

How the News Media Activate Public Expression and Influence National Agendas¹

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

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 - Effects: Persuasion, attitude formation, diffusion, gatekeeping, priming, issue framing, etc.
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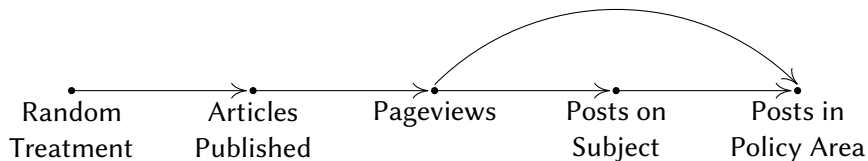
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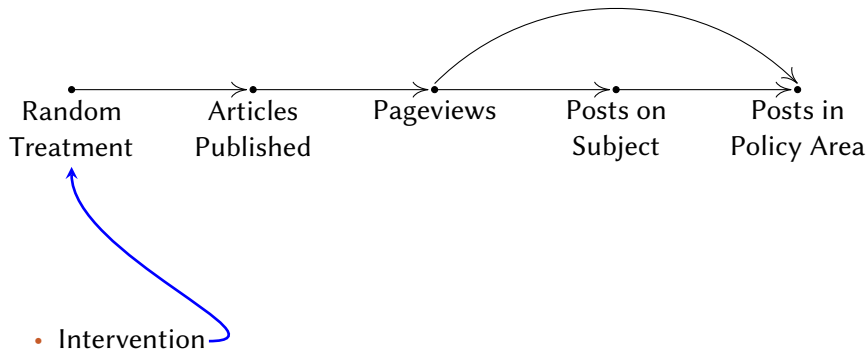
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- **(Ex post:** Automated text analysis & qualitative evidence: indistinguishable from normal publications & practices; no outlet received a single complaint)

Quantities of Interest (& observable implications)

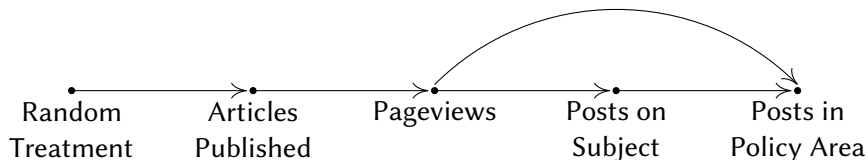
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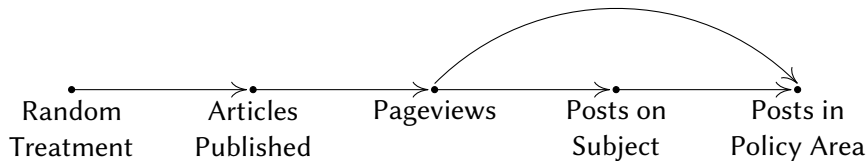
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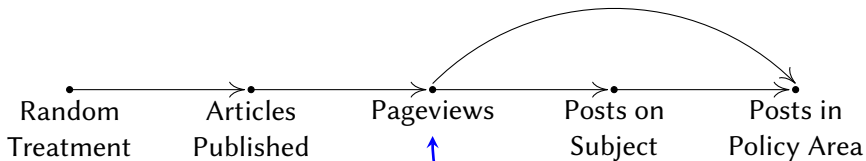
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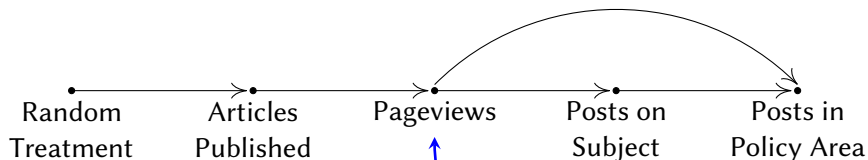
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Results from Sequential Hypothesis Tests

