How the News Media Activate Public Expression and Influence National Agendas

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

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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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Political Problems: They Won’t Let Us Randomize

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

Scientists require:

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Our Approach:

Let's Randomize

• 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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Define Outcome Variable: Types of News Media Effects

• 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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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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  - race, immigration, jobs, abortion, climate, food policy, water, education policy, refugees, domestic energy production, and reproductive rights
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  - Using 11 rather than 1: more representative; larger $n$ needed
Treatment

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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- Matched Pair Randomization
  - Select pair of weeks: matched on similarity of predicted news
  - One coin flip: which week is treatment and which control
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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)
- Few experiments/outlet: less interference; more heterogeneity
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Methods:
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Intervention

Downloads from outlets

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Research Design

11/23
Quantities of Interest (& observable implications)

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Research Design
Determining $n$ via Sequential Hypothesis Testing

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:

• Evaluate robustness under frequentist theory
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- Our Stopping Rule:
  - \( p \leq 0.05 \), joint test: day 1, 2, 3, policy, subject;
  - for \( n, n-1, \) & \( n-2 \)

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

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  • and logistics are complicated (they might stop us!)

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$n = 70$ (35 experiments)

Frequentist validation: extensive [non]parametric tests
Results from Sequential Hypothesis Tests

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```
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<th>Days</th>
<th>Classical p-values</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.0</td>
</tr>
<tr>
<td>1-2</td>
<td>0.1</td>
</tr>
<tr>
<td>1-3</td>
<td>0.2</td>
</tr>
<tr>
<td>1-4</td>
<td>0.3</td>
</tr>
<tr>
<td>1-5</td>
<td>0.4</td>
</tr>
<tr>
<td>1-6</td>
<td>0.5</td>
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</tbody>
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```

Frequentist validation: extensive [non]parametric tests

14/23
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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

- **Red Dots**: model-based estimate (assumes linearity over days)
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Causal Effect: Indistinguishable Across Subgroups
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Results
Causal Effect: Indistinguishable Across Subgroups

Effect on the national conversation in major policy areas is national
Causal Effect: Indistinguishable Across Subgroups

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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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Supporting Analyses

Implications
High Experimental Compliance

- Articles published by pack in policy area
- Average # media outlets per pack: 3.1
- 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 views) increase
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Supporting Analyses 19/23
High Experimental Compliance

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- 1st day: 454% increase,
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- Large news media outlets: Observational evidence, >15x effect
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  - Removing bots, retweets: No real change
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- More Results
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Summary

• Small outlets: very large average effects on pageviews, agenda (subject & policy), opinion change

• Larger outlets: even bigger average effects

• 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

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• We wrote a paper, built a platform, & showed how others can

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GaryKing.org/media
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• Outcome Variable: $y_{ped}$, # social media posts in policy area $p$ ($p = 1, \ldots, 11$)

• Experiment $e$ ($e = 1, \ldots, E$)

• Day of and after intervention ($d = 1, \ldots, 6$)

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

• Treated weeks: $T_{ped1} = \ldots = T_{ped6} = 1$

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• 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:
    \[ \eta_d = \eta_0 + \eta_1 d \]
    \[ \gamma_d = \gamma_0 + \gamma_1 d \]
  - 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:
  \[ E(z_{ped} | T_{ped}) = \beta_0 + \beta_p T_{ped} + \eta_d + \gamma_d T_{ped} \]

  - \( \beta_0 \): 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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    - $\beta^0$: constant term

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