How the News Media Activate Public Expression and Influence National Agendas[1]

Gary King[2]

Institute for Quantitative Social Science
Harvard University

University of Toronto, Department of Political Science, 1/12/2018

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

Introduction

Research Design

Results

Supporting Analyses

Implications

Statistical Problems: We Can't Randomize

Statistical Problems: We Can't Randomize

- Statistical Problems

Statistical Problems: We Can't Randomize

- Statistical Problems
  - Randomization: usually impossible

Statistical Problems: We Can't Randomize

- Statistical Problems
  - Randomization: usually impossible
  - Endogeneity: media outlets compete for readers

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

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)

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

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

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

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…

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

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

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
    $\rightsquigarrow$ "Profound biases," > 600% difference from truth

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
    $\rightsquigarrow$ "Profound biases," > 600% difference from truth
  - Estimands: different, of sometimes questionable relevance

Political Problems: They Won't Let Us Randomize

Political Problems: They Won't Let Us Randomize

- What we'd do without constraints

Political Problems: They Won't Let Us Randomize

- What we'd do without constraints
  - Sign up many news media outlets

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

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

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?

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

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

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)

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,

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,

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,

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

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

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:

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

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:

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

Our Approach:

Our Approach: Let's Randomize

Our Approach: Let's Randomize

- Build trust: 5 years of negotiating & communicating

Our Approach: Let's Randomize

- Build trust: 5 years of negotiating & communicating
- Develop *incentive compatible* research design:

Our Approach: Let's Randomize

- Build trust: 5 years of negotiating & communicating
- Develop *incentive compatible* research design: both get 100%, no compromises;

Our Approach: Let's Randomize

- Build trust: 5 years of negotiating & communicating
- Develop *incentive compatible* research design: both get 100%, no compromises; $\rightsquigarrow$ solve a political problem technologically

Our Approach: Let's Randomize

- Build trust: 5 years of negotiating & communicating
- Develop *incentive compatible* research design: both get 100%, no compromises; $\rightsquigarrow$ solve a political problem technologically
- Convince 48 media outlets to let us experiment on them

Our Approach: Let's Randomize

- Build trust: 5 years of negotiating & communicating
- Develop *incentive compatible* research design: both get 100%, no compromises; $\rightsquigarrow$ solve a political problem technologically
- Convince 48 media outlets to let us experiment on them
- Whenever possible, choose realism (even if inconvenient)

Our Approach: Let's Randomize

- Build trust: 5 years of negotiating & communicating
- Develop *incentive compatible* research design: both get 100%, no compromises; $\rightsquigarrow$ 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

Our Approach: Let's Randomize

- Build trust: 5 years of negotiating & communicating
- Develop *incentive compatible* research design: both get 100%, no compromises; $\rightsquigarrow$ 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

Our Approach: Let's Randomize

- Build trust: 5 years of negotiating & communicating
- Develop *incentive compatible* research design: both get 100%, no compromises; $\rightsquigarrow$ 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
  - $\rightsquigarrow$ More expensive, logistically complicated, and time-consuming, but more generalizable

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

Our Approach: Let's Randomize

- Build trust: 5 years of negotiating & communicating
- Develop *incentive compatible* research design: both get 100%, no compromises; $\rightsquigarrow$ 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
  - $\rightsquigarrow$ More expensive, logistically complicated, and time-consuming, but more generalizable
- Goal: Build platform to continue experiments
- A work of: political science

Our Approach: Let's Randomize

- Build trust: 5 years of negotiating & communicating
- Develop *incentive compatible* research design: both get 100%, no compromises; $\rightsquigarrow$ 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
    - $\rightsquigarrow$ More expensive, logistically complicated, and time-consuming, but more generalizable
- Goal: Build platform to continue experiments
- A work of: political science

Our Approach: Let's Randomize

- Build trust: 5 years of negotiating & communicating
- Develop *incentive compatible* research design: both get 100%, no compromises; $\rightsquigarrow$ 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
  - $\rightsquigarrow$ More expensive, logistically complicated, and time-consuming, but more generalizable
- Goal: Build platform to continue experiments
- A work of: political science

Types of News Media Effects

Types of News Media Effects

- Individual-level Effects

Types of News Media Effects

- Individual-level Effects

- Collective Effects: Impact on the national conversation

Types of News Media Effects

- Individual-level Effects
  - Outcome variable: individual knowledge and opinion

- Collective Effects: Impact on the national conversation

Types of News Media Effects

- Individual-level Effects
  - Outcome variable: individual knowledge and opinion
  - Effects: Persuasion, attitude formation, diffusion, gatekeeping, priming, issue framing,
- Collective Effects: Impact on the national conversation

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

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

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

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

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.

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

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!

