How the News Media Activate Public Expression and Influence National Agendas

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1 Based on joint work with Benjamin Schneer and Ariel White (Science 2017)
2 GaryKing.org
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Supporting Analyses

Implications
Statistical Problems: We Can’t Randomize

• Statistical Problems
  • Randomization: usually impossible
  • Endogeneity: media outlets compete for readers
  • Spillover: 1 intervention may affect all potential subjects

• Clever Research Designs (trying to approximate randomization)
  • New TV tower. Some behind hill, in radio shadow
  • Before/after studies of “surprise” media events
  • Roll out of Fox News to some towns and not others
  • Many others…

• But we still can’t randomize
  • Assumptions: better, but unavoidably dubious
    ⇝ “Profound biases,” > 600% difference from truth
  • Estimands: different, of sometimes questionable relevance
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• What we’d do without constraints

  • Sign up many news media outlets
  • Randomize news content and timing for each
  • Control collaboration to induce cross-outlet correlations

• Why is this plan so hard for media outlets?

  • Need to take actions few (if any) have ever before agreed to
  • Outlets are competitors: trying to scoop each other
  • Must share information with us (even if not with each other)

  • Need numerous agreements, bandwidth for large scale collaboration, extensive coordination, high levels of trust

• More specifically, to randomize

  • Journalists require: total control over what’s published & when
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Our Approach:

- Build trust: 5 years of negotiating & communicating
- Develop incentive compatible research design: both get 100%, no compromises; ⇝ solve a political problem technologically
- Convince 48 media outlets to let us experiment on them
- Whenever possible, choose realism (even if inconvenient)
- Stick close to outlets’ standard operating procedures
- Embed treatment within ordinary routines; ⇝ More expensive, logistically complicated, and time-consuming, but more generalizable
- Goal: Build platform to continue experiments
- A work of political science
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Individual-level Effects

- Outcome variable: individual knowledge and opinion
- Effects: persuasion, attitude formation, diffusion, gatekeeping, priming, issue framing, etc.
- Measurement: survey research

Collective Effects: Impact on the national conversation

- Outcome variable: activated public opinion, views of all those trying to express themselves publicly about policy and politics
- Classic definition of public opinion, predating survey research
- Measurement
  - Previously: hallway conversations, "water-cooler events", soapbox speeches in public squares, editorials, etc.
  - Now: 750M public social media posts/day
- Target population: different than survey research!
  - Surveys: pop quizzes of everyone, even uninformed & inactive
  - Social media: counts only activated opinion
- Democracies: can ignore individuals, but collective expression sets agendas
- Autocracies: ignore criticism, but censor expression about collective action
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    • **Previously:** hallway conversations, “water-cooler events”, soapbox speeches in public squares, editorials, etc.
    • **Now:** 750M *public* social media posts/day
  • **Target population:** different than survey research!
    • **Surveys:** pop quizzes of everyone, even uninformed & inactive
    • **Social media:** counts only activated opinion
  • **Democracies:** Can ignore individuals, but collective expression sets agendas
  • **Autocracies:** Ignore criticism, but censor expression about collective action
Introduction

Research Design

Results

Supporting Analyses

Implications
Setup

• Signup 48 small media outlets (& > 12 others just for info)
  • 17 for trial runs, 33 in experiment, 2 in both
  • Median size: The Progressive, 50,000 subscribers
  • Other examples: Dissent Magazine, Truthout, Ms. Magazine, Yes!

• Establish 11 broad policy areas
  • Rules: (a) major national importance; (b) interest to outlets
  • race, immigration, jobs, abortion, climate, food policy, water, education policy, refugees, domestic energy production, and reproductive rights
  • Using 11 rather than 1: more representative; larger $n$ needed
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We choose a policy area (1 of 11)

Outlets volunteer for a pack of 2–5 (with our approval), following "project manager" protocol (e.g., Panama Papers)

The pack chooses subject for articles

We approve:
If rejected outlets can publish outside experiment

Requirement:
No breaking news (stories may be held for weeks)

Options:
large investigations, interview-based journalism, opinion pieces, or others normally published by pack members

Example.
Policy area: technology policy.
Subject: what Uber drivers think about driverless cars, or how a trade agreement affects hiring in Philadelphia

Outlets Publish Simultaneously:
(following usual procedures)

One article on subject per pack member

Distribute via website, print, video, podcast, etc.

Promote via Google adwords, social media, email lists, SEO…

Co- and cross-promote with outlets in same pack
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• Select pair of weeks: matched on similarity of predicted news
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(Ex post: Predictions accurate; flips, news shocks uncorrelated)

Reasoning

• Cf. complete randomization: more power, efficiency, & "political" robustness; less bias, model dependence, & research costs; SEs as much as 600% smaller (Imai, King, Nall 2008)
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11/23
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Most analysts: fix $n$, run experiment, discover $p$-value

• If $n$ is too large: waste time & resources
• If $n$ is too small: waste the entire experiment
  $\Rightarrow$ neither is acceptable with such massive logistical costs

Power calculations: require knowing QOI!

• Better: fix $p$-value, run experiment sequentially, discover $n$
  • Collect only as much data as you need
    (Why should you be in grad school longer than necessary?)
  • Valid statistically under likelihood or Bayes
    (Careful of misinformation in some applied literatures)

We introduce new methods to:

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Results from Sequential Hypothesis Tests

Our Stopping Rule:

\[ p \leq 0.05 \]

Joint test: day 1, 2, 3, policy, subject; for \( n, n-1, \) & \( n-2 \)

Recognizing more data is better and logistics are complicated (they might stop us!)

