

Social Media, News Consumption, and Polarization: Evidence from a Field Experiment

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Motivation: Concerns Over Social Media

- Consumption of news through social media is increasing
 - 12% (2008) → 72% (2019)
- Pro-attitudinal news → polarization?
 - News based on social network
 - News based on algorithm
 - Users personalize their feed
- Users easily manipulated?



Overview

- **Research questions**

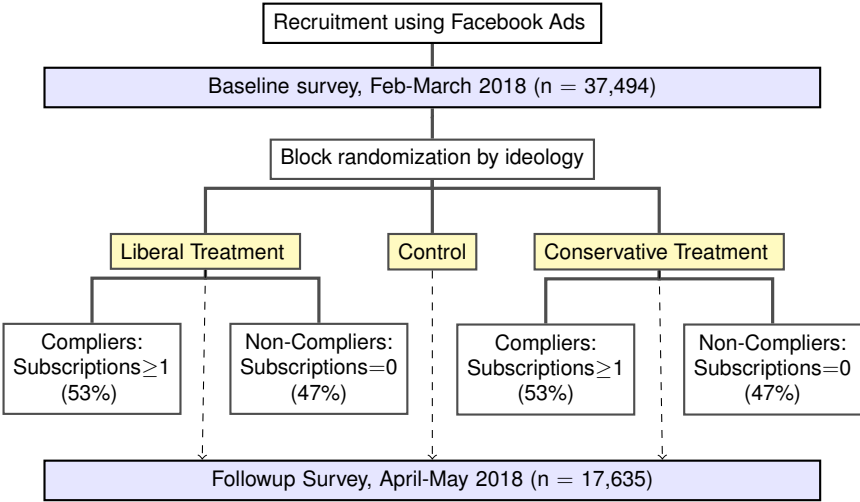
1. How does social media affect news consumption?
2. How does exposure to news through social media affect political opinions and polarization?

- **Approach**

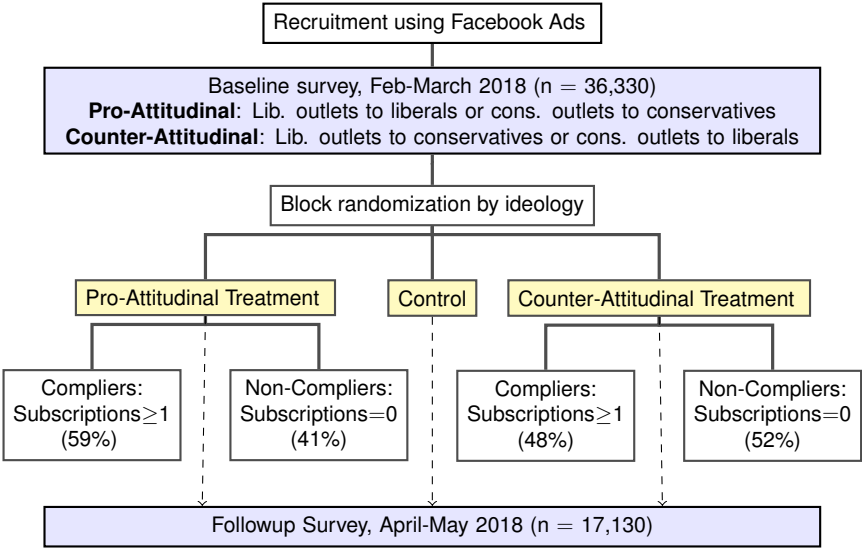
- Descriptive - collect social media and news consumption data
 - Social media associated with extreme, pro-attitudinal news
- Causal - field experiment varying social media feeds
 - Analyze chain of media effects: exposure on Facebook, visits to news sites, changes in political opinions and attitudes