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

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

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

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

Setup

Setup

- Signup 48 small media outlets (& > 12 others just for info)

Setup

- Signup 48 small media outlets (& > 12 others just for info)
  - 17 for trial runs, 33 in experiment, 2 in both

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

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!*

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*

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

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

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

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
- Repeat the following as many times "as needed": New methods to determine (described shortly)

Treatment

Treatment

- We choose a policy areas (1 of 11)

Treatment

- We choose a policy areas (1 of 11)
- Outlets volunteer for a *pack* of 2–5 (with our approval), following "project manager" protocol (e.g., Panama Papers)

Treatment

- We choose a policy areas (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

Treatment

- We choose a policy areas (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
- Outlets Publish Simultaneously: (following usual procedures)

Treatment

- We choose a policy areas (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
- Outlets Publish Simultaneously: (following usual procedures)

Treatment

- We choose a policy areas (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)

- Outlets Publish Simultaneously: (following usual procedures)

Treatment

- We choose a policy areas (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
- Outlets Publish Simultaneously: (following usual procedures)

Treatment

- We choose a policy areas (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.
- Outlets Publish Simultaneously: (following usual procedures)

Treatment

- We choose a policy areas (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.
- Outlets Publish Simultaneously: (following usual procedures)

Treatment

- We choose a policy areas (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,
- Outlets Publish Simultaneously: (following usual procedures)

Treatment

- We choose a policy areas (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)

Treatment

- We choose a policy areas (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

Treatment

- We choose a policy areas (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.

Treatment

- We choose a policy areas (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 social media, Google adwords, email lists, SEO...

Treatment

- We choose a policy areas (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 social media, Google adwords, email lists, SEO...
  - Co- and cross-promote with outlets in same pack

Randomization

Randomization

Matched Pair Randomization

Randomization

Matched Pair Randomization

Reasoning

Randomization

Matched Pair Randomization

- Select pair of weeks: matched on similarity of *predicted* news

Reasoning

Randomization

Matched Pair Randomization

- Select pair of weeks: matched on similarity of *predicted* news
- *One* coin flip: which week is treatment and which control

Reasoning

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)

Reasoning

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

Reasoning

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)

Reasoning

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)

Reasoning

- Cf. complete randomization:

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)

Reasoning

- Cf. complete randomization: more power, efficiency, & "political" robustness;

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)

Reasoning

- Cf. complete randomization: more power, efficiency, & "political" robustness; less bias, model dependence, & research costs;

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)

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)

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)

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

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)

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

Randomization

Matched Pair Randomization

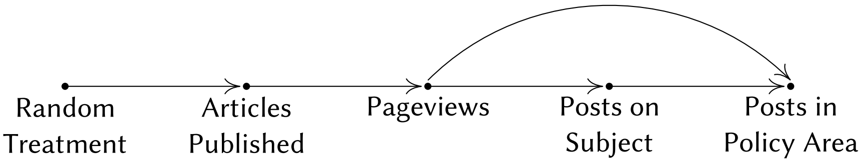
- Select pair of weeks: matched on similarity of *predicted* news
- *One* coin flip: which week is treatment and which control
    - Treatment week: publish & promote articles (usually Tuesday)
    - Control week: no compensation or special actions
- (Ex post: Predictions accurate; flips, news shocks uncorrelated)

Reasoning

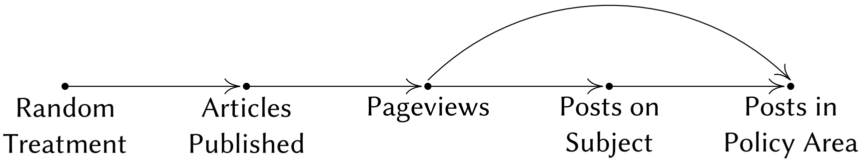
- Cf. complete randomization: more power, efficiency, & "political" robustness; less bias, model dependence, & research costs; SEs as much as 600% smaller (Imai, King, Nall 2008)
- Few experiments/outlet: Less interference; more heterogeneity
- Nation as unit of treatment: no spillover, more cost
- (Ex post: Automated text analysis & qualitative evidence: indistinguishable from normal publications & practices; no outlet received a single complaint)

Quantities of Interest (& observable implications)

Quantities of Interest (& observable implications)

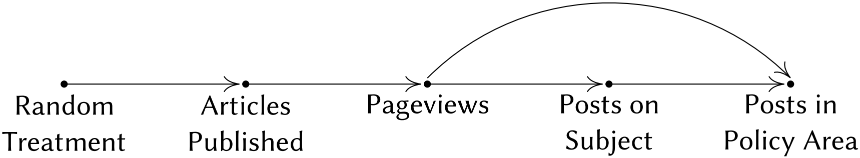


Quantities of Interest (& observable implications)



- Intervention

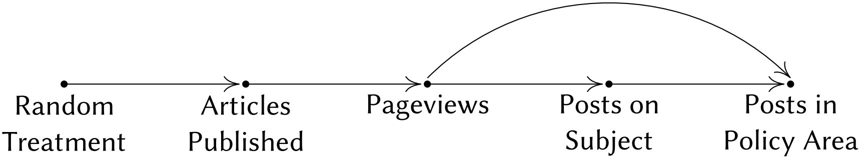
Quantities of Interest (& observable implications)



- Intervention

- Social media: Hopkins and King (“readme”, 2010); Jerzak, King, and Strezhnev (“readme2,” 2018)

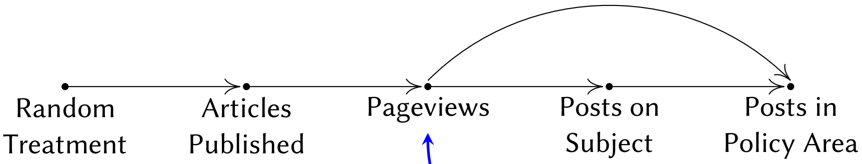
Quantities of Interest (& observable implications)



- Intervention
- Downloads from outlets

- Social media: Hopkins and King (“readme”, 2010); Jerzak, King, and Strezhnev (“readme2,” 2018)

