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

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[1] Based on joint work with Benjamin Schneer and Ariel White (*Science* 2017)
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Introduction

Research Design

Results

Supporting Analyses

Implications

Statistical Problems: We Can't Randomize

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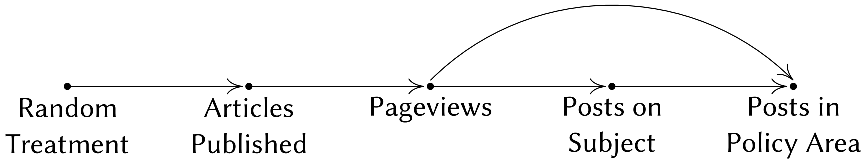

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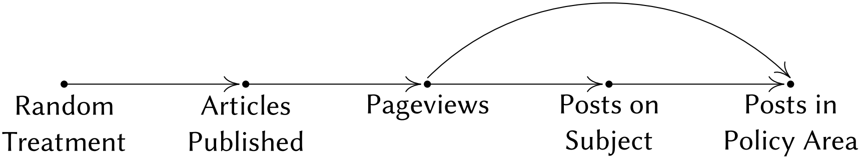

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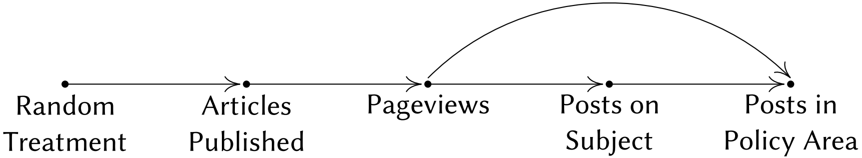

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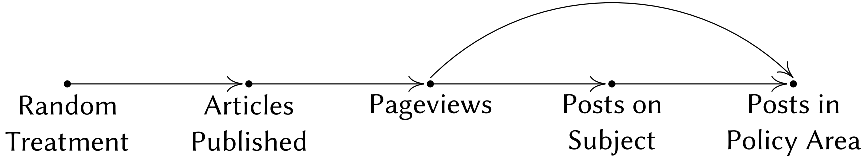

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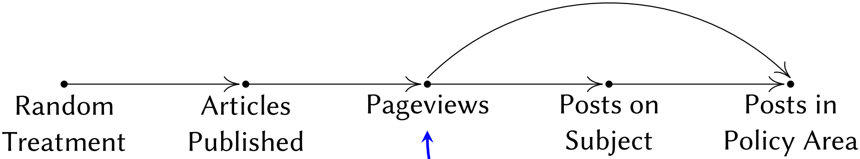

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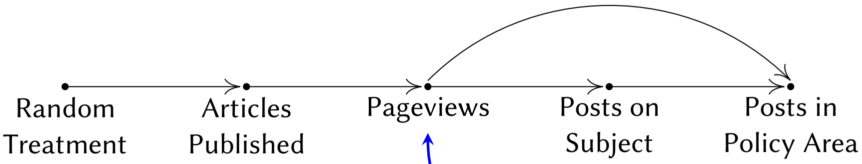

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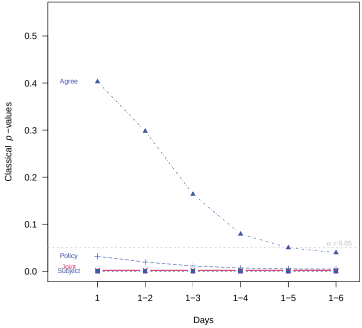

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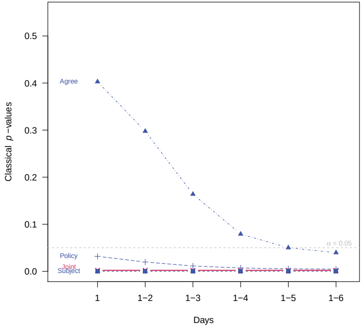

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Main Causal Effect: Public Expression in Policy Areas

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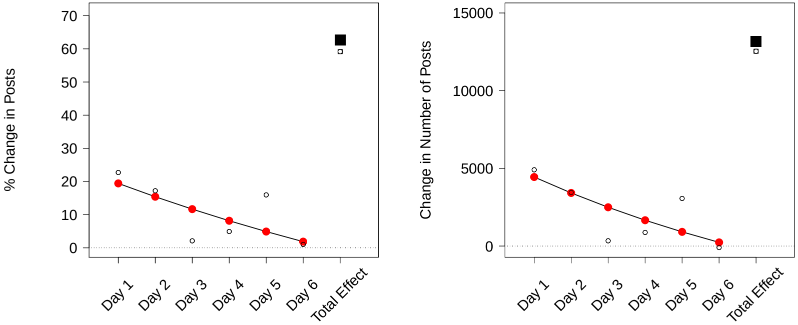

