to $i$ on issue $j$:

$$s_{pij} = \theta_j^* + I_{pj}^* + \epsilon_{pij}$$

“True state of the world on issue $j$”

Prior position of $i$: $\theta_j \sim N\left(\theta_{ij0}, \frac{1}{\tau_{ij0}}\right)$
Primitives

News source $p$ sends a signal to $i$ on issue $j$:

$$S_{pij} = \theta_j^* + I_{pj}^* + \epsilon_{pij}$$

“Media bias of news source $p$ on issue $j$”

Subjective assessment of $i$: $I_{pj} \sim N\left(I_{pji}, \frac{1}{\tau_{ipi}}\right)$
Primitives

News source $p$ sends a signal to $i$ on issue $j$:

$$s_{pij} = \theta_j^* + I_{pj}^* + \epsilon_{pij}$$

Priors

$$\theta_j \sim N\left(\theta_{ijo}, \frac{1}{\tau_{ijo}}\right)$$

$$I_{pj} \sim N\left(I_{pji}, \frac{1}{\tau_{lpji}}\right)$$
Primitives

News source $p$ sends a signal to $i$ on issue $j$:

$$s_{pij} = \theta_j^* + I_{pj}^* + \epsilon_{ pij}$$

Two news sources: $p \in \{F, A\}$

Prior distribution:

$$\theta_j \sim N \left( \theta_{ij0}, \frac{1}{\tau_{ij0}} \right)$$

$$I_{pj} \sim N \left( I_{pji}, \frac{1}{\tau_{lpji}} \right)$$
Primitives

News source $p$ sends a signal to $i$ on issue $j$:

$$S_{pij} = \theta_j^* + I_{pj}^* + \epsilon_{pij}$$

Two news sources: $p \in \{F, A\}$

\[
\forall j: \tau_{IFji} > \tau_{IAji}
\]
Primitives

News source \( p \) sends a signal to \( i \) on issue \( j \):

\[
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\]

Two news sources: \( p \in \{F, A\} \)

\( \forall j: \tau_{IFji} > \tau_{IAji} \)
Timeline

An issue \( j \) is randomly selected by nature

The agent selects a news source, and then gets a distorted signal

The agent updates position about \( \theta^* \) using Bayes' rule, and chooses an action \( a_{ij} \in \mathbb{R} \) to maximize utility:

\[
U(a_{ij} | \theta^* j) = - (a_{ij} - \theta^* j)^2
\]
An issue \((j)\) is randomly selected by nature

\[
\begin{align*}
\text{1. } & \text{An issue } (j) \text{ is randomly selected by nature} \\
\end{align*}
\]
1. An issue \((j)\) is randomly selected by nature
2. The agent selects a news source, and then gets a distorted signal
1. An issue ($j$) is randomly selected by nature
2. The agent selects a news source, and then gets a distorted signal
3. The agent updates position about $\theta^*_j$ using Bayes’ rule, and chooses an action $a_{ij} \in \mathbb{R}$ to maximize utility:

$$U(a_{ij} \mid \theta^*_j) = -(a_{ij} - \theta^*_j)^2$$
Position updating: consistent with typical Bayesian models

- Backward induction: assuming $s_{pij}$ is given, the posterior position:

$$\theta_j|s_{pij} \sim \mathcal{N}(\theta_{ij1}, \tau_{ij1})$$

where

$$\theta_{ij1} = (1 - \omega(\tau_{ij0}, \tau_{ipji})) \theta_{ij0} + \omega(\tau_{ij0}, \tau_{ipji})(s_{pij} - I_{pji})$$

- Posterior mean is affected by both prior mean and signal
- Affected less by signal when prior confidence is higher
- Affected more by signal when familiarity is higher
Position updating: consistent with typical Bayesian models