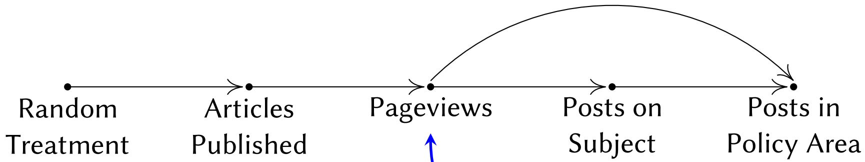
Quantities of Interest (& observable implications)



- Intervention
- Downloads from outlets
- Special access to Google Analytics

- Social media: Hopkins and King ("readme", 2010); Jerzak, King, and Strezhnev ("readme2," 2018)

Quantities of Interest (& observable implications)



- Intervention
- Downloads from outlets
- Special access to Google Analytics
- Social media: King, Pan, Roberts (2017)
- Social media: Hopkins and King (“readme”, 2010); Jerzak, King, and Strezhnev (“readme2,” 2018)

Determining n via Sequential Hypothesis Testing

Determining n via Sequential Hypothesis Testing

- *Most analysts:* fix n, run experiment, discover p-value

Determining n via Sequential Hypothesis Testing

- Most analysts: fix n, run experiment, discover p-value
  - If n is too large: waste time & resources

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

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

    $\rightsquigarrow$ neither is acceptable with such massive logistical costs

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
    $\rightsquigarrow$ neither is acceptable with such massive logistical costs
  - Power calculations: require knowing QOI!

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
    $\rightsquigarrow$ neither is acceptable with such massive logistical costs
  - Power calculations: require knowing QOI!
- Better: fix p-value, run experiment sequentially, discover n

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
    $\rightsquigarrow$ 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

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
    $\rightsquigarrow$ 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?)

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
    $\rightsquigarrow$ 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

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
    $\rightsquigarrow$ 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)

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
    $\rightsquigarrow$ 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:

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
    $\rightsquigarrow$ 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

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
    $\rightsquigarrow$ 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
    - Remove parametric assumptions

Results from Sequential Hypothesis Tests

Results from Sequential Hypothesis Tests

- Our Stopping Rule:

Results from Sequential Hypothesis Tests

- Our Stopping Rule:
  - $p \leq 0.05$,

Results from Sequential Hypothesis Tests

- Our Stopping Rule:
  - $p \leq 0.05$, joint test: day 1,2,3, policy, subject;

Results from Sequential Hypothesis Tests

- Our Stopping Rule:
  - $p \leq 0.05$, joint test: day 1,2,3, policy, subject; for n, $n-1$, & $n-2$

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

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!)

Results from Sequential Hypothesis Tests

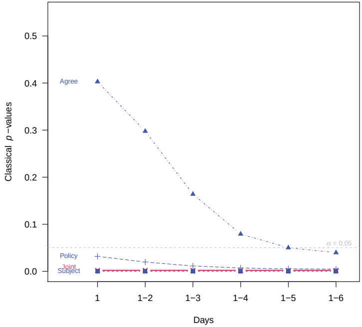
- Our Stopping Rule:
  - $p \leq 0.05$, joint test: day 1,2,3, policy, subject; for n, $n-1$, & $n-2$
  - recognizing more data is better
  - and logistics are complicated (they might stop us!)
- Empirical result:

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)

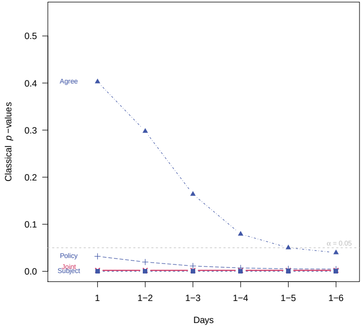
Results from Sequential Hypothesis Tests

- 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)



Results from Sequential Hypothesis Tests

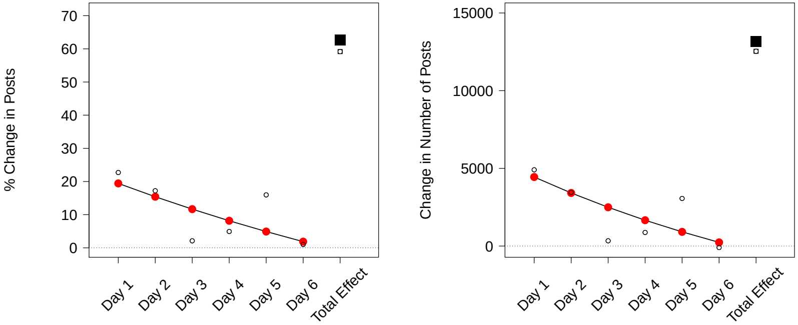
- Our Stopping Rule:
  - $p \leq 0.05$, joint test: day 1,2,3, policy, subject; for n, $n-1$, & $n-2$
  - recognizing more data is better
  - and logistics are complicated (they might stop us!)
- Empirical result: $n = 70$ (35 experiments)



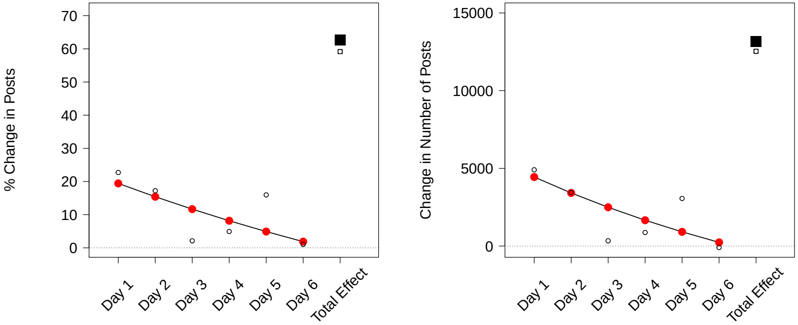
- Frequentist validation: extensive [non]parametric tests

