

# Progressive Media Impact: Metrics, Evaluation, and Improvement

Gary King

Institute for Quantitative Social Science  
Harvard University

(talk at The Media Consortium, San Francisco, 10/13/2011)

# Goals

- **Measure** public discourse

# Goals

- **Measure** public discourse
- Estimate the **causal effect** of the progressive media on discourse

# Goals

- **Measure** public discourse
- Estimate the **causal effect** of the progressive media on discourse
- **Learn together** how to make the progressive media more effective

- **Measure** public discourse
- Estimate the **causal effect** of the progressive media on discourse
- **Learn together** how to make the progressive media more effective
- Take advantage of **recent dramatic scientific advances**:

- **Measure** public discourse
- Estimate the **causal effect** of the progressive media on discourse
- **Learn together** how to make the progressive media more effective
- Take advantage of **recent dramatic scientific advances**:
  - Informative data now available on the public debate

- **Measure** public discourse
- Estimate the **causal effect** of the progressive media on discourse
- **Learn together** how to make the progressive media more effective
- Take advantage of **recent dramatic scientific advances**:
  - Informative data now available on the public debate
  - Measurement methods: meaning, not word counts



- **Measure** public discourse
- Estimate the **causal effect** of the progressive media on discourse
- **Learn together** how to make the progressive media more effective
- Take advantage of **recent dramatic scientific advances**:
  - Informative data now available on the public debate
  - Measurement methods: meaning, not word counts
  - Experimental designs: avoiding confounding factors

- **Measure** public discourse
- Estimate the **causal effect** of the progressive media on discourse
- **Learn together** how to make the progressive media more effective
- Take advantage of **recent dramatic scientific advances**:
  - Informative data now available on the public debate
  - Measurement methods: meaning, not word counts
  - Experimental designs: avoiding confounding factors
  - Causal effect estimation: less bias & inefficiency

- **Measure** public discourse
- Estimate the **causal effect** of the progressive media on discourse
- **Learn together** how to make the progressive media more effective
- Take advantage of **recent dramatic scientific advances**:
  - Informative data now available on the public debate
  - Measurement methods: meaning, not word counts
  - Experimental designs: avoiding confounding factors
  - Causal effect estimation: less bias & inefficiency
  - New ways of working together to improve impact

# Who Frames the Public Debate?

# Who Frames the Public Debate?

“Do you approve of how George W. Bush is handling his job?”

# Who Frames the Public Debate?

“Do you approve of how George W. Bush is handling his job?”

- On 9/10/2001, 55% of Americans approved of the way George W. Bush was “handling his job as president”.

# Who Frames the Public Debate?

“Do you approve of how George W. Bush is handling his job?”

- On 9/10/2001, 55% of Americans approved of the way George W. Bush was “handling his job as president”.
- The next day — which the president spent in hiding — 90% approved.

# Who Frames the Public Debate?

“Do you approve of how George W. Bush is handling his job?”

- On 9/10/2001, 55% of Americans approved of the way George W. Bush was “handling his job as president”.
- The next day — which the president spent in hiding — 90% approved.
- Was this massive opinion change, or did the 9/11 frame change how we viewed the question?



# Who Frames the Public Debate?

“Do you approve of how George W. Bush is handling his job?”

- On 9/10/2001, **55%** of Americans approved of the way George W. Bush was “handling his job as president”.
- The next day — which the president spent in hiding — **90%** approved.
- Was this massive opinion change, or did the **9/11 frame** change how we viewed the question?
- **The frame: imposed by events, not the media**

# Who Frames the Public Debate?

“Do you approve of how George W. Bush is handling his job?”

- On 9/10/2001, **55%** of Americans approved of the way George W. Bush was “handling his job as president”.
- The next day — which the president spent in hiding — **90%** approved.
- Was this massive opinion change, or did the **9/11 frame** change how we viewed the question?
- **The frame: imposed by events, not the media**
- **Public opinion polls: measuring what?**

# Who Frames the Public Debate?

“Do you approve of how George W. Bush is handling his job?”