Empirical result: \( n = 70 \) (35 experiments)

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- **Our Stopping Rule:**
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Main Causal Effect: Public Expression in Policy Areas
Main Causal Effect: Public Expression in Policy Areas

Results
Main Causal Effect: Public Expression in Policy Areas

- **Red Dots**: model-based estimate (assumes linearity over days)
Main Causal Effect: Public Expression in Policy Areas

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Main Causal Effect: Public Expression in Policy Areas

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- **Causal effects:** 1st day: 19.4% increase,
Main Causal Effect: Public Expression in Policy Areas

- **Red Dots:** model-based estimate (assumes linearity over days)
- **Open circles:** model-free estimate (no model, higher variance)
- **Causal effects:** 1st day: 19.4% increase, Total: 62.7% increase
Causal Effect: Indistinguishable Across Subgroups
Causal Effect: Indistinguishable Across Subgroups

Results
Causal Effect: Indistinguishable Across Subgroups

Effect on the national conversation in major policy areas is national
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Causal Heterogeneity: Leave-One-Outlet-Out

• Red Dots: Original (model-based) estimates
• Open circles: same, with one outlet dropped from any packs
• Results: no dominant outlet; high heterogeneity
Causal Heterogeneity: Leave-One-Outlet-Out

Jackknife Estimation on Policy Area Effects
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Introduction

Research Design

Results

Supporting Analyses

Implications
High Experimental Compliance

• # Articles published by pack in policy area

• Causal effect on # articles:

• \(2.94\)

\(\Rightarrow\) high compliance

• Pageviews (on subject of articles, relative to a day’s volume)

• Causal effect on # pageviews:

• \(969.6\% (52,223 \text{ views})\) increase

\(\Rightarrow\) high compliance

Supporting Analyses
High Experimental Compliance

- # Articles published by pack in policy area
High Experimental Compliance

- # Articles published by pack in policy area
  - What’s the goal? Average # media outlets per pack:
    - Causal effect on # articles: 2.94
    - Causal effect on # pageviews: 969.6% (52,223 views) increase
      - \( \Rightarrow \) high compliance
High Experimental Compliance

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Causal Effect on Subject of Articles

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Causal Effect on Subject of Articles

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**Causal effects:**
1st day: 454% increase,
Total: 1,666% increase
Causal Effect on Subject of Articles

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Other Supporting Analyses

- **More Results**
  - Opinion change: 2.3% change in direction of article opinion

- **Large news media outlets**
  - Observational evidence, 15x effect

- **Robustness checks**
  - # of unique authors: little change from effect on posts
  - Removing bots, retweets: No real change
  - Week 1 to 2 spillover, noncompliance: No evidence
  - Treatment articles: representative of all on complexity, type
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• Small outlets: very large average effects on pageviews, agenda (subject & policy), opinion change
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• Heterogeneous effects: large, highly variable viral patterns

Implications: for individual journalists
• Remarkable power; serious responsibility; not just another job

Implications: for ecosystem of media outlets
• Control over editorial boards and mastheads
• Balance and diversity of outlet opinion
• Effects of fake news
• Impact on agendas, elections, public policy, discourse

Journalism jobs: 25% drop in last decade

What should be next?
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Implications 23/23
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Notation and Quantities of Interest

- **Outcome Variable:** $y_{ped}$, number of social media posts in each policy area ($p = 1, \ldots, 11$)
- **Experiment:** $e$ ($e = 1, \ldots, E$)
- **Day of and after intervention:** $d$ ($d = 1, \ldots, 6$)

- **Treatment Variable:** $T_{ped}$, instruction to pack (of 2-5 outlets) to write, publish, and promote articles, like a project manager

- **Treated weeks:** $T_{pe1} = \ldots = T_{pe6} = 1$
- **Control weeks:** $T_{pe1} = \ldots = T_{pe6} = 0$

- **Quantities of Interest**
  - **Absolute Increase:** $\lambda_d = \text{mean}_{p,e}[y_{ped}(1)] - \text{mean}_{p,e}[y_{ped}(0)]$
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Estimation Approaches

- **Model-Based Approach**
  - Transform outcome variable for normality & homoskedasticity:
    \[ z_{ped} = \ln(y_{ped} + 0.5) \]
  - The Model:
    \[ E(z_{ped} | T_{ped}) = \beta_0 + \beta_p + \eta_d + \gamma_d T_{ped} \]
    - \[ \beta_0 \]: constant term
    - \[ \beta_p \]: fixed effects for the 11 policy areas
    - Assume linearity over days:
      \[ \eta_d = \eta_0 + \eta_1 d \]
      \[ \gamma_d T_{ped} \]
    - Assume conditional independence over \( p, e, d \)

- **Model-Free Approach**
  - Drop linearity & conditional independence assumptions
  - Regress \( z_{ped} \) on \( T_{ped} \) separately for each \( d \)
    - Equivalent to difference in means for each day
      (perhaps with policy fixed effects)
Estimation Approaches

• Model-Based Approach

\[ z_{ped} = \ln(y_{ped} + 0.5) \]

The Model:
\[ E(z_{ped} | T_{ped}) = \beta_0 + \beta_p + \eta_d + \gamma_d T_{ped} \]

- \( \beta_0 \): constant term
- \( \beta_p \): fixed effects for the 11 policy areas
- Assume linearity over days:
  \[ \eta_d = \eta_0 + \eta_1 d \]
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Assume conditional independence over \( p, e, d \)

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