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

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Stony Brook University, Political Science, 2/16/2018

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

Research Design

Results

Supporting Analyses

Implications

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- (Ex post: Automated text analysis & qualitative evidence: indistinguishable from normal publications & practices; no outlet received a single complaint)

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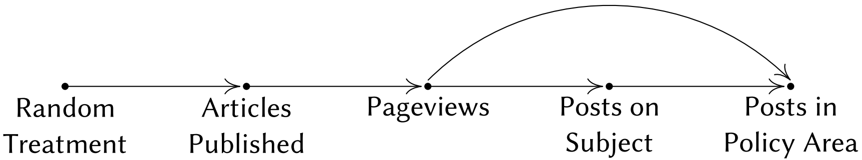

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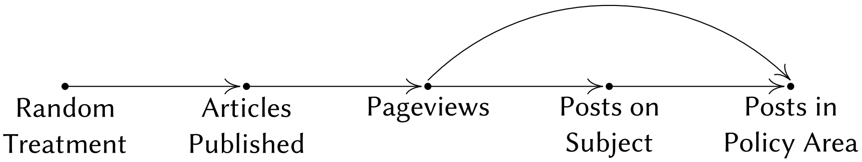

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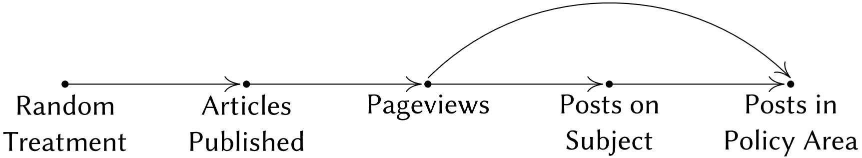

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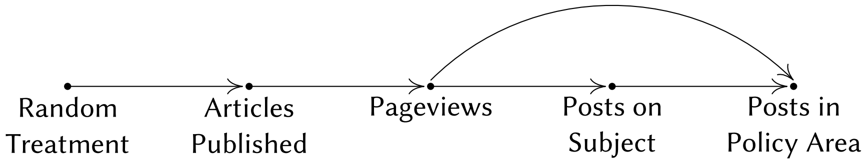

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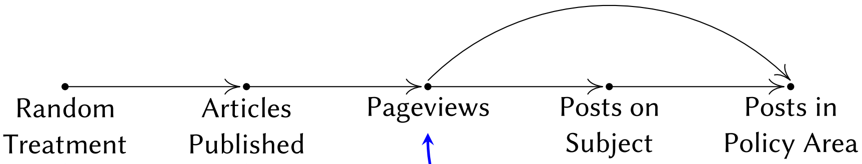

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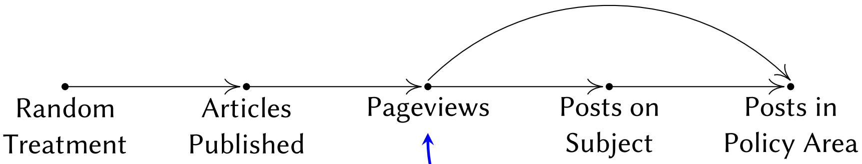

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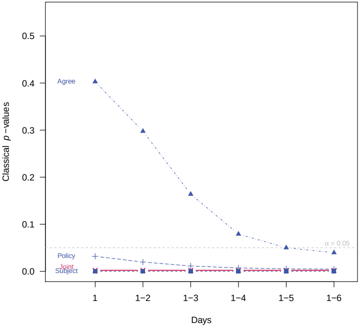

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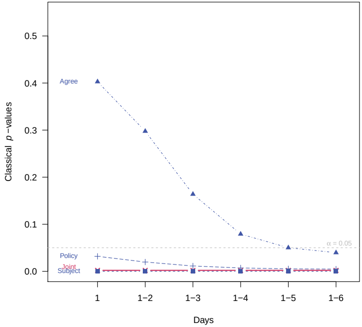

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Main Causal Effect: Public Expression in Policy Areas

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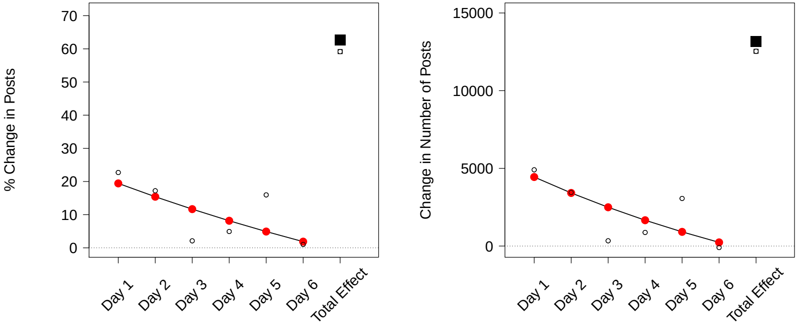