- On 9/10/2001, **55%** of Americans approved of the way George W. Bush was “handling his job as president”.
- The next day — which the president spent in hiding — **90%** approved.
- Was this massive opinion change, or did the **9/11 frame** change how we viewed the question?
- **The frame: imposed by events, not the media**
- **Public opinion polls: measuring what?**

Support for Ban on “Partial Birth” Abortion

# Who Frames the Public Debate?

## “Do you approve of how George W. Bush is handling his job?”

- On 9/10/2001, **55%** of Americans approved of the way George W. Bush was “handling his job as president”.
- The next day — which the president spent in hiding — **90%** approved.
- Was this massive opinion change, or did the **9/11 frame** change how we viewed the question?
- **The frame: imposed by events, not the media**
- **Public opinion polls: measuring what?**

## Support for Ban on “Partial Birth” Abortion

- Supporters: use “baby”

# Who Frames the Public Debate?

## “Do you approve of how George W. Bush is handling his job?”

- On 9/10/2001, **55%** of Americans approved of the way George W. Bush was “handling his job as president”.
- The next day — which the president spent in hiding — **90%** approved.
- Was this massive opinion change, or did the **9/11 frame** change how we viewed the question?
- **The frame: imposed by events, not the media**
- **Public opinion polls: measuring what?**

## Support for Ban on “Partial Birth” Abortion

- Supporters: use “baby”
- Opponents: use “fetus”

# Who Frames the Public Debate?

## “Do you approve of how George W. Bush is handling his job?”

- On 9/10/2001, **55%** of Americans approved of the way George W. Bush was “handling his job as president”.
- The next day — which the president spent in hiding — **90%** approved.
- Was this massive opinion change, or did the **9/11 frame** change how we viewed the question?
- **The frame: imposed by events, not the media**
- **Public opinion polls: measuring what?**

## Support for Ban on “Partial Birth” Abortion

- Supporters: use “baby”
- Opponents: use “fetus”
- In surveys, “baby” increases support for the ban by  $\approx 30\%$ !

# Who Frames the Public Debate?

## “Do you approve of how George W. Bush is handling his job?”

- On 9/10/2001, **55%** of Americans approved of the way George W. Bush was “handling his job as president”.
- The next day — which the president spent in hiding — **90%** approved.
- Was this massive opinion change, or did the **9/11 frame** change how we viewed the question?
- **The frame: imposed by events, not the media**
- **Public opinion polls: measuring what?**

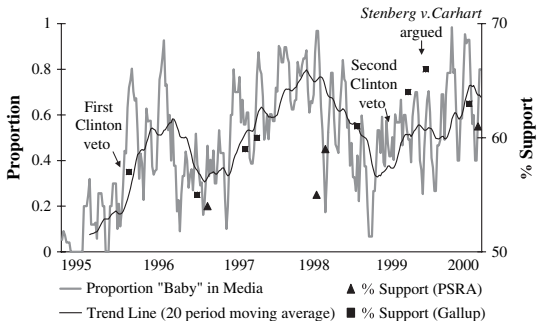
## Support for Ban on “Partial Birth” Abortion

- Supporters: use “baby”
- Opponents: use “fetus”
- In surveys, “baby” increases support for the ban by  $\approx 30\%$ !
- **Control the frame & you control the debate and policy outcome**

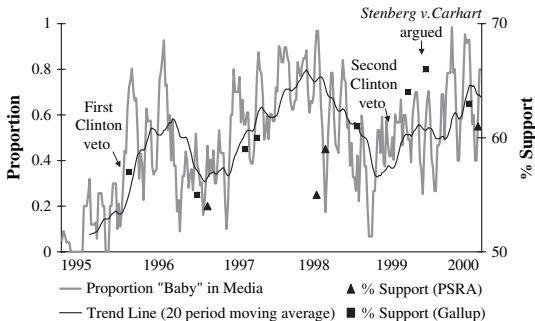
# “Partial Birth” Abortion Ban: Who controls the frame?