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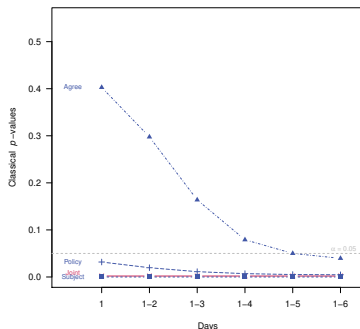
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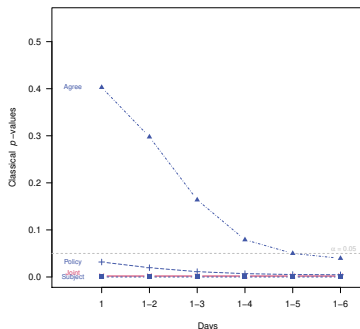
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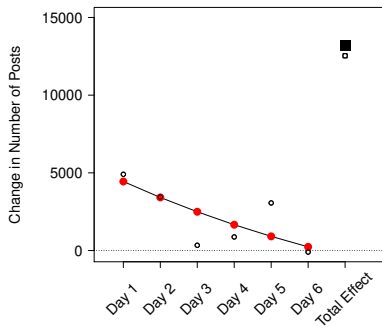
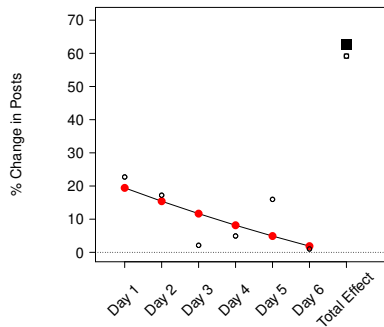
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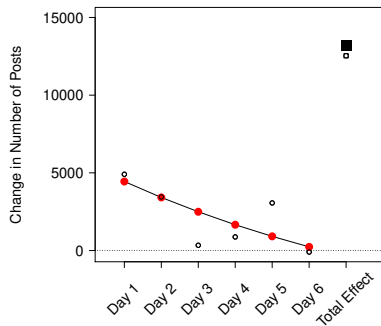
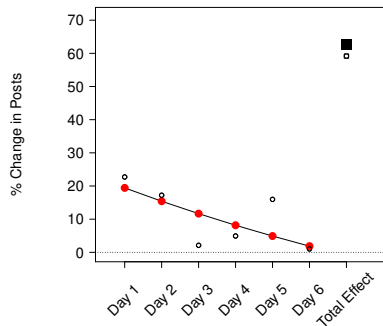
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Main Causal Effect: Public Expression in Policy Areas

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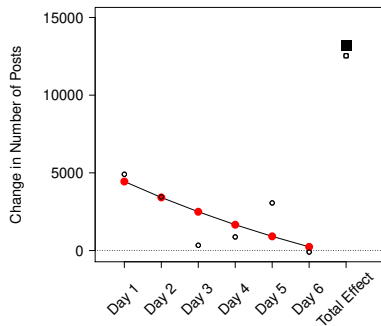
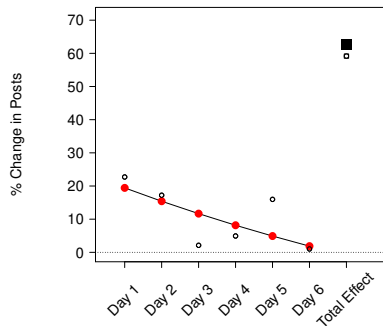