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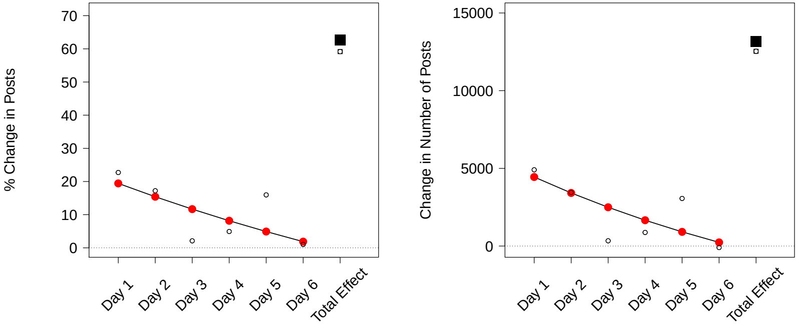

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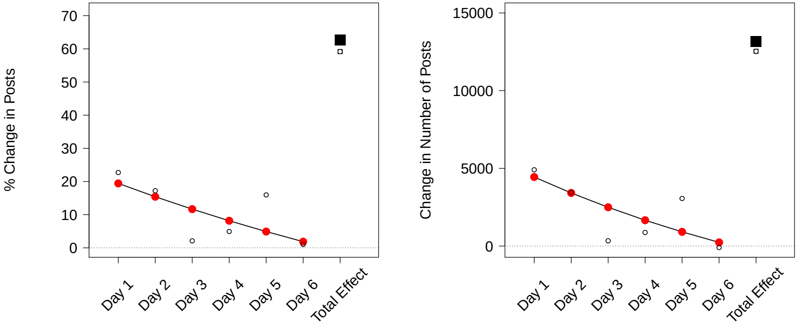

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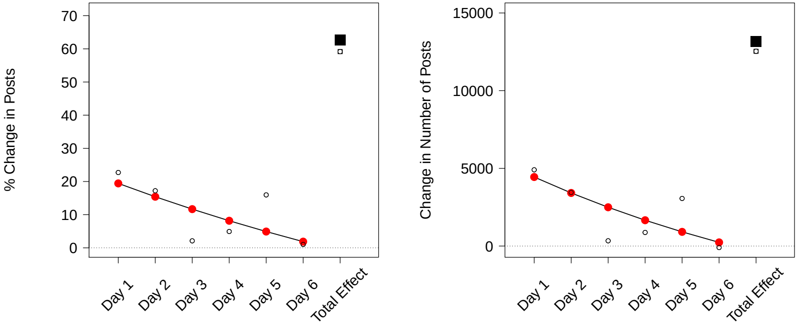

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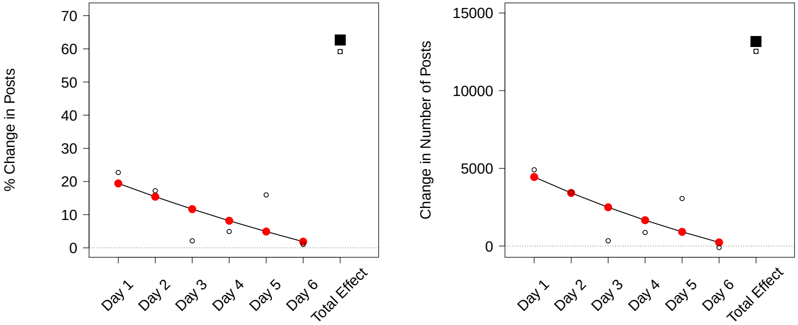

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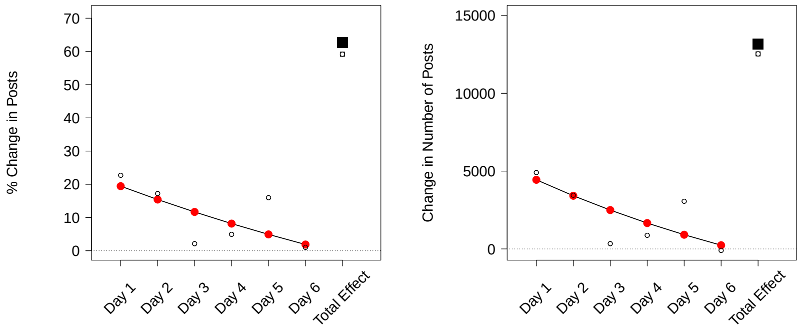

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Causal Effect: Indistinguishable Across Subgroups

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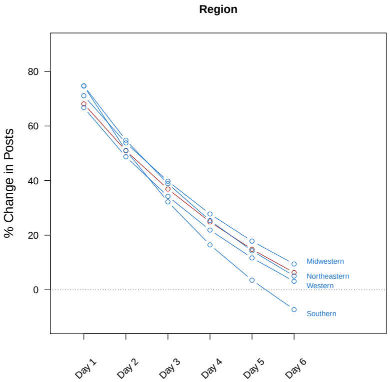