# "Partial Birth" Abortion Ban: Who controls the frame?

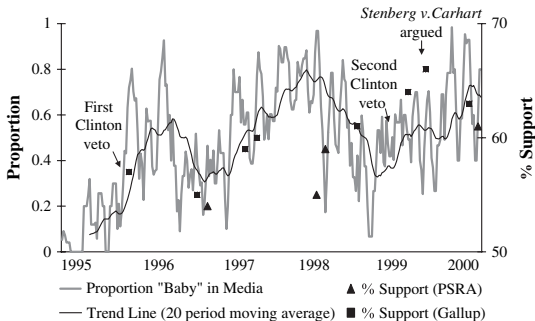


# “Partial Birth” Abortion Ban: Who controls the frame?



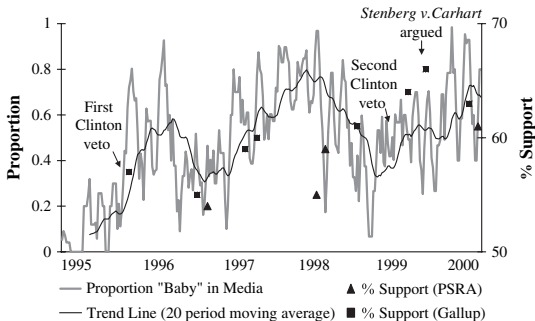
- When “baby” is used in the media, support for PBA ban increases

# “Partial Birth” Abortion Ban: Who controls the frame?



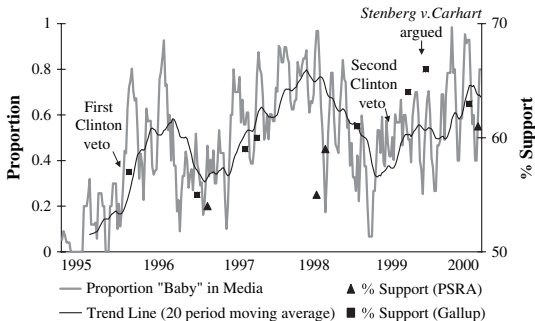
- When “baby” is used in the media, support for PBA ban increases
- Did the media influence public support **or** did public support influence the media?

# “Partial Birth” Abortion Ban: Who controls the frame?



- When “baby” is used in the media, support for PBA ban increases
- Did the media influence public support **or** did public support influence the media? **How can we tell?**

# “Partial Birth” Abortion Ban: Who controls the frame?



- When “baby” is used in the media, support for PBA ban increases
- Did the media influence public support **or** did public support influence the media? **How can we tell?**
- **Do “baby” and “fetus” word counts even measure what we intend?**

# The Plan, 1: Collect New Data

# The Plan, 1: Collect New Data

## Data on Public Discourse

# The Plan, 1: Collect New Data

## Data on Public Discourse

- **Until recently, measures of public discourse were inadequate:** public opinion polls, content analyses of newspaper editorials; systematic, real time, informative data nonexistent



# The Plan, 1: Collect New Data

## Data on Public Discourse

- **Until recently, measures of public discourse were inadequate:** public opinion polls, content analyses of newspaper editorials; systematic, real time, informative data nonexistent
- **Now:**

# The Plan, 1: Collect New Data

## Data on Public Discourse

- **Until recently, measures of public discourse were inadequate:** public opinion polls, content analyses of newspaper editorials; systematic, real time, informative data nonexistent
- **Now:**
  - Hallway conversations appear in the **1.4B social media posts a week**

# The Plan, 1: Collect New Data

## Data on Public Discourse

- **Until recently, measures of public discourse were inadequate:** public opinion polls, content analyses of newspaper editorials; systematic, real time, informative data nonexistent
- **Now:**
  - Hallway conversations appear in the **1.4B social media posts a week**
  - Growing sources: blogs, Twitter, Facebook, forums, chat rooms, etc.

# The Plan, 1: Collect New Data

## Data on Public Discourse

- **Until recently, measures of public discourse were inadequate:** public opinion polls, content analyses of newspaper editorials; systematic, real time, informative data nonexistent
- **Now:**
  - Hallway conversations appear in the **1.4B social media posts a week**
  - Growing sources: blogs, Twitter, Facebook, forums, chat rooms, etc.

## Data on Media Outlets

Work together to find or create

# The Plan, 1: Collect New Data

## Data on Public Discourse

- **Until recently, measures of public discourse were inadequate:** public opinion polls, content analyses of newspaper editorials; systematic, real time, informative data nonexistent
- **Now:**
  - Hallway conversations appear in the **1.4B social media posts a week**
  - Growing sources: blogs, Twitter, Facebook, forums, chat rooms, etc.

## Data on Media Outlets

Work together to find or create

- **Existing data on outputs** (web traffic, donations, comments, emails, phone logs, etc.)