Design

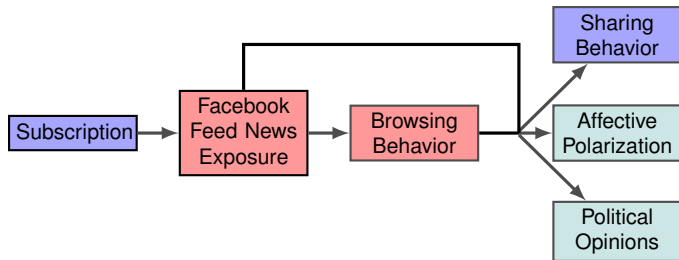
Design Overview



Design Overview



Data: Causal Chain of Media Effects



Data sources

- FB data: subscriptions (N=37,494) and post sharing (N=34,592)
 - Facebook app Facebook Data Screenshots
- Extension data: exposure and browsing behavior (N=1,835)
 - Chrome extension Extension Data Screenshots
- Survey data: political opinions and attitudes (N=17,635)
 - Endline survey, analysis pre-registered Survey Data

External Validity

- Intervention similar to common social media nudges
- Natural behavior in every other aspect:
 - Media content
 - Platform algorithms
 - Individual decisions
- Important setting
 - Dominant social network
 - Popular news outlets

Nudges Examples

Facebook Dominant

Outlets

News Content

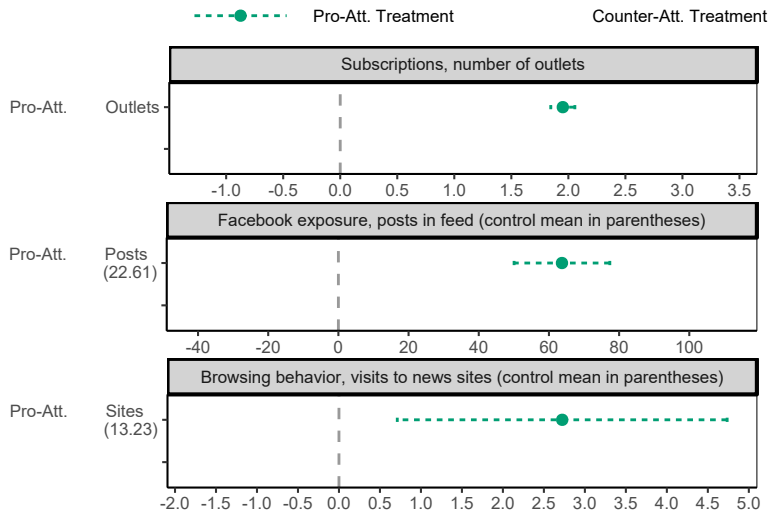
Experimenter Effect

Results

Results

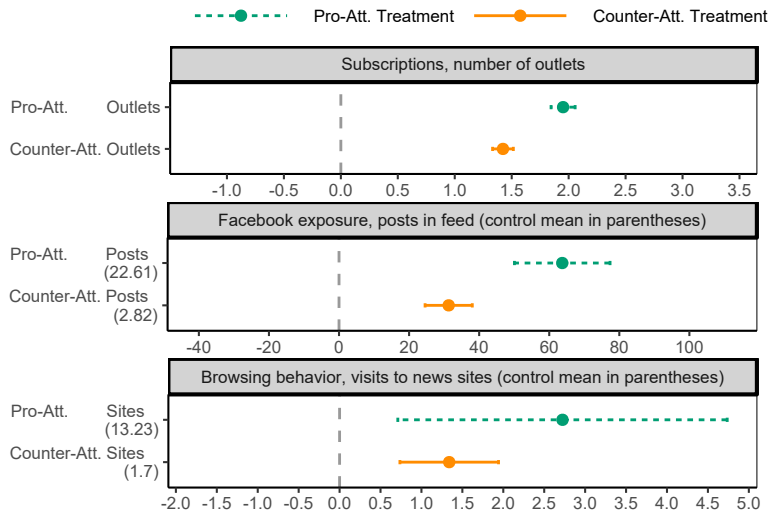
- Individuals engage with new outlets when nudged
- Social media feed substantially affects online news consumption
- No evidence that outlets' slant affect political opinions
- Counter-attitudinal news decreases affective polarization, compared to pro-attitudinal news
- Algorithm limits exposure to counter-att. posts, conditional on subscription

