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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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: 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
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- 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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- 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*
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  ![Magazines](image)

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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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  ![Magazine Covers]

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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
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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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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
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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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  • $p \leq 0.05$, joint test: day 1,2,3, policy, subject; for $n$, $n - 1$, & $n - 2$
  • recognizing more data is better
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Main Causal Effect: Public Expression in Policy Areas
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Results

- 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
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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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Implications
High Experimental Compliance

• Articles published by pack in policy area
  - What's the goal?
  - Average # media outlets per pack: 3.1
  - 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
- 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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• 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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• Outcome Variable: \( y_{ped} \), number of 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: \( T_{pe1} = \cdots = T_{pe6} = 1 \)

• Control weeks: \( T_{pe1} = \cdots = T_{pe6} = 0 \)

• 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:
      \[ \eta_d = \eta_0 + \eta_1 d \]
      \[ \gamma_d T_{ped} = \gamma_0 + \gamma_1 d \]
    - Assume conditional independence over \( p, e, d \)

• Model-Free Approach:
  - Drop linearity & conditional independence assumptions
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- 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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