# The Plan, 1: Collect New Data

## Data on Public Discourse

- **Until recently, measures of public discourse were inadequate:** public opinion polls, content analyses of newspaper editorials; systematic, real time, informative data nonexistent
- **Now:**
  - Hallway conversations appear in the **1.4B social media posts a week**
  - Growing sources: blogs, Twitter, Facebook, forums, chat rooms, etc.

## Data on Media Outlets

Work together to find or create

- **Existing data on outputs** (web traffic, donations, comments, emails, phone logs, etc.)
- **Existing data on content:** e.g., tagged story databases, web artifacts, listener information, etc.

# The Plan, 1: Collect New Data

## Data on Public Discourse

- **Until recently, measures of public discourse were inadequate:** public opinion polls, content analyses of newspaper editorials; systematic, real time, informative data nonexistent
- **Now:**
  - Hallway conversations appear in the **1.4B social media posts a week**
  - Growing sources: blogs, Twitter, Facebook, forums, chat rooms, etc.

## Data on Media Outlets

Work together to find or create

- **Existing data on outputs** (web traffic, donations, comments, emails, phone logs, etc.)
- **Existing data on content:** e.g., tagged story databases, web artifacts, listener information, etc.
- **New systematic data** from texts of stories, audio-to-text, etc.

# The Plan, 2: Adapt New Methods to Understand Billions of Social Media Posts, & News Stories



# The Plan, 2: Adapt New Methods to Understand Billions of Social Media Posts, & News Stories

- Until recently, methods were inadequate:

# The Plan, 2: Adapt New Methods to Understand Billions of Social Media Posts, & News Stories

- **Until recently, methods were inadequate:**
  - Misleading word counts

# The Plan, 2: Adapt New Methods to Understand Billions of Social Media Posts, & News Stories

- **Until recently, methods were inadequate:**
  - Misleading word counts
  - Impossible amounts of reading

# The Plan, 2: Adapt New Methods to Understand Billions of Social Media Posts, & News Stories

- **Until recently, methods were inadequate:**
  - Misleading word counts
  - Impossible amounts of reading
- **Now, new statistical methods for text analytics:**

# The Plan, 2: Adapt New Methods to Understand Billions of Social Media Posts, & News Stories

- **Until recently, methods were inadequate:**
  - Misleading word counts
  - Impossible amounts of reading
- **Now, new statistical methods for text analytics:**
  - Accurately summarize huge volumes of information

# The Plan, 2: Adapt New Methods to Understand Billions of Social Media Posts, & News Stories

- **Until recently, methods were inadequate:**
  - Misleading word counts
  - Impossible amounts of reading
- **Now, new statistical methods for text analytics:**
  - Accurately summarize huge volumes of information
  - Better than humans alone, or computers alone, we **amplify human intelligence**

# The Plan, 2: Adapt New Methods to Understand Billions of Social Media Posts, & News Stories

- **Until recently, methods were inadequate:**
  - Misleading word counts
  - Impossible amounts of reading
- **Now, new statistical methods for text analytics:**
  - Accurately summarize huge volumes of information
  - Better than humans alone, or computers alone, we **amplify human intelligence**
  - Works fast, in near real time

# The Plan, 2: Adapt New Methods to Understand Billions of Social Media Posts, & News Stories

- **Until recently, methods were inadequate:**
  - Misleading word counts
  - Impossible amounts of reading
- **Now, new statistical methods for text analytics:**
  - Accurately summarize huge volumes of information
  - Better than humans alone, or computers alone, we **amplify human intelligence**
  - Works fast, in near real time
  - Can measure media frames (about politicians or policies) by volume, sentiment, topics, perspectives — or any categories we think of



# The Plan, 2: Adapt New Methods to Understand Billions of Social Media Posts, & News Stories

- **Until recently, methods were inadequate:**
  - Misleading word counts
  - Impossible amounts of reading
- **Now, new statistical methods for text analytics:**
  - Accurately summarize huge volumes of information
  - Better than humans alone, or computers alone, we **amplify human intelligence**
  - Works fast, in near real time
  - Can measure media frames (about politicians or policies) by volume, sentiment, topics, perspectives — or any categories we think of
  - Measure as far back in time as feasible (6-24 months?)