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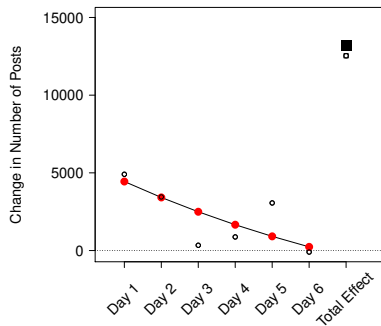
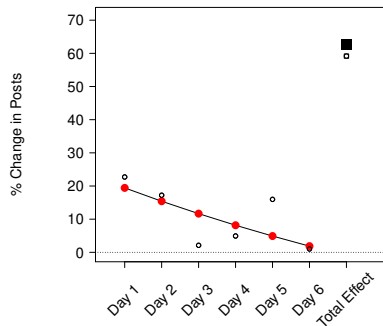
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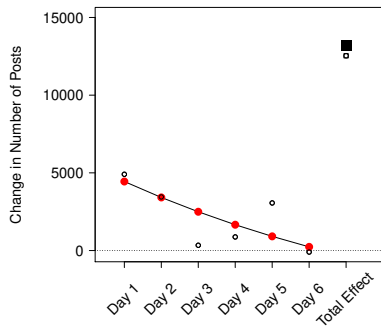
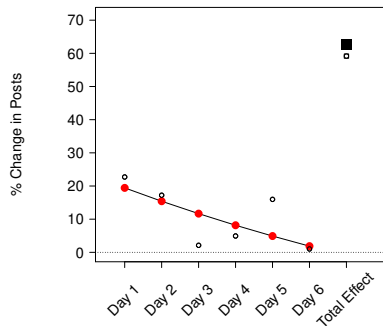
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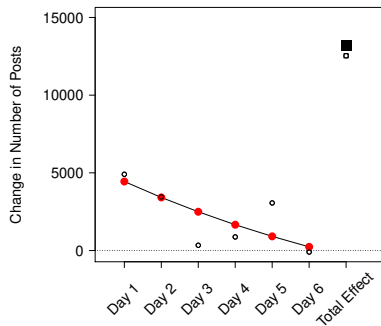
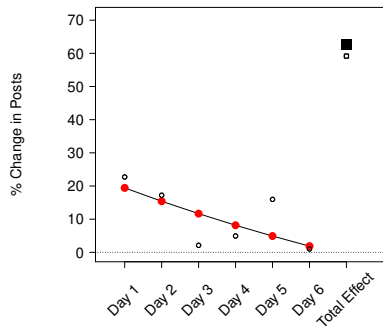
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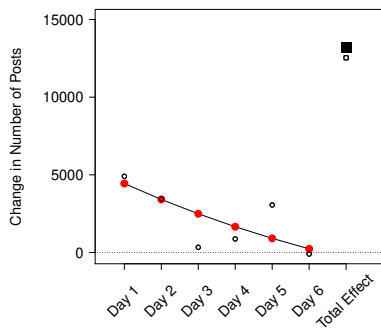
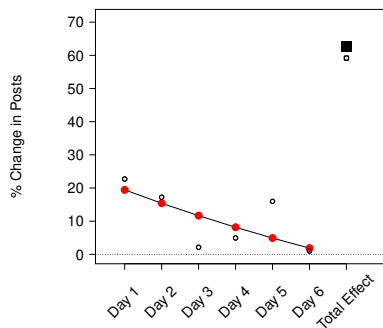
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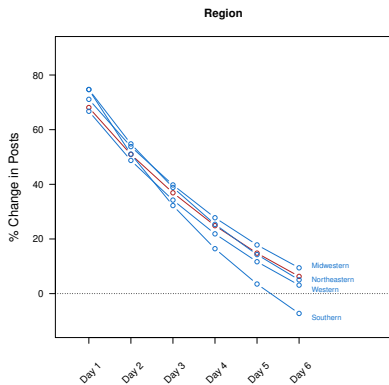
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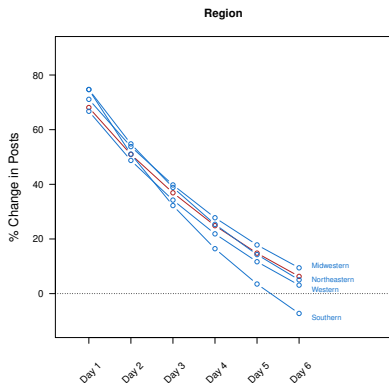
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Causal Effect: Indistinguishable Across Subgroups

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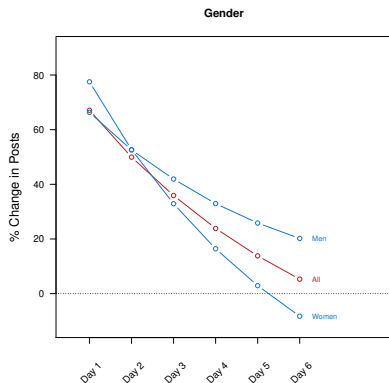


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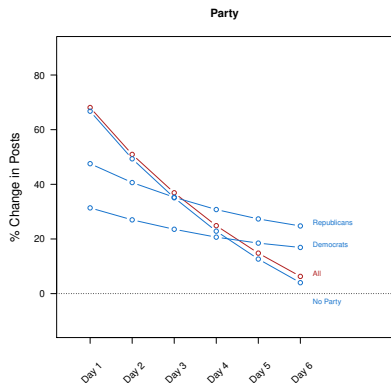
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