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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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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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/year
  - 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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- 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

- Repeat the following as many times “as needed”:
  - New methods to determine (described shortly)
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• **Repeat the following as many times “as needed”:** New methods to determine (described shortly)
Treatment

- We choose policy areas following "project manager" protocol (e.g., Panama Papers).

- Outlets volunteer for a pack of 2–5, subject for articles.

- We approve if rejected outlets can publish outside the 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 social media, Google adwords, email lists, SEO...

- Co- and cross-promote with outlets in the same pack.
Treatment

- We choose a policy areas (1 of 11)
Treatment

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- **Outlets Publish Simultaneously:** (following usual procedures)
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Matched Pair Randomization

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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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Random Treatment → Articles Published → Pageviews → Posts on Subject → Posts in Policy Area
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- Social media: King, Pan, Roberts (2017)
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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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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  - and logistics are complicated (they might stop us!)

- **Empirical result:**
Results from Sequential Hypothesis Tests

- **Our Stopping Rule:**
  - $p \leq 0.05$, joint test: day 1,2,3, policy, subject; for $n, n-1,$ & $n-2$
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Main Causal Effect: Public Expression in Policy Areas

Results
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Main Causal Effect: Public Expression in Policy Areas

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- **Causal effects**: 1st day: 19.4% increase, Total: 62.7% increase
Causal Effect: Indistinguishable Across Subgroups
Causal Effect: Indistinguishable Across Subgroups

Results

<table>
<thead>
<tr>
<th>Region</th>
<th>Day 1</th>
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<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
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Effect on the national conversation in major policy areas is national
Causal Effect: Indistinguishable Across Subgroups

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<tr>
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<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
<th>Day 6</th>
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</thead>
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<tr>
<td>Republicans</td>
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<tr>
<td>No Party</td>
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Causal Effect: Indistinguishable Across Subgroups

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

- Articles published by pack in policy area
- Causal effect on # articles: 2.94
  - \[\implies\] 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
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**Causal effects:**
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  • Large news media outlets: Observational evidence, >15x effect

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  • # of unique authors: little change from effect on posts
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  - 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
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For more information:
GaryKing.org/media
Notation and Quantities of Interest

- **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:** $d$ ($d = 1, \ldots, 6$)

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

- **Treated weeks:** $T_{pe1} = \ldots = T_{pe6} = 1$
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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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• **Quantities of Interest**
  • Absolute Increase: $\lambda_d = \text{mean}_{p,e}[Y_{ped}(1)] - \text{mean}_{p,e}[Y_{ped}(0)]$
Notation and Quantities of Interest

- **Outcome Variable:** $y_{ped}$, # social media posts in
  - policy area $p$ ($p = 1, \ldots, 11$)
  - experiment $e$ ($e = 1, \ldots, E_p$)
  - day $d$ of and after intervention ($d = 1, \ldots, 6$)

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  - Proportionate Increase: $\phi_d = \frac{\lambda_d}{\text{mean}_{p,e}[Y_{ped}(0)]}$
Estimation Approaches

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