# The Plan, 2: Adapt New Methods to Understand Billions of Social Media Posts, & News Stories

- **Until recently, methods were inadequate:**
  - Misleading word counts
  - Impossible amounts of reading
- **Now, new statistical methods for text analytics:**
  - Accurately summarize huge volumes of information
  - Better than humans alone, or computers alone, we **amplify human intelligence**
  - Works fast, in near real time
  - Can measure media frames (about politicians or policies) by volume, sentiment, topics, perspectives — or any categories we think of
  - Measure as far back in time as feasible (6-24 months?)
  - Design systematic measurement going forward

# [Some detail on innovations in text analytics]

# [Some detail on innovations in text analytics]

- How can humans understand large numbers of social media posts (or news stories)?

# [Some detail on innovations in text analytics]

- How can humans understand large numbers of social media posts (or news stories)?
  - Read & interpret: infeasible

# [Some detail on innovations in text analytics]

- How can humans understand large numbers of social media posts (or news stories)?
  - Read & interpret: infeasible
  - Sort into a few categories; track category percentages over time

# [Some detail on innovations in text analytics]

- How can humans understand large numbers of social media posts (or news stories)?
  - Read & interpret: infeasible
  - Sort into a few categories; track category percentages over time
  - Example of categories: Wisconsin budget standoff is

# [Some detail on innovations in text analytics]

- How can humans understand large numbers of social media posts (or news stories)?
  - Read & interpret: infeasible
  - Sort into a few categories; track category percentages over time
  - Example of categories: Wisconsin budget standoff is (1) a responsible effort to fix budget deficit



# [Some detail on innovations in text analytics]

- How can humans understand large numbers of social media posts (or news stories)?
  - Read & interpret: infeasible
  - Sort into a few categories; track category percentages over time
  - Example of categories: Wisconsin budget standoff is (1) a responsible effort to fix budget deficit, (2) an attack on public sector workers

# [Some detail on innovations in text analytics]

- How can humans understand large numbers of social media posts (or news stories)?
  - Read & interpret: infeasible
  - Sort into a few categories; track category percentages over time
  - Example of categories: Wisconsin budget standoff is (1) a responsible effort to fix budget deficit, (2) an attack on public sector workers, (3) an attack on the progressive movement generally

## [Some detail on innovations in text analytics]

- How can humans understand large numbers of social media posts (or news stories)?
  - Read & interpret: infeasible
  - Sort into a few categories; track category percentages over time
  - Example of categories: Wisconsin budget standoff is (1) a responsible effort to fix budget deficit, (2) an attack on public sector workers, (3) an attack on the progressive movement generally, or (4) due to an arrogant publicity-hungry Governor

## [Some detail on innovations in text analytics]

- How can humans understand large numbers of social media posts (or news stories)?
  - Read & interpret: infeasible
  - Sort into a few categories; track category percentages over time
  - Example of categories: Wisconsin budget standoff is (1) a responsible effort to fix budget deficit, (2) an attack on public sector workers, (3) an attack on the progressive movement generally, or (4) due to an arrogant publicity-hungry Governor
- How to sort billions of social media posts into categories?

# [Some detail on innovations in text analytics]

- **How can humans understand large numbers of social media posts (or news stories)?**
  - Read & interpret: infeasible
  - Sort into a few categories; track category percentages over time
  - Example of categories: Wisconsin budget standoff is (1) a responsible effort to fix budget deficit, (2) an attack on public sector workers, (3) an attack on the progressive movement generally, or (4) due to an arrogant publicity-hungry Governor
- **How to sort billions of social media posts into categories?**
  - Classify by hand: infeasible for more than a sample at one point in time

# [Some detail on innovations in text analytics]

- **How can humans understand large numbers of social media posts (or news stories)?**
  - Read & interpret: infeasible
  - Sort into a few categories; track category percentages over time
  - Example of categories: Wisconsin budget standoff is (1) a responsible effort to fix budget deficit, (2) an attack on public sector workers, (3) an attack on the progressive movement generally, or (4) due to an arrogant publicity-hungry Governor
- **How to sort billions of social media posts into categories?**
  - Classify by hand: infeasible for more than a sample at one point in time
  - Guess what words imply which categories: inaccurate

# [Some detail on innovations in text analytics]


- **How can humans understand large numbers of social media posts (or news stories)?**
  - Read & interpret: infeasible
  - Sort into a few categories; track category percentages over time
  - Example of categories: Wisconsin budget standoff is (1) a responsible effort to fix budget deficit, (2) an attack on public sector workers, (3) an attack on the progressive movement generally, or (4) due to an arrogant publicity-hungry Governor
- **How to sort billions of social media posts into categories?**
  - Classify by hand: infeasible for more than a sample at one point in time
  - Guess what words imply which categories: inaccurate
  - Use “machine learning” methods with hand-coded training set to automatically classify: at best 60-70% accuracy (useful for Google searches, useless for category percentages)