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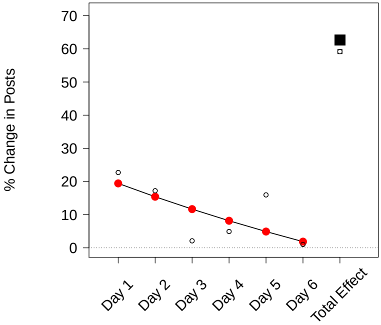

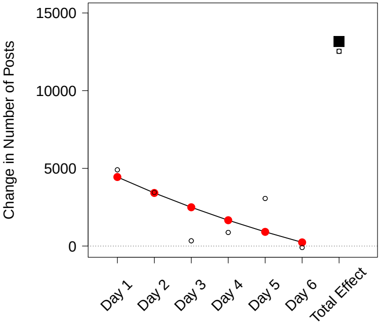

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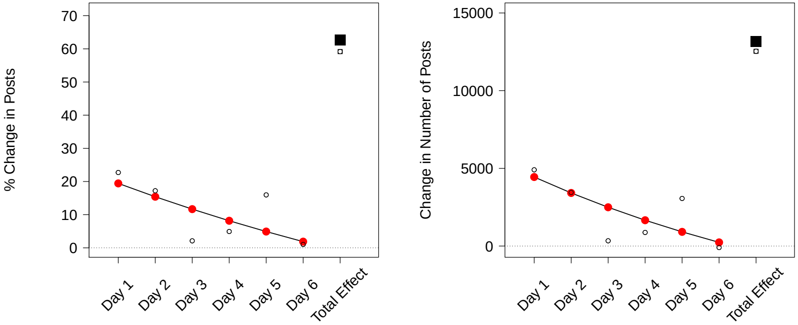

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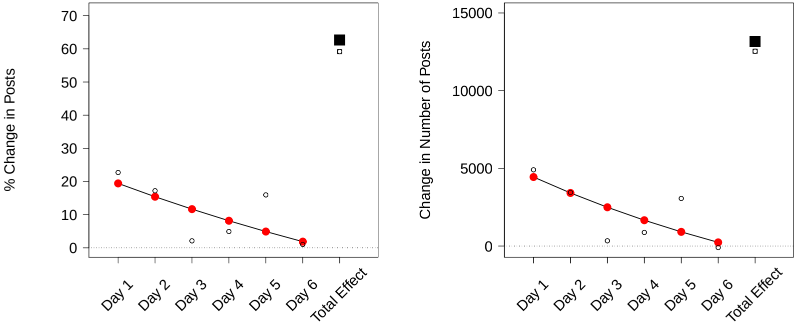

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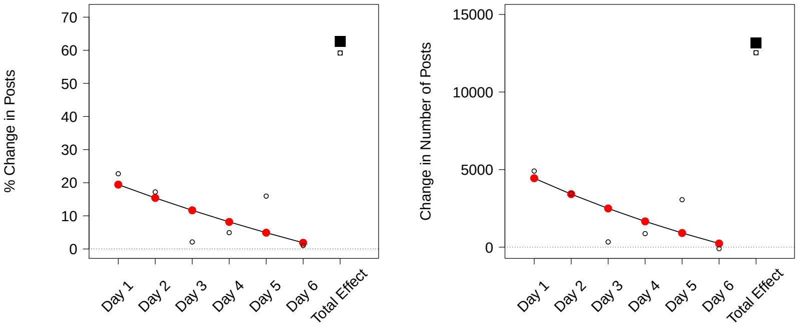

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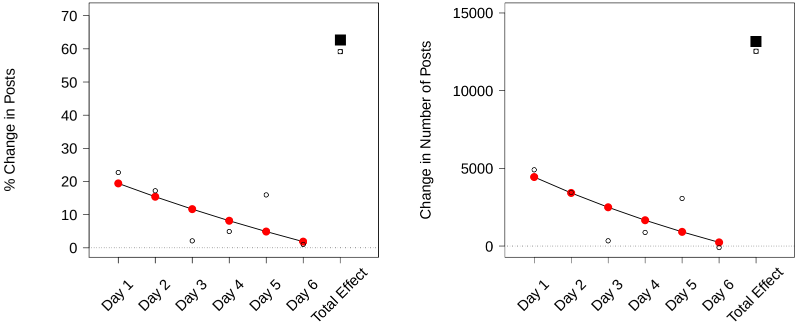

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Causal Effect: Indistinguishable Across Subgroups

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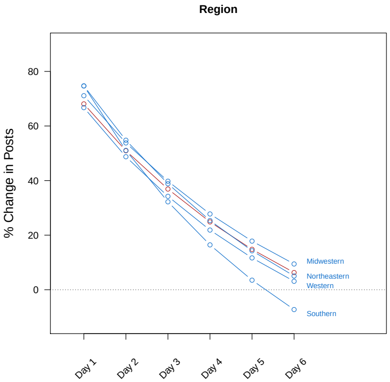