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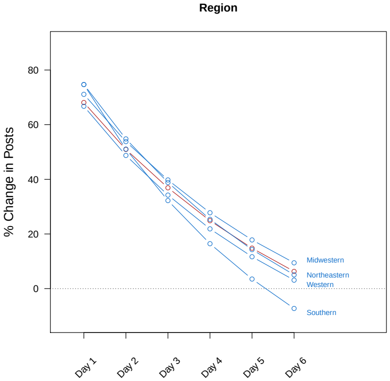

Effect on the national conversation in major policy areas is national

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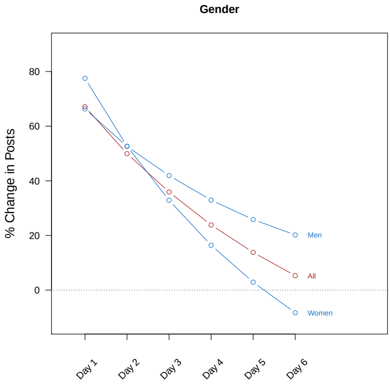

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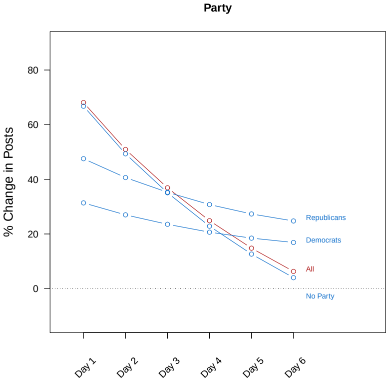

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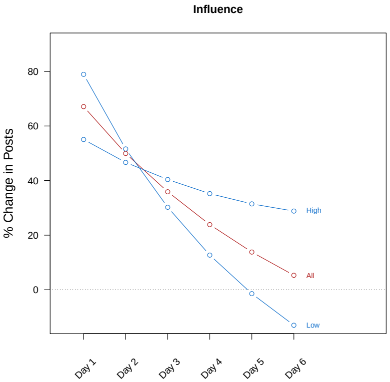

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Causal Heterogeneity: Leave-One-Outlet-Out

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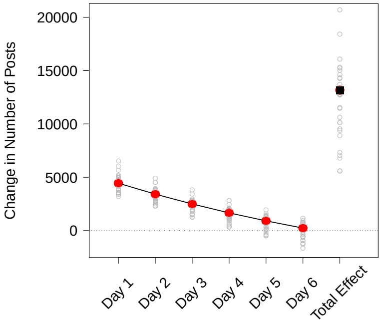

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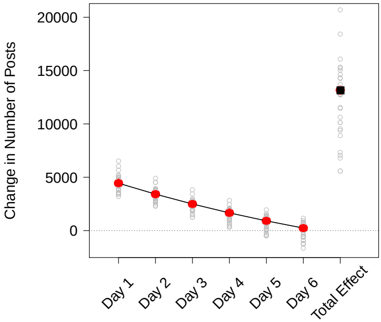

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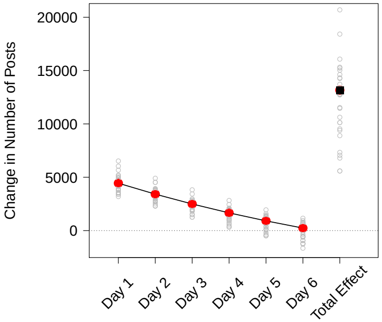

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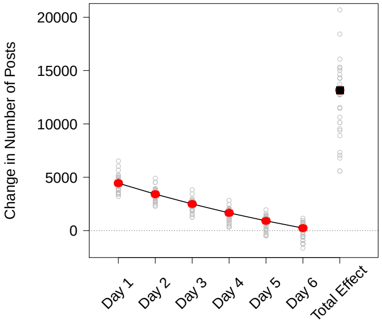

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Research Design

Results

Supporting Analyses

Implications

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- Pageviews (on subject of articles, relative to a day's volume)
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High Experimental Compliance

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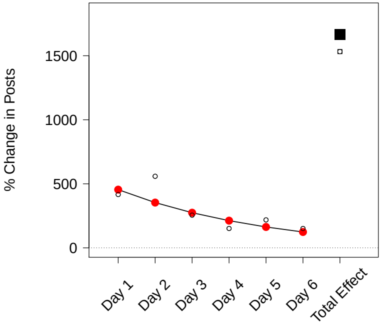