- Backward induction: assuming \(s_{pij}\) is given, the posterior position:

\[
\theta_j \mid s_{pij} \sim \mathcal{N} \left( \theta_{ij1}, \frac{1}{\tau_{ij1}} \right)
\]

where
Position updating: consistent with typical Bayesian models

- Backward induction: assuming \( s_{pij} \) is given, the posterior position:

\[
\theta_j \mid s_{pij} \sim N \left( \theta_{ij1}, \frac{1}{\tau_{ij1}} \right)
\]

where

\[
\theta_{ij1} = (1 - \omega(\tau_{ij0}, \tau_{Ipji})) \theta_{ij0} + \omega(\tau_{ij0}, \tau_{Ipji})(s_{pij} - I_{pji})
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- Backward induction: assuming $s_{pij}$ is given, the posterior position:

$$\theta_j | s_{pij} \sim N \left( \theta_{ij1}, \frac{1}{\tau_{ij1}} \right)$$

where

$$\theta_{ij1} = (1 - \omega(\tau_{ij0}, \tau_{Ipji})) \theta_{ij0} + \omega(\tau_{ij0}, \tau_{Ipji}) (s_{pij} - I_{pji})$$

**P1:** Posterior mean is affected by both prior mean and signal
Position updating: consistent with typical Bayesian models

- Backward induction: assuming $s_{pij}$ is given, the posterior position:

$$
\theta_j \mid s_{pij} \sim \mathcal{N}\left(\theta_{ij1}, \frac{1}{\tau_{ij1}}\right)
$$

where

$$
\theta_{ij1} = (1 - \omega(\tau_{ij0}, \tau_{I_{pji}})) \theta_{ij0} + \omega(\tau_{ij0}, \tau_{I_{pji}})(s_{pij} - I_{pji})
$$

P1: Posterior mean is affected by both prior mean and signal

P2: Affected less by signal when prior confidence is higher
Position updating: consistent with typical Bayesian models

- Backward induction: assuming $s_{pij}$ is given, the posterior position:

$$\theta_j | s_{pij} \sim N \left( \theta_{ij1}, \frac{1}{\tau_{ij1}} \right)$$

where

$$\theta_{ij1} = (1 - \omega(\tau_{ij0}, \tau_{Ipji})) \theta_{ij0} + \omega(\tau_{ij0}, \tau_{Ipji})(s_{pij} - I_{pji})$$

P1: Posterior mean is affected by both prior mean and signal

P2: Affected less by signal when prior confidence is higher

P3: Affected more by signal when familiarity is higher
Position updating: consistent with typical Bayesian models

- Backward induction: assuming $s_{pij}$ is given, the posterior position:

$$\theta_j \mid s_{pij} \sim N \left( \theta_{ij1}, \frac{1}{\tau_{ij1}} \right)$$

where

$$\theta_{ij1} = (1 - \omega(\tau_{ij0}, \tau_{Ipji})) \theta_{ij0} + \omega(\tau_{ij0}, \tau_{Ipji})(s_{pij} - I_{pji})$$

**P1:** Posterior mean is affected by both prior mean and signal

**P2:** Affected less by signal when prior confidence is higher

**P3:** Affected more by signal when familiarity is higher

$$\tau_{ij1} = \tau_{ij1}(\tau_{ij0}, \tau_{Ipji})$$
\[
\text{argmax}_p E_{i0} \left[ U(a_{ij} \mid \theta_j) \mid s_{pij} \right] = \text{argmax}_p E_{i0} \left[ -(a_{ij} - \theta_j^*)^2 \mid s_{pij} \right] \\
= \text{argmax}_p \tau_{ij1} \left( \tau_{ij0}, \tau_{Ipji} \right) \\
= \{F\}
\]
argmax_p P(E_{i0} | a_{ij}, \theta_j, s_{pij}) = argmax_p P(E_{i0} | -(a_{ij} - \theta^*_j)^2, s_{pij})
= argmax_p \tau_{ij1} (\tau_{ij0}, \tau_{Ipji})
= \{F\}

P4: *The familiar news source is selected*
Source selection allowed vs random exposure to either
News source selection → more learning