ITT After Two Weeks: Pro vs. Counter Attitudinal



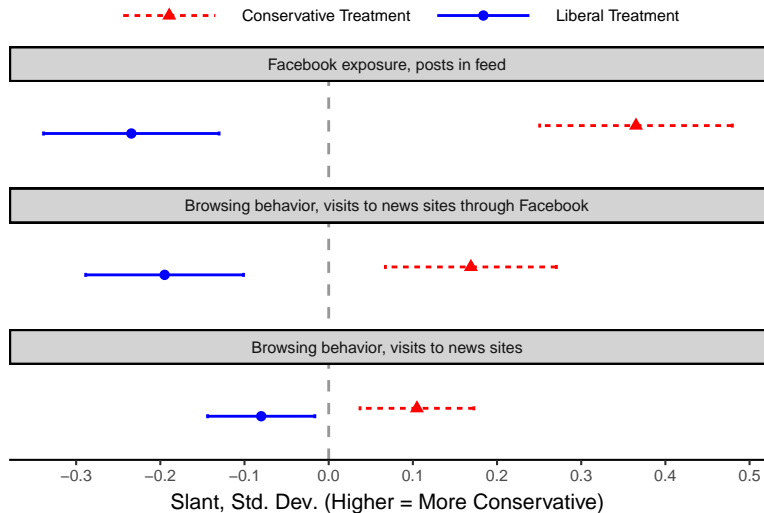
Participants in Post Sharing and Extension Subsamples with an ideological leaning (N=1,648)

ITT After Two Weeks: Pro vs. Counter Attitudinal



Participants in Post Sharing and Extension Subsamples with an ideological leaning (N=1,648)

Slant (Higher = More Conservative)



Participants in Post Sharing and Extension Subsamples ($N \leq 1,699$)

[Regressions](#)
[Match](#)
[By Sample](#)
[Article Level](#)
[Crowdout](#)
[Within Outlet](#)
[Persistent](#)
[Shared](#)

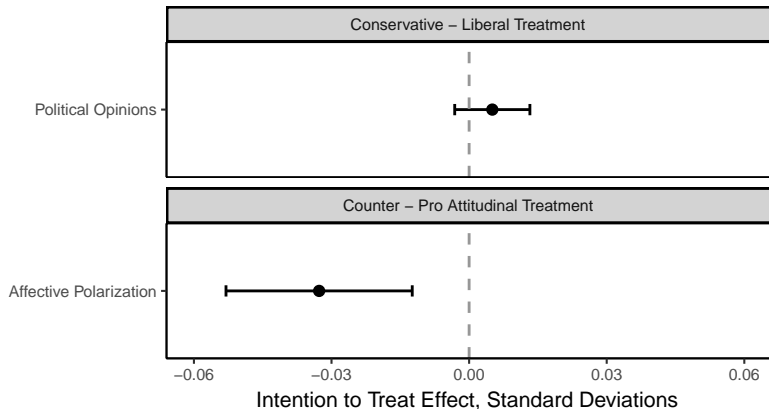
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Followup Survey Primary Outcomes

- Political Opinions Index (\uparrow = More conservative)
 - 20 questions on issues covered during the study period
 - March for Our Lives, Stormy Daniels, Mueller investigation, etc.
 - Compare conservative and liberal treatments
- Affective Polarization Index (\uparrow = More partisan hostility)
 - 5 questions, measuring attitudes toward political parties
 - Feeling thermometer
 - Difficult to see things from Dem/Rep point of view
 - Important to consider the perspective of Dem/Rep
 - Dem/Rep party has good ideas
 - Son or daughter married other party
 - Compare pro- and counter-attitudinal treatments

Treatment Effects on Primary Outcomes



Participants in Endline Survey Subsample (N=17,130-17,635)

