How the News Media Activate Public Expression and Influence National Agendas

Gary King

Institute for Quantitative Social Science
Harvard University

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

Research Design

Results

Supporting Analyses

Implications
Statistical Problems: We Can’t Randomize

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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3/23
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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,
technical infrastructure for large scale collaboration & data collection,
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:

- 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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- **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
• Examples:
  • 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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  ![Magazines]

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  ![Magazine covers]

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We choose a policy area

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.
Treatment

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

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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

• Treatment week: publish & promote articles (usually Tuesday)

• Control week: no compensation or special actions

(Ex post: Predictions accurate; flips, news shocks uncorrelated)
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![September 2015 Calendar](calendar-image.png)
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Research Design
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**SEPTMBER 2015**

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- (Ex post: Automated text analysis & qualitative evidence: indistinguishable from normal publications & practices; no outlet received a single complaint)
Quantities of Interest (& observable implications)
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Random Treatment → Articles Published → Pageviews → Posts on Subject → Posts in Policy Area

Intervention
Downloads from outlets
Special access to Google Analytics
Social media: King, Pan, Roberts (2017)
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Research Design
Quantities of Interest (& observable implications)

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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
    ⇝ 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)
  • Need to check sensitivity to priors and models
• 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)

- Frequentist validation: extensive [non]parametric tests
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![Graph showing classical p-values decreasing over days](image)
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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

Context:
3 small media outlets have huge effect on the national conversation
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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
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Jackknife Estimation on Policy Area Effects

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Supporting Analyses

Implications
High Experimental Compliance

• Articles published by pack in policy area
• What's the goal?
• Causal effect on # articles: 2.94
• ⟹ 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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• 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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• 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
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    - Impact on agendas, elections, public policy, discourse

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• Outcome Variable: $y_{ped}$, # social media posts in
  policy area $p = 1, \ldots, 11$

• 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: $T_{ped1} = \cdots = T_{ped6} = 1$

• Control weeks: $T_{ped1} = \cdots = T_{ped6} = 0$

• 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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- **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:
    \[ \eta_d = \eta_0 + \eta_1 d \]
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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 \( d \)
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