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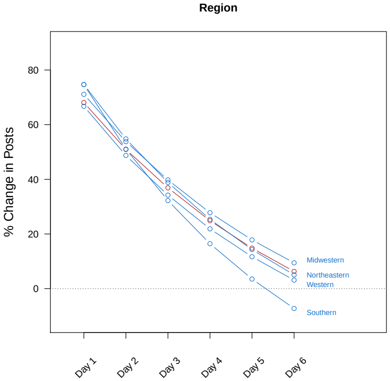

Effect on the national conversation in major policy areas is national

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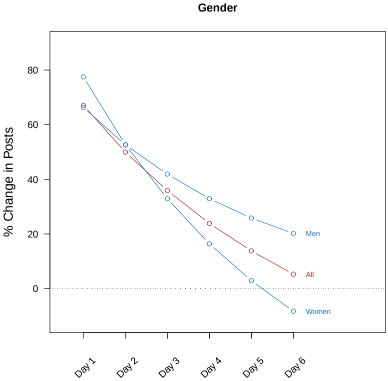

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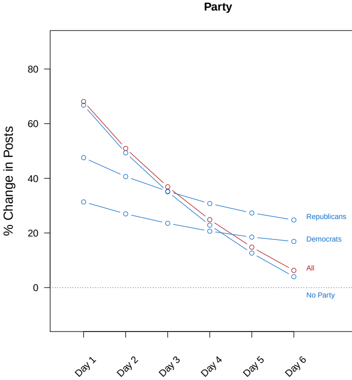

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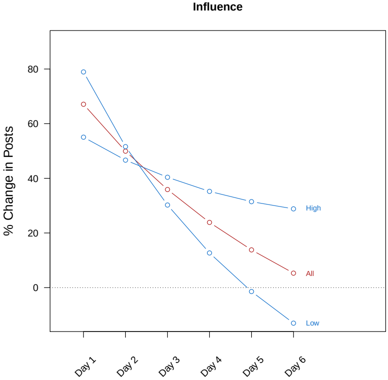

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Causal Heterogeneity: Leave-One-Outlet-Out

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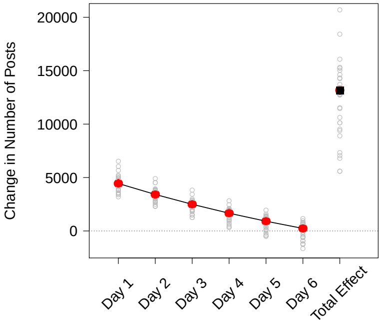
Jackknife Estimation on Policy Area Effects



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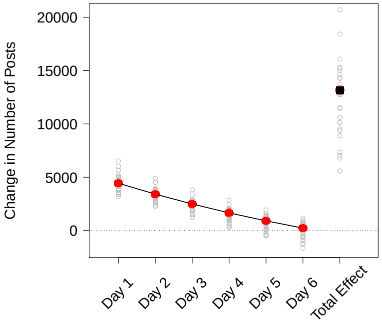

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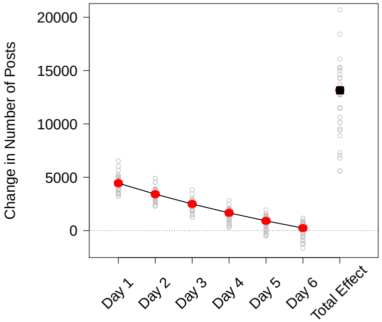

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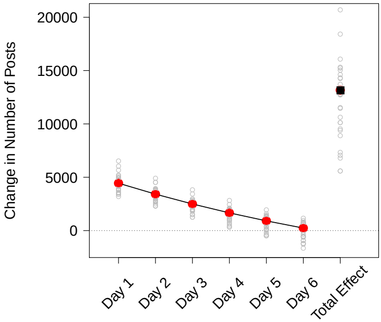

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- Results: no dominant outlet; high heterogeneity

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- 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)
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Causal Effect on Subject of Articles

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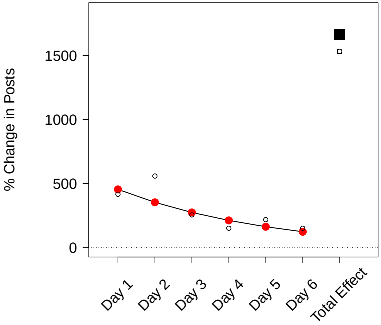

