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)
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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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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
• Scientists 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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- **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
Introduction

Research Design

Results

Supporting Analyses

Implications
Setup

- Signup 48 small media outlets (and >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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  ![Magazines Images](image1.jpg)

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![Magazines](image)

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Research Design
Treatment

• 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
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Randomization

• 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**

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*Treatment Week*
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![Calendar](image_url)
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### 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
- Nation as unit of treatment: no spillover, more cost
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Quantities of Interest (& observable implications)
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Random Treatment • Articles Published • Pageviews • Posts on Subject • Posts in Policy Area

Methods: readme, 2010; readme2, 2018

Social media: King, Pan, Roberts (2017)
Quantities of Interest (& observable implications)

Random Treatment → Articles Published → Pageviews → Posts on Subject → Posts in Policy Area

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Downloads from outlets
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 $\Rightarrow$ 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)
• Need to check sensitivity to priors and models
• We introduce new methods to:
  • Evaluate robustness under frequentist theory
  • Remove parametric assumptions
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Introduction

Research Design

Results

Supporting Analyses

Implications
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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- **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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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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- Articles published by pack in policy area
- What's the goal?
- 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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19/23
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- 1st day: 454% increase,
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  - 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
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• 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

• What should be next?
  - We wrote a paper, built a platform, & showed how others can

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

**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:**
\[ \lambda_d = \text{mean}_{p,e} \left[ y_{ped}(1) \right] - \text{mean}_{p,e} \left[ y_{ped}(0) \right] \]

**Proportionate Increase:**
\[ \phi_d = \frac{\lambda_d}{\text{mean}_{p,e} \left[ y_{ped}(0) \right]} \]
Notation and Quantities of Interest

- **Outcome Variable:** $y_{ped}$, # social media posts in
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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: $\eta_d = \eta_0 + \eta_1 d$ and $\gamma_d = \gamma_0 + \gamma_1 d$
    - 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)
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