Main Causal Effect: Public Expression in Policy Areas

Main Causal Effect: Public Expression in Policy Areas

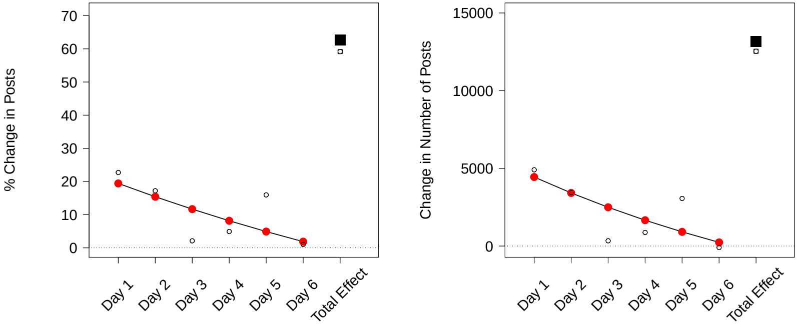


Main Causal Effect: Public Expression in Policy Areas



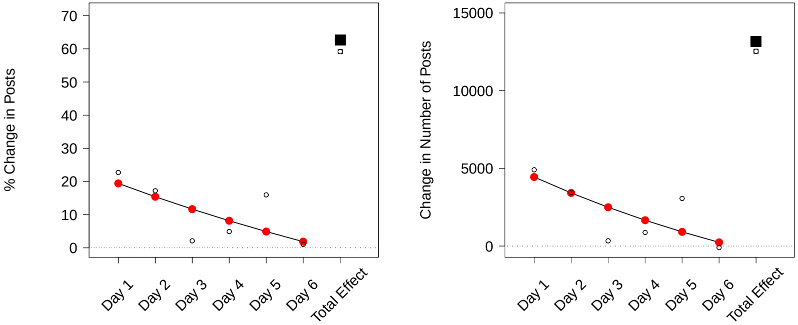
- Red Dots: model-based estimate (assumes linearity over days)

Main Causal Effect: Public Expression in Policy Areas



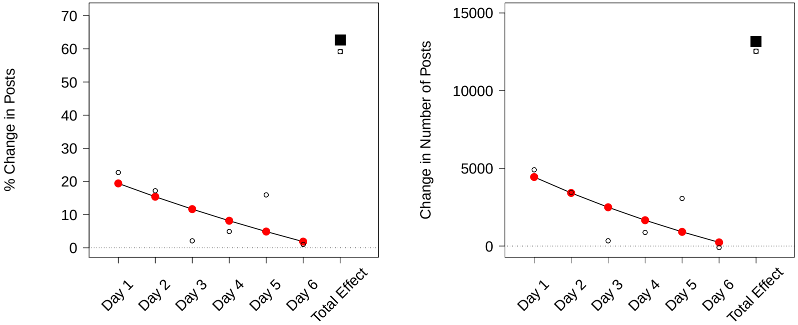
- Red Dots: model-based estimate (assumes linearity over days)
- Open circles: model-free estimate (no model, higher variance)

Main Causal Effect: Public Expression in Policy Areas



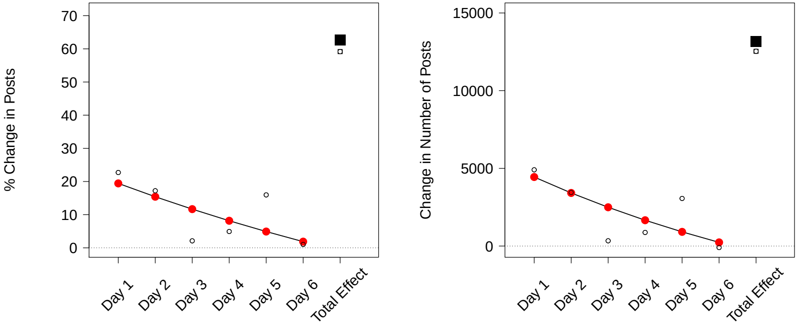
- Red Dots: model-based estimate (assumes linearity over days)
- Open circles: model-free estimate (no model, higher variance)
- Causal effects:

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,

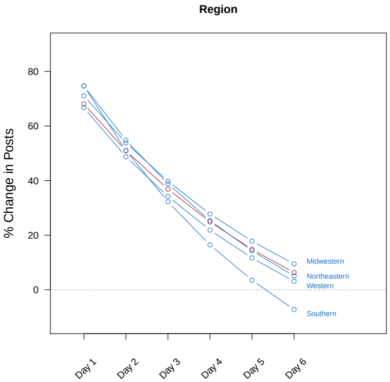
Main Causal Effect: Public Expression in Policy Areas