# [Some detail on innovations in text analytics]

- **How can humans understand large numbers of social media posts (or news stories)?**
  - Read & interpret: infeasible
  - Sort into a few categories; track category percentages over time
  - Example of categories: Wisconsin budget standoff is (1) a responsible effort to fix budget deficit, (2) an attack on public sector workers, (3) an attack on the progressive movement generally, or (4) due to an arrogant publicity-hungry Governor
- **How to sort billions of social media posts into categories?**
  - Classify by hand: infeasible for more than a sample at one point in time
  - Guess what words imply which categories: inaccurate
  - Use “machine learning” methods with hand-coded training set to automatically classify: at best 60-70% accuracy (useful for Google searches, useless for category percentages)
  - **Use new statistical method with hand-coded training set to estimate category percentages (without individual classifications): Extremely accurate**



# [Some detail on innovations in text analytics]

- **How can humans understand large numbers of social media posts (or news stories)?**
  - Read & interpret: infeasible
  - Sort into a few categories; track category percentages over time
  - Example of categories: Wisconsin budget standoff is (1) a responsible effort to fix budget deficit, (2) an attack on public sector workers, (3) an attack on the progressive movement generally, or (4) due to an arrogant publicity-hungry Governor
- **How to sort billions of social media posts into categories?**
  - Classify by hand: infeasible for more than a sample at one point in time
  - Guess what words imply which categories: inaccurate
  - Use “machine learning” methods with hand-coded training set to automatically classify: at best 60-70% accuracy (useful for Google searches, useless for category percentages)
  - **Use new statistical method with hand-coded training set to estimate category percentages (without individual classifications): Extremely accurate**
  - $\rightsquigarrow$  Finding the needle in the haystack (Google search)  $\neq$  characterizing the haystack, and so new methods were required 

# The Plan, 3: Use New Methods of Causal Inference for Observational Data

# The Plan, 3: Use New Methods of Causal Inference for Observational Data

- **Until recently:** Estimating causal effects from observational data was very risky and often illusory

# The Plan, 3: Use New Methods of Causal Inference for Observational Data

- **Until recently:** Estimating causal effects from observational data was very risky and often illusory
- **Now, new methods:**

# The Plan, 3: Use New Methods of Causal Inference for Observational Data

- **Until recently:** Estimating causal effects from observational data was very risky and often illusory
- **Now, new methods:**
  - Give strong hints about causal relationships

# The Plan, 3: Use New Methods of Causal Inference for Observational Data

- **Until recently:** Estimating causal effects from observational data was very risky and often illusory
- **Now, new methods:**
  - Give strong hints about causal relationships
  - Reveal all hidden assumptions (ignorability, interference, etc.)

# The Plan, 3: Use New Methods of Causal Inference for Observational Data

- **Until recently:** Estimating causal effects from observational data was very risky and often illusory
- **Now, new methods:**
  - Give strong hints about causal relationships
  - Reveal all hidden assumptions (ignorability, interference, etc.)
  - Help inform what experiments to run

# The Plan, 3: Use New Methods of Causal Inference for Observational Data

- **Until recently:** Estimating causal effects from observational data was very risky and often illusory
- **Now, new methods:**
  - Give strong hints about causal relationships
  - Reveal all hidden assumptions (ignorability, interference, etc.)
  - Help inform what experiments to run
- **We'll use new methods to:**



# The Plan, 3: Use New Methods of Causal Inference for Observational Data

- **Until recently:** Estimating causal effects from observational data was very risky and often illusory
- **Now, new methods:**
  - Give strong hints about causal relationships
  - Reveal all hidden assumptions (ignorability, interference, etc.)
  - Help inform what experiments to run
- **We'll use new methods to:**
  - Estimate the effect of progressive media on use of media frames, & sentiment about them, in public discourse

# The Plan, 3: Use New Methods of Causal Inference for Observational Data

- **Until recently:** Estimating causal effects from observational data was very risky and often illusory
- **Now, new methods:**
  - Give strong hints about causal relationships
  - Reveal all hidden assumptions (ignorability, interference, etc.)
  - Help inform what experiments to run
- **We'll use new methods to:**
  - Estimate the effect of progressive media on use of media frames, & sentiment about them, in public discourse
  - Develop strong testable hypotheses about what do next