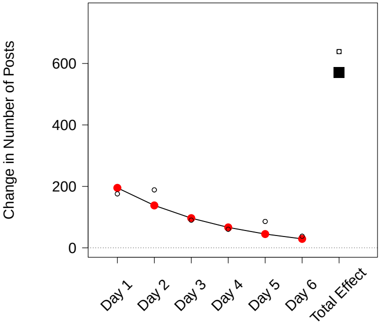

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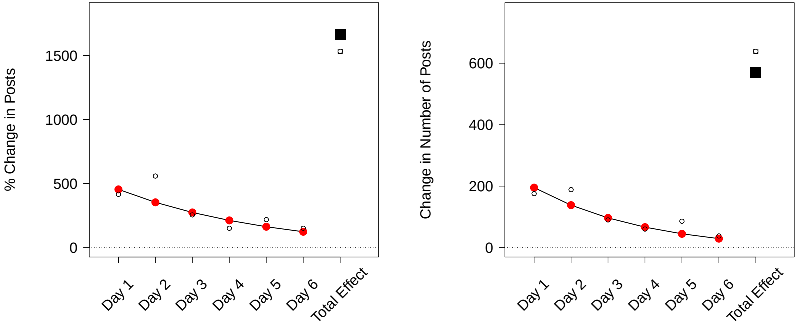

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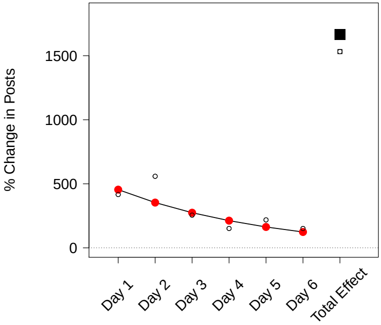

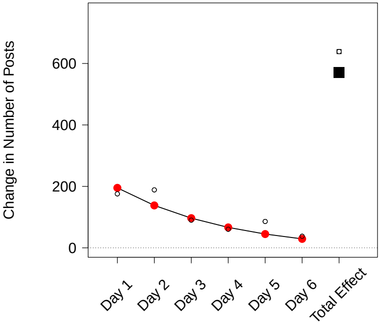

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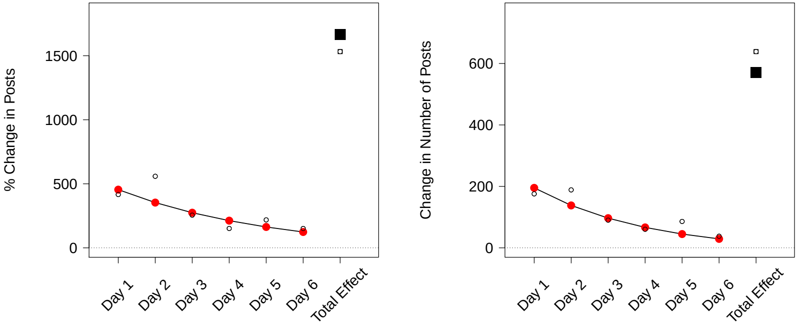

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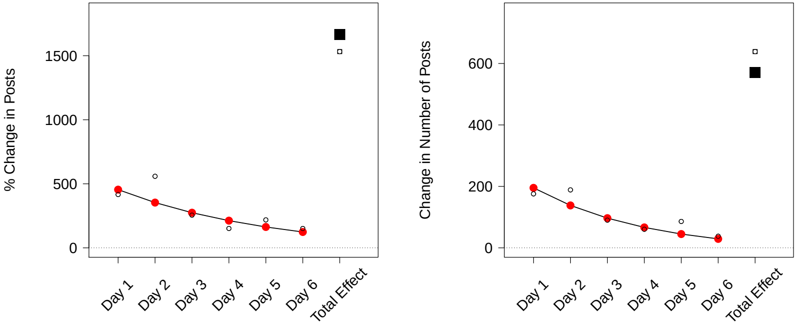

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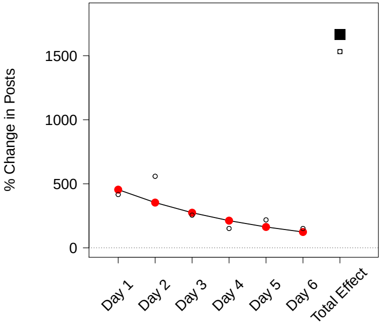

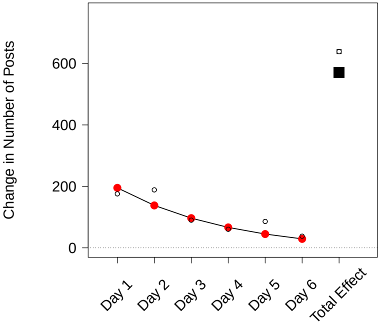

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  - Treatment articles: representative of all on complexity, type

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For more information:

GaryKing.org/media

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  - (perhaps with policy fixed effects)