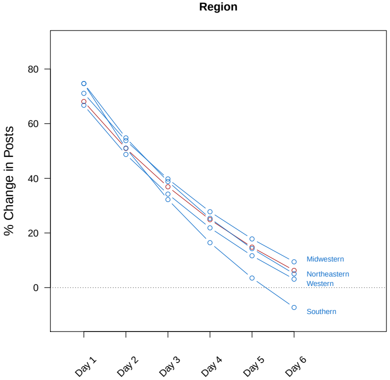
- Red Dots: model-based estimate (assumes linearity over days)
- Open circles: model-free estimate (no model, higher variance)
- Causal effects: 1st day: 19.4% increase, Total: 62.7% increase

Causal Effect: Indistinguishable Across Subgroups

Causal Effect: Indistinguishable Across Subgroups

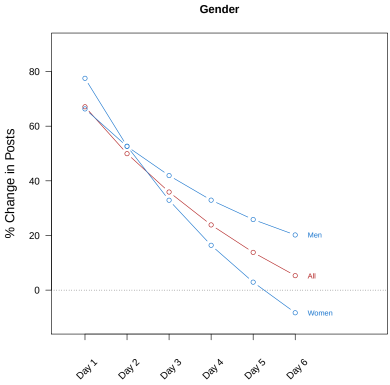


Causal Effect: Indistinguishable Across Subgroups



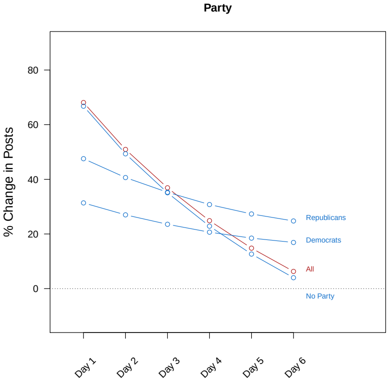
Effect on the national conversation in major policy areas is national

Causal Effect: Indistinguishable Across Subgroups



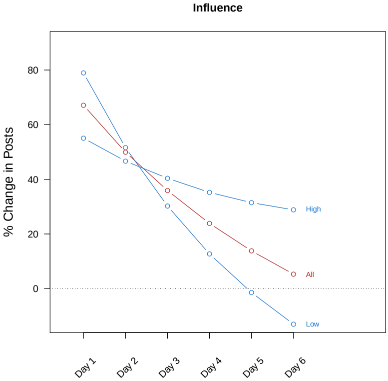
Effect on the national conversation in major policy areas is national

Causal Effect: Indistinguishable Across Subgroups



Effect on the national conversation in major policy areas is national

Causal Effect: Indistinguishable Across Subgroups

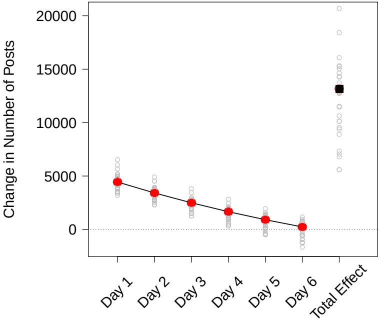


Effect on the national conversation in major policy areas is national

Causal Heterogeneity: Leave-One-Outlet-Out

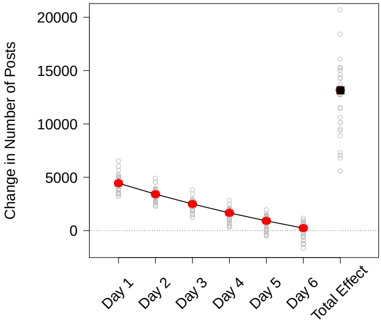
Causal Heterogeneity: Leave-One-Outlet-Out

Jackknife Estimation on Policy Area Effects



Causal Heterogeneity: Leave-One-Outlet-Out

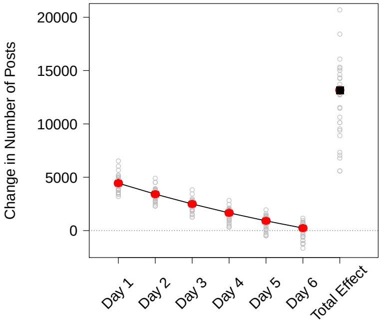
Jackknife Estimation on Policy Area Effects



- Red Dots: Original (model-based) estimates

Causal Heterogeneity: Leave-One-Outlet-Out

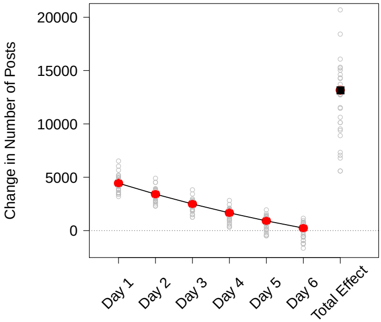
Jackknife Estimation on Policy Area Effects



- Red Dots: Original (model-based) estimates
- Open circles: same, with one outlet dropped from any packs

Causal Heterogeneity: Leave-One-Outlet-Out

Jackknife Estimation on Policy Area Effects



- Red Dots: Original (model-based) estimates
- Open circles: same, with one outlet dropped from any packs
- Results: no dominant outlet; high heterogeneity

High Experimental Compliance

High Experimental Compliance

- # Articles published by pack in policy area

High Experimental Compliance

- # Articles published by pack in policy area
  - What's the goal? Average # media outlets per pack:

High Experimental Compliance

- # Articles published by pack in policy area
  - What's the goal? Average # media outlets per pack: 3.1

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:

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 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
  - $\implies$ high compliance

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
  - $\implies$ high compliance
- Pageviews (on subject of articles, relative to a day's volume)