• Source selection allowed vs random exposure to either
• If people have approximately correct assessment of bias
News source selection $\rightarrow$ more learning

- Source selection allowed vs random exposure to either
- If people have approximately correct assessment of bias
  - Selection $\Rightarrow$ learning $\uparrow$ (distance to true state $\downarrow$), positions change $\uparrow$
  - Polarization $\downarrow$
- ▶ Proof (math)
News source selection → more learning

- Source selection allowed vs random exposure to either
- If people have approximately correct assessment of bias
  - Selection ⇒ learning ↑ (distance to true state ↓), positions change ↑
  - Polarization ↓
- ▶ Proof (math)

P5: *Positions of “Selection Group” change more, conv. more to bliss point*
Proof: prediction 5

- **Assumption**: (Approximately Correct Bias Assessment) $I_{pji} = I_j^* + \nu_{pji}$, where $|\nu_{pji}| < M_j \frac{1}{\gamma_{pji}}$ for some $M_j > 0$, where $\gamma_{pji} \equiv \frac{\tau_{I_{pji}} \tau_s}{\tau_s \tau_{ij0} + \tau_{ij0} \tau_{I_{pji}} + \tau_{I_{pji}} \tau_s}$.

- **Proposition**: There exists $M_j > 0$ such that allowing source selection, as opposed to equal-chance exposure to either $F$ or $A$, facilitates learning ($|\theta_{ij0} - \theta_{ij1}|$ is larger) on average.

- **Proof**:

  $$|\theta_{ij1} - \theta_{ij0}| = \gamma_{pji} |s_{pji} - I_{pji} - \theta_{ij0}|$$
  $$= \gamma_{pji} |\theta_j^* + I_j^* + \epsilon_{pji} - I_j^* - \nu_{pi} - \theta_j^* - \eta_{ij0}|$$
  $$= \gamma_{pji} |\epsilon_{pji} - \nu_{pji} - \eta_{ij0}|$$

  Taking expectations over the continuum of agents,

  $$E \left[ |\theta_{ij1} - \theta_{ij0}| \mid p = F \right] = \int \gamma_{pji} |\epsilon_{pji} - \nu_{pji} - \eta_{ij0}| dF(\epsilon_{pji}) \ dF(\nu_{pji}) \ dF(\eta_{ij0}) \ dF(\gamma_{Fij}, \gamma_{Aij})$$
Proof: prediction 5 (continued)

We need to prove that \( E \left[ \left| \theta_{ij1} - \theta_{ij0} \right| \mid p = F \right] \) and \( E \left[ \left| \theta_{ij1} - \theta_{ij0} \right| \mid p = A \right] \). Take \( M_j \) such that:

\[
0 < M_j < \int \int \int \gamma_{Fij} \left| \epsilon_{Fij} - \eta_{ij0} \right| dF(\epsilon_{Fij}) dF(\eta_{ij0}) dF(\gamma_{Fij}, \gamma_{Aij}) \\
\left( \frac{1}{2} \right) \int \int \int \gamma_{Aij} \left| \epsilon_{Aij} - \eta_{ij0} \right| dF(\epsilon_{Aij}) dF(\eta_{ij0}) dF(\gamma_{Aij}, \gamma_{Aij}) \\
\left( \frac{1}{2} \right)
\]

which exists because \( \gamma_{Fij} > \gamma_{Aij} \) according to the Familiarity Assumption. Then,

\[
E \left[ \left| \theta_{ij1} - \theta_{ij0} \right| \mid p = F \right] = \int \int \int \gamma_{Fij} \left| \epsilon_{Fij} - \nu_{Fji} - \eta_{ij0} \right| dF(\cdot) \\
\int \int \int \gamma_{Aij} \left| \epsilon_{Aij} - \nu_{Aji} - \eta_{ij0} \right| dF(\cdot)
\]