# The Plan, 3: Use New Methods of Causal Inference for Observational Data

- **Until recently:** Estimating causal effects from observational data was very risky and often illusory
- **Now, new methods:**
  - Give strong hints about causal relationships
  - Reveal all hidden assumptions (ignorability, interference, etc.)
  - Help inform what experiments to run
- **We'll use new methods to:**
  - Estimate the effect of progressive media on use of media frames, & sentiment about them, in public discourse
  - Develop strong testable hypotheses about what do next
  - We'll do everything that can be done this way before turning to experiments (and using your time!)

# The Plan, 4: Use New Experimental Designs

# The Plan, 4: Use New Experimental Designs

- **Observational analysis:** some evidence of what might have worked in the past

## The Plan, 4: Use New Experimental Designs

- **Observational analysis:** some evidence of what might have worked in the past
- **Experiments:** gold standard for evaluating causal claims

# The Plan, 4: Use New Experimental Designs

- **Observational analysis:** some evidence of what might have worked in the past
- **Experiments:** gold standard for evaluating causal claims
- **Experiments benefits from:** investigator control (usually randomized) over the “treatment” (drugs, stories)

# The Plan, 4: Use New Experimental Designs

- **Observational analysis:** some evidence of what might have worked in the past
- **Experiments:** gold standard for evaluating causal claims
- **Experiments benefits from:** investigator control (usually randomized) over the “treatment” (drugs, stories)
- **What randomized treatments get us:** a variable unrelated to *all* confounders



# The Plan, 4: Use New Experimental Designs

- **Observational analysis:** some evidence of what might have worked in the past
- **Experiments:** gold standard for evaluating causal claims
- **Experiments benefits from:** investigator control (usually randomized) over the “treatment” (drugs, stories)
- **What randomized treatments get us:** a variable unrelated to *all* confounders
- **How experiments fail:**

# The Plan, 4: Use New Experimental Designs

- **Observational analysis:** some evidence of what might have worked in the past
- **Experiments:** gold standard for evaluating causal claims
- **Experiments benefits from:** investigator control (usually randomized) over the “treatment” (drugs, stories)
- **What randomized treatments get us:** a variable unrelated to *all* confounders
- **How experiments fail:**
  - Insensitivity to research subjects, political interests, or local context

# The Plan, 4: Use New Experimental Designs

- **Observational analysis:** some evidence of what might have worked in the past
- **Experiments:** gold standard for evaluating causal claims
- **Experiments benefits from:** investigator control (usually randomized) over the “treatment” (drugs, stories)
- **What randomized treatments get us:** a variable unrelated to *all* confounders
- **How experiments fail:**
  - Insensitivity to research subjects, political interests, or local context
  - Examples: Drug trials; Mexico's Anti-Poverty program

# The Plan, 4: Use New Experimental Designs

- **Observational analysis:** some evidence of what might have worked in the past
- **Experiments:** gold standard for evaluating causal claims
- **Experiments benefits from:** investigator control (usually randomized) over the “treatment” (drugs, stories)
- **What randomized treatments get us:** a variable unrelated to *all* confounders
- **How experiments fail:**
  - Insensitivity to research subjects, political interests, or local context
  - Examples: Drug trials; Mexico's Anti-Poverty program
  - ~> solutions always exist; we'll find them together

# The Plan, 4: Use New Experimental Designs

- **Observational analysis:** some evidence of what might have worked in the past
- **Experiments:** gold standard for evaluating causal claims
- **Experiments benefits from:** investigator control (usually randomized) over the “treatment” (drugs, stories)
- **What randomized treatments get us:** a variable unrelated to *all* confounders
- **How experiments fail:**
  - Insensitivity to research subjects, political interests, or local context
  - Examples: Drug trials; Mexico’s Anti-Poverty program
  - $\rightsquigarrow$  solutions always exist; we’ll find them together
- **New experimental designs: let randomization survive disruption**

# The Plan, 5: Implementation Strategy

# The Plan, 5: Implementation Strategy

- Examples of how to experiment without infringing on editorial discretion:

# The Plan, 5: Implementation Strategy

- Examples of how to experiment without infringing on editorial discretion:
  - Offer optional small grants to media outlets to encourage covering particular stories (everyone will get a chance, no requirements, all decision making over content remains with organization)



# The Plan, 5: Implementation Strategy

- Examples of how to experiment without infringing on editorial discretion:
  - Offer optional small grants to media outlets to encourage covering particular stories (everyone will get a chance, no requirements, all decision making over content remains with organization)
  - Find otherwise arbitrary decisions to randomize (e.g., a story we're indifferent to being above or below the fold; the order of stories to present)

# The Plan, 5: Implementation Strategy

- Examples of how to experiment without infringing on editorial discretion:
  - Offer optional small grants to media outlets to encourage covering particular stories (everyone will get a chance, no requirements, all decision making over content remains with organization)
  - Find otherwise arbitrary decisions to randomize (e.g., a story we're indifferent to being above or below the fold; the order of stories to present)
  - Example: Mexico's Health Insurance evaluation

# The Plan, 5: Implementation Strategy

- Examples of how to experiment without infringing on editorial discretion:
  - Offer optional small grants to media outlets to encourage covering particular stories (everyone will get a chance, no requirements, all decision making over content remains with organization)
  - Find otherwise arbitrary decisions to randomize (e.g., a story we're indifferent to being above or below the fold; the order of stories to present)
  - Example: Mexico's Health Insurance evaluation
- Our scarcest resource: your time (so observational work first)

# The Plan, 5: Implementation Strategy

- Examples of how to experiment without infringing on editorial discretion:
  - Offer optional small grants to media outlets to encourage covering particular stories (everyone will get a chance, no requirements, all decision making over content remains with organization)
  - Find otherwise arbitrary decisions to randomize (e.g., a story we're indifferent to being above or below the fold; the order of stories to present)
  - Example: Mexico's Health Insurance evaluation
- Our scarcest resource: your time (so observational work first)
- Experiments will

# The Plan, 5: Implementation Strategy

- Examples of how to experiment without infringing on editorial discretion:
  - Offer optional small grants to media outlets to encourage covering particular stories (everyone will get a chance, no requirements, all decision making over content remains with organization)
  - Find otherwise arbitrary decisions to randomize (e.g., a story we're indifferent to being above or below the fold; the order of stories to present)
  - Example: Mexico's Health Insurance evaluation
- Our scarcest resource: your time (so observational work first)
- Experiments will **start small** (probably individual media outlets)

# The Plan, 5: Implementation Strategy

- Examples of how to experiment without infringing on editorial discretion:
  - Offer optional small grants to media outlets to encourage covering particular stories (everyone will get a chance, no requirements, all decision making over content remains with organization)
  - Find otherwise arbitrary decisions to randomize (e.g., a story we're indifferent to being above or below the fold; the order of stories to present)
  - Example: Mexico's Health Insurance evaluation
- Our scarcest resource: your time (so observational work first)
- Experiments will **start small** (probably individual media outlets), be **sequential** (each will build on the previous)

# The Plan, 5: Implementation Strategy

- Examples of how to experiment without infringing on editorial discretion:
  - Offer optional small grants to media outlets to encourage covering particular stories (everyone will get a chance, no requirements, all decision making over content remains with organization)
  - Find otherwise arbitrary decisions to randomize (e.g., a story we're indifferent to being above or below the fold; the order of stories to present)
  - Example: Mexico's Health Insurance evaluation
- Our scarcest resource: your time (so observational work first)
- Experiments will **start small** (probably individual media outlets), be **sequential** (each will build on the previous), and **grow in extent** (larger experiments, with more outlets, as we learn more)

# The Plan, 5: Implementation Strategy

- Examples of how to experiment without infringing on editorial discretion:
  - Offer optional small grants to media outlets to encourage covering particular stories (everyone will get a chance, no requirements, all decision making over content remains with organization)
  - Find otherwise arbitrary decisions to randomize (e.g., a story we're indifferent to being above or below the fold; the order of stories to present)
  - Example: Mexico's Health Insurance evaluation
- Our scarcest resource: your time (so observational work first)
- Experiments will **start small** (probably individual media outlets), be **sequential** (each will build on the previous), and **grow in extent** (larger experiments, with more outlets, as we learn more)
- **Our goal: Turn evidence of what has worked into increasingly effective strategies**



GKing.Harvard.edu