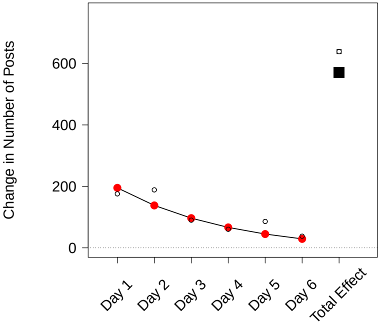

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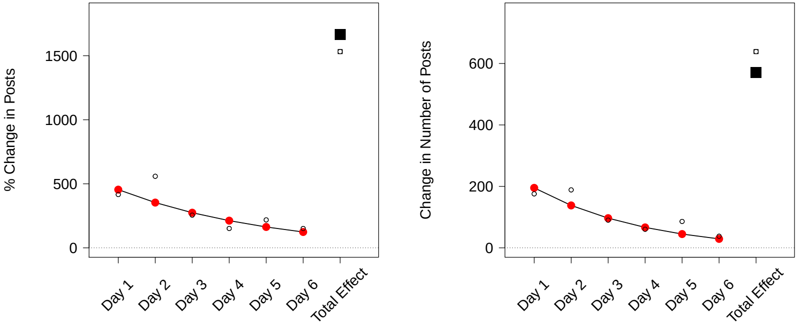

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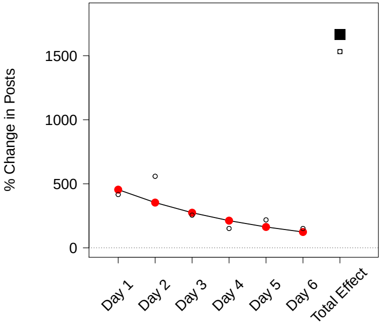

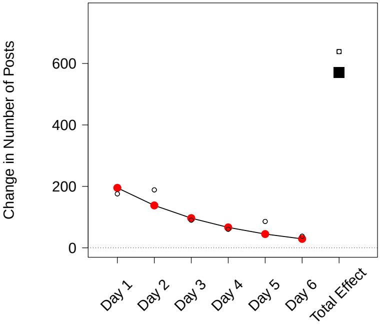

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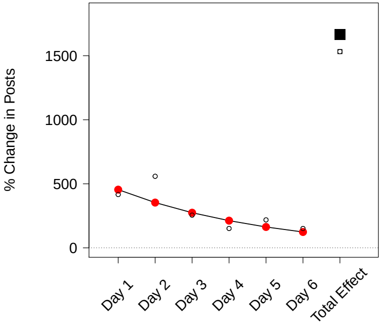

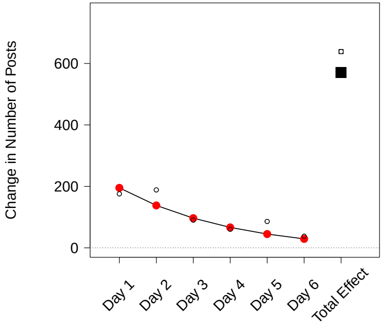

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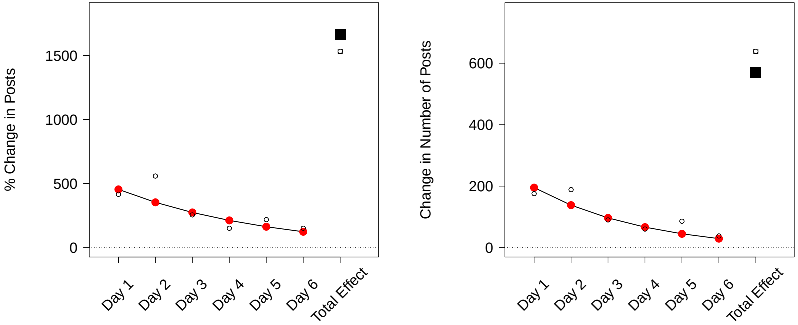

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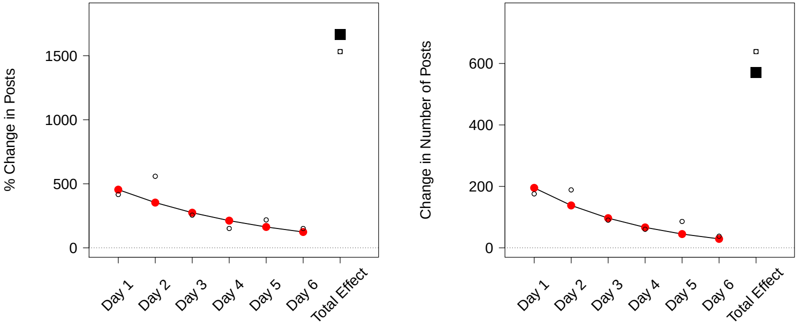

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Results

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Summary and Implications

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For more information:

GaryKing.org/media

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  - Drop linearity & conditional independence assumptions
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