High Experimental Compliance

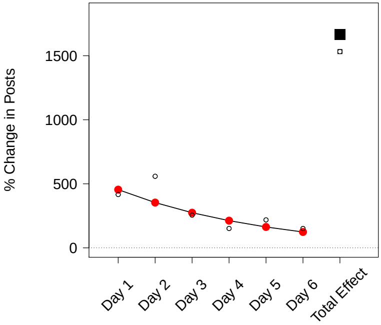
- # Articles published by pack in policy area
    - What's the goal? Average # media outlets per pack: 3.1
    - Causal effect on # articles: 2.94
    - $\implies$ high compliance
- Pageviews (on subject of articles, relative to a day's volume)
    - Causal effect on # pageviews: 969.6% (52,223 views) increase

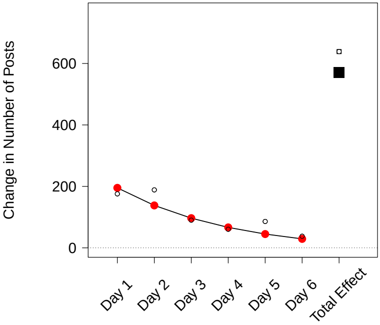
High Experimental Compliance

- # Articles published by pack in policy area
  - What's the goal? Average # media outlets per pack: 3.1
  - Causal effect on # articles: 2.94
  - $\implies$ high compliance
- Pageviews (on subject of articles, relative to a day's volume)
  - Causal effect on # pageviews: 969.6% (52,223 views) increase
  - $\implies$ high compliance

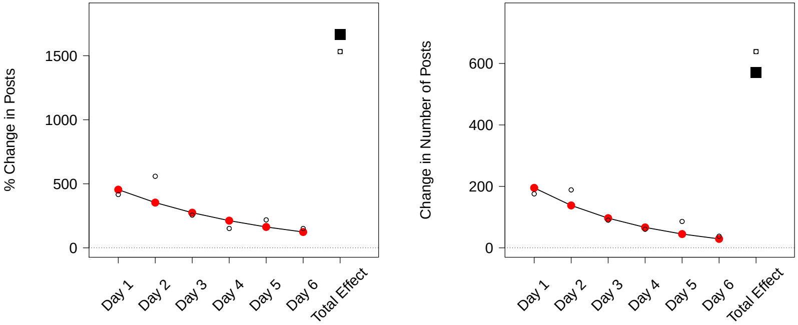
Causal Effect on Subject of Articles

Causal Effect on Subject of Articles



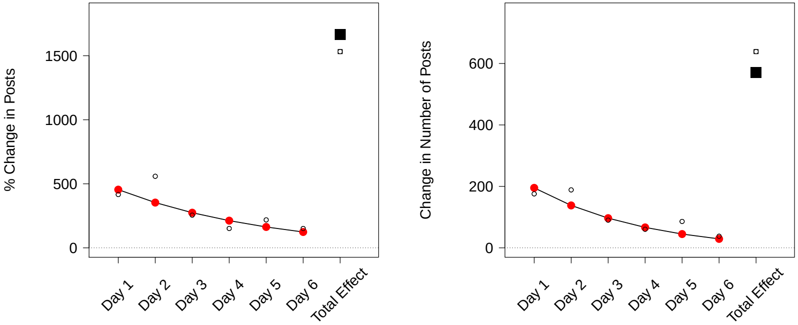


Causal Effect on Subject of Articles



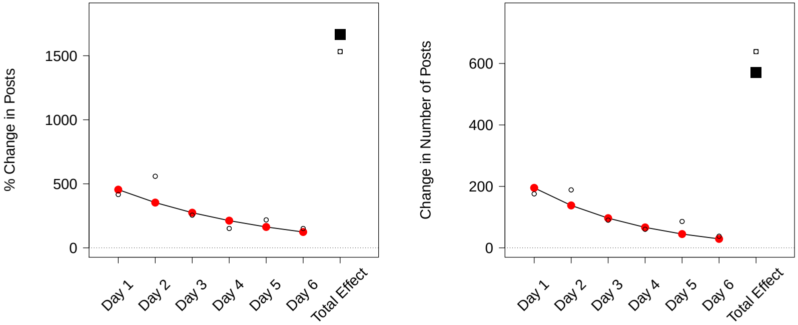
- Red Dots: model-based estimate (assumes linearity over days)

Causal Effect on Subject of Articles



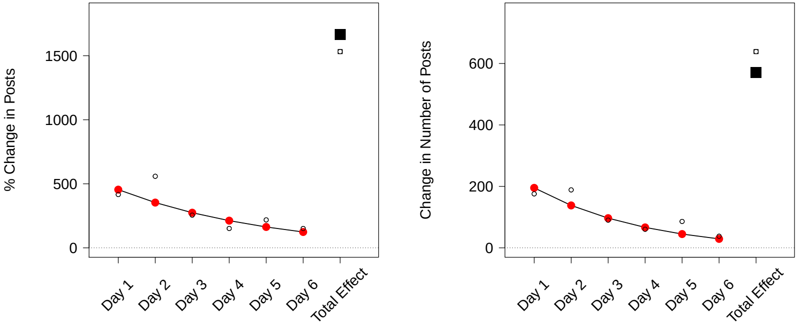
- Red Dots: model-based estimate (assumes linearity over days)
- Open circles: model-free estimate (no model, higher variance)