- Effect on attitudes, not political opinions; in line with long-term trend

Regressions

By Treatment

Primary Outlets

Subsamples

Heterogeneity

Null Effect

Mechanisms

Treatment Effect Magnitude

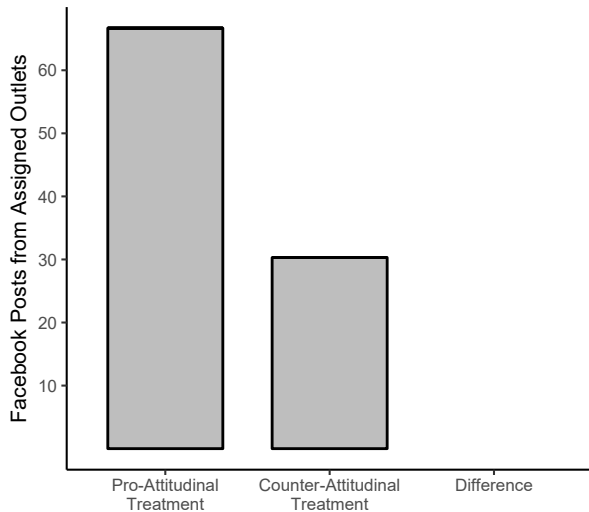
- Focus on feeling thermometer questions (0-100 degrees)
- Counter vs. pro-attitudinal treatment
 - ITT: -0.58
 - TOT: -0.96
- Benchmarks
 - Secular trend 1996-2016 (ANES): 3.83-10.52
 - One month Facebook disconnection (Allcott et al., 2020): -2.09

[Components](#)[By Party](#)[Robustness to Component](#)[Affective Polarization Implications](#)[Counterfactuals](#)

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Differential Exposure to Matching vs. Opposing Posts



Participants for whom FB posts and subscriptions are observed for at least 2 weeks (N=1,059)

Explaining Differential Exposure

- The exposure of individual i to posts shared by outlet j :

$$E_{ij} = S_{ij}P_{ij}U_i$$

- $S_{ij} \in \{0, 1\}$ is i 's subscription to outlet j (“selective exposure”)
- P_{ij} is posts supplied from j to i conditional on subscription (“filter bubble”)
- U_i is the total number of posts i observed (usage)

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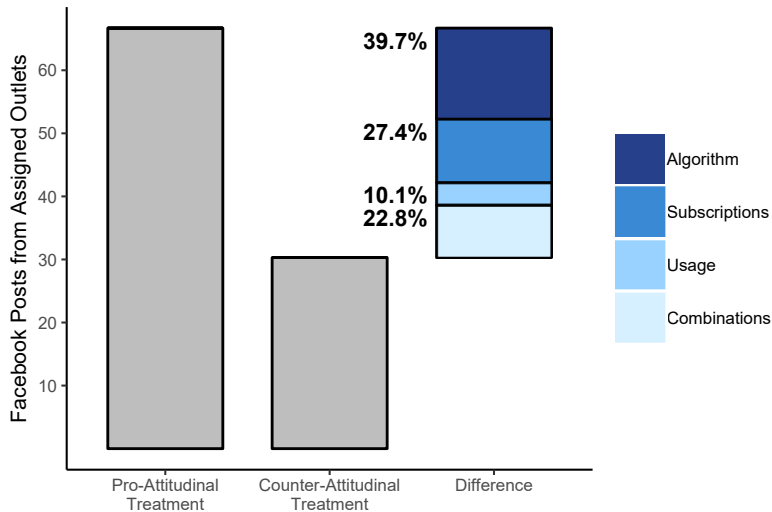
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$$\Delta E = \underbrace{S_{\Delta} * P_C * U_C}_{\text{Subscriptions}} + \underbrace{S_C * P_{\Delta} * U_C}_{\text{Platform Algorithms}} + \underbrace{S_C * P_C * U_{\Delta}}_{\text{Platform Usage}} + \underbrace{\dots}_{\text{Combinations}}$$

- S_C is subscriptions in the counter-attitudinal treatment
- S_{Δ} is the difference in subscriptions between the treatments

Differential Exposure to Matching vs. Opposing Posts



Participants for whom FB posts and subscriptions are observed for at least 2 weeks (N=1,059)

[Specifications](#)

[Regressions](#)

[Alt. Decompositions](#)

[Not Only Social](#)

Conclusions