\[
> \int \int \int \gamma_{Fij} \left| \epsilon_{Fij} - \eta_{ij0} \right| dF(\cdot) - \int \int \gamma_{Fij} \left| \nu_{Fji} \right| dF(\cdot) \\
\int \int \int \gamma_{Aij} \left| \epsilon_{Aij} - \eta_{ij0} \right| dF(\cdot) + \int \int \int \gamma_{Aij} \left| \nu_{Aji} \right| dF(\cdot)
\]

\[
> \int \int \int \gamma_{Fij} \left| \epsilon_{Fij} - \eta_{ij0} \right| dF(\epsilon_{Fij}) dF(\eta_{ij0}) dF(\gamma_{Fij}, \gamma_{Aij}) - M_j \\
\int \int \int \gamma_{Aij} \left| \epsilon_{Aij} - \eta_{ij0} \right| dF(\epsilon_{Aij}) dF(\eta_{ij0}) dF(\gamma_{Aij}, \gamma_{Aij}) + M_j
\]

\[
> 1
\]
I used triangle inequality both on the denominator and the numerator for the first inequality. $dF(\cdot)$ is an abuse of notation for simplicity, indicating the distribution of all relevant variables. For the second inequality, I applied Correct Assessment Assumption above.

The final inequality can be derived by applying Equation for $M_j$.

$$\frac{E[|\theta_{ij1} - \theta_{ij0}| \mid p=F]}{E[|\theta_{ij1} - \theta_{ij0}| \mid p=A]} > 1$$

implies that there will be more learning when the reader receives the signal from the familiar source than from the alien source.

It then immediately implies that selective exposure to the familiar source will give, on average, a bigger movement in positions than an equal-chance encounter.
The proposed mechanism

Selection Group

VS

Random Provision Group
The proposed mechanism

Selection Group

VS

Random Provision Group

News consumption from more familiar media (e.g., pre-exposed media)

Random exposure

News consumption from less familiar media
The proposed mechanism

Selection Group

VS

Random Provision Group

Media selection for facilitated learning (A)

News consumption from more familiar media (e.g., pre-exposed media)

Random exposure

News consumption from less familiar media
The proposed mechanism

Selection Group → Media selection for facilitated learning (A) → News consumption from more familiar media (e.g., pre-exposed media) → Better understanding of media bias, better bias deduction (B) → Random Provision Group

VS → Random exposure → News consumption from less familiar media
The proposed mechanism:

- **Selection Group**
  - Media selection for facilitated learning (A)
  - News consumption from more familiar media (e.g., pre-exposed media)

- **Random Provision Group**
  - Random exposure
  - News consumption from less familiar media

- Better understanding of media bias, better bias deduction (B)

- More learning, which manifests itself as less extremism (C)
The proposed mechanism

Selection Group

VS

Random Provision Group

Media selection for facilitated learning (A)

News consumption from more familiar media (e.g., pre-exposed media)

Better understanding of media bias, better bias deduction (B)

More learning, which manifests itself as less extremism (C)

News consumption from less familiar media
The proposed mechanism

Selection Group

Taste-based selection

Random Provision Group

Random exposure

Media selection for facilitated learning (A)

News consumption from more familiar media
(e.g., pre-exposed media)

Better understanding of media bias, better bias deduction (B)

More learning, which manifests itself as less extremism (C).
The proposed mechanism

Selection Group

VS

Random Provision Group

Media selection for facilitated learning (A)
Taste-based selection

News consumption from more familiar media (e.g., pre-exposed media)

Better understanding of media bias, better bias deduction (B)

More learning, which manifests itself as less extremism (C)

News consumption from less familiar media
The proposed mechanism

The diagram illustrates the following steps:

1. **Selection Group**
   - Media selection for facilitated learning (A)
   - Taste-based selection

2. **Random Provision Group**
   - Random exposure

3. **News consumption from more familiar media** (e.g., pre-exposed media)

4. Better understanding of media bias, better bias deduction (B)

5. **More learning**, which manifests itself as less extremism (C).