Causal Effect on Subject of Articles



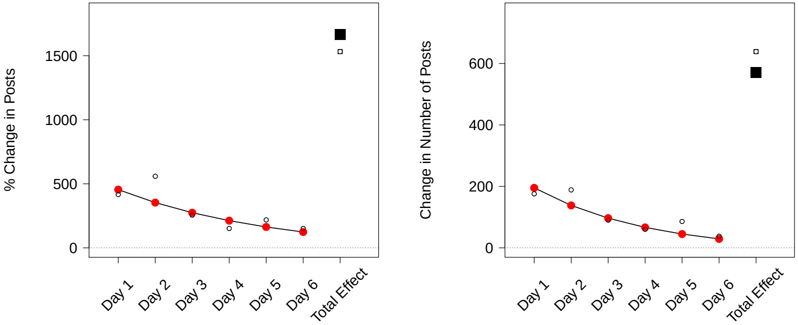
- Red Dots: model-based estimate (assumes linearity over days)
- Open circles: model-free estimate (no model, higher variance)
- Causal effects:

Causal Effect on Subject of Articles



- Red Dots: model-based estimate (assumes linearity over days)
- Open circles: model-free estimate (no model, higher variance)
- Causal effects: 1st day: 454% increase,

Causal Effect on Subject of Articles



- Red Dots: model-based estimate (assumes linearity over days)
- Open circles: model-free estimate (no model, higher variance)
- Causal effects: 1st day: 454% increase, Total: 1,666% increase

Other Supporting Analyses

Other Supporting Analyses

- More Results

Other Supporting Analyses

- More Results
  - Opinion change: 2.3% change in direction of article opinion

Other Supporting Analyses

- More Results
  - Opinion change: 2.3% change in direction of article opinion
  - Cross-experiment causal heterogeneity: Large

Other Supporting Analyses

- More Results
  - Opinion change: 2.3% change in direction of article opinion
  - Cross-experiment causal heterogeneity: Large
  - Large news media outlets: Observational evidence, >15x effect

Other Supporting Analyses

- More Results
  - Opinion change: 2.3% change in direction of article opinion
  - Cross-experiment causal heterogeneity: Large
  - Large news media outlets: Observational evidence, >15x effect
- Robustness checks

Other Supporting Analyses

- More Results
  - Opinion change: 2.3% change in direction of article opinion
  - Cross-experiment causal heterogeneity: Large
  - Large news media outlets: Observational evidence, >15x effect
- Robustness checks
  - # of unique authors: little change from effect on posts

Other Supporting Analyses

- More Results
  - Opinion change: 2.3% change in direction of article opinion
  - Cross-experiment causal heterogeneity: Large
  - 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

Other Supporting Analyses

- More Results
  - Opinion change: 2.3% change in direction of article opinion
  - Cross-experiment causal heterogeneity: Large
  - 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

Other Supporting Analyses

- More Results
  - Opinion change: 2.3% change in direction of article opinion
  - Cross-experiment causal heterogeneity: Large
  - 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

Summary and Implications

Summary and Implications

- Summary

Summary and Implications

- Summary

- Implications: for individual journalists

Summary and Implications

- Summary

- Implications: for individual journalists

- Implications: for ecosystem of media outlets

Summary and Implications

- Summary
- Implications: for individual journalists
- Implications: for ecosystem of media outlets
- What should be next?

Summary and Implications

- Summary
  - Small outlets: very large average effects

- Implications: for individual journalists

- Implications: for ecosystem of media outlets

- What should be next?

Summary and Implications

- Summary
  - Small outlets: very large average effects
- Implications: for individual journalists
- Implications: for ecosystem of media outlets
- What should be next?

Summary and Implications

- Summary
  - Small outlets: very large average effects on pageviews,
- Implications: for individual journalists
- Implications: for ecosystem of media outlets
- What should be next?

Summary and Implications

- Summary
  - Small outlets: very large average effects on pageviews, agenda (subject & policy),
- Implications: for individual journalists
- Implications: for ecosystem of media outlets
- What should be next?

Summary and Implications

- Summary
  - Small outlets: very large average effects
    on pageviews, agenda (subject & policy), opinion change
- Implications: for individual journalists
- Implications: for ecosystem of media outlets
- What should be next?

Summary and Implications

- Summary
  - Small outlets: very large average effects
    on pageviews, agenda (subject & policy), opinion change
  - Larger outlets: even bigger average effects

- Implications: for individual journalists

- Implications: for ecosystem of media outlets

- What should be next?

Summary and Implications

- 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
- Implications: for ecosystem of media outlets
- What should be next?

Summary and Implications

- 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
- What should be next?

Summary and Implications

- 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
- What should be next?

Summary and Implications

- 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
- What should be next?

Summary and Implications

- 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
- What should be next?

Summary and Implications

- 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

- What should be next?

Summary and Implications

- 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
- What should be next?

Summary and Implications

- 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
- What should be next?
  - We wrote a paper,

Summary and Implications

- 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
- What should be next?
  - We wrote a paper, built a platform,

Summary and Implications

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

Summary and Implications

- 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
- What should be next?
  - We wrote a paper, built a platform, & showed how others can
  - What experiment would you (or should we) run next?

Summary and Implications

- 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
- What should be next?
  - We wrote a paper, built a platform, & showed how others can
  - What experiment would you (or should we) run next?

For more information:
GaryKing.org/media

Notation and Quantities of Interest

Notation and Quantities of Interest

- Outcome Variable: y_{ped}, # social media posts in

Notation and Quantities of Interest

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

Notation and Quantities of Interest

- Outcome Variable: y_{ped}, # social media posts in
  - policy area p ($p = 1, \ldots, 11$)
  - experiment e ($e = 1, \ldots, E_p$)

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 ($d = 1, \ldots, 6$)

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 ($d = 1, \ldots, 6$)
- Treatment Variable: T_{ped}, instruction to pack (of 2-5 outlets) to write, publish, and promote articles, like a project manager

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 ($d = 1, \ldots, 6$)
- Treatment Variable: T_{ped}, instruction to pack (of 2-5 outlets) to write, publish, and promote articles, like a project manager
  - Treated weeks: $T_{pe1} = \cdots = T_{pe6} = 1$

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 ($d = 1, \ldots, 6$)
- 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: $T_{pe1} = \cdots = T_{pe6} = 0$

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

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 ($d = 1, \ldots, 6$)
- 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: $\lambda_d = \underset{p,e}{\text{mean}}[Y_{ped}(1)] - \underset{p,e}{\text{mean}}[Y_{ped}(0)]$

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 ($d = 1, \ldots, 6$)
- 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: $\lambda_d = \underset{p,e}{\text{mean}}[Y_{ped}(1)] - \underset{p,e}{\text{mean}}[Y_{ped}(0)]$
  - Proportionate Increase: $\phi_d = \dfrac{\lambda_d}{\text{mean}_{p,e}[Y_{ped}(0)]}$

Estimation Approaches

Estimation Approaches

- Model-Based Approach

Estimation Approaches

- Model-Based Approach
  - Transform outcome variable for normality & homoskedasticity: $z_{ped} = \ln(y_{ped} + 0.5)$

Estimation Approaches

- Model-Based Approach
  - Transform outcome variable for normality & homoskedasticity: $z_{ped} = \ln(y_{ped} + 0.5)$
  - The Model: $E(z_{ped}|T_{ped}) = \beta^0 + \beta_p + \eta_d + \gamma_d T_{ped}$

Estimation Approaches

- Model-Based Approach
  - Transform outcome variable for normality & homoskedasticity: $z_{ped} = \ln(y_{ped} + 0.5)$
  - The Model: $E(z_{ped}|T_{ped}) = \beta^0 + \beta_p + \eta_d + \gamma_d T_{ped}$
    - β^0: constant term

Estimation Approaches

- Model-Based Approach
  - Transform outcome variable for normality & homoskedasticity: $z_{ped} = \ln(y_{ped} + 0.5)$
  - The Model: $E(z_{ped}|T_{ped}) = \beta^0 + \beta_p + \eta_d + \gamma_d T_{ped}$
    - β^0: constant term
    - β_p: fixed effects for the 11 policy areas

Estimation Approaches

- Model-Based Approach
  - Transform outcome variable for normality & homoskedasticity: $z_{ped} = \ln(y_{ped} + 0.5)$
  - The Model: $E(z_{ped}|T_{ped}) = \beta^0 + \beta_p + \eta_d + \gamma_d T_{ped}$
    - β^0: constant term
    - β_p: fixed effects for the 11 policy areas
    - Assume linearity over days: $\eta_d = \eta^0 + \eta^1 d$ and $\gamma_d = \gamma^0 + \gamma^1 d$

Estimation Approaches

- Model-Based Approach
  - Transform outcome variable for normality & homoskedasticity: $z_{ped} = \ln(y_{ped} + 0.5)$
  - The Model: $E(z_{ped}|T_{ped}) = \beta^0 + \beta_p + \eta_d + \gamma_d T_{ped}$
    - β^0: constant term
    - β_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

Estimation Approaches

- Model-Based Approach
  - Transform outcome variable for normality & homoskedasticity: $z_{ped} = \ln(y_{ped} + 0.5)$
  - The Model: $E(z_{ped}|T_{ped}) = \beta^0 + \beta_p + \eta_d + \gamma_d T_{ped}$
    - β^0: constant term
    - β_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:

Estimation Approaches

- Model-Based Approach
  - Transform outcome variable for normality & homoskedasticity: $z_{ped} = \ln(y_{ped} + 0.5)$
  - The Model: $E(z_{ped}|T_{ped}) = \beta^0 + \beta_p + \eta_d + \gamma_d T_{ped}$
    - β^0: constant term
    - β_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

Estimation Approaches

- Model-Based Approach
  - Transform outcome variable for normality & homoskedasticity: $z_{ped} = \ln(y_{ped} + 0.5)$
  - The Model: $E(z_{ped}|T_{ped}) = \beta^0 + \beta_p + \eta_d + \gamma_d T_{ped}$
    - β^0: constant term
    - β_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

Estimation Approaches

- Model-Based Approach
  - Transform outcome variable for normality & homoskedasticity: $z_{ped} = \ln(y_{ped} + 0.5)$
  - The Model: $E(z_{ped}|T_{ped}) = \beta^0 + \beta_p + \eta_d + \gamma_d T_{ped}$
    - β^0: constant term
    - β_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

Estimation Approaches

- Model-Based Approach
  - Transform outcome variable for normality & homoskedasticity: $z_{ped} = \ln(y_{ped} + 0.5)$
  - The Model: $E(z_{ped}|T_{ped}) = \beta^0 + \beta_p + \eta_d + \gamma_d T_{ped}$
    - β^0: constant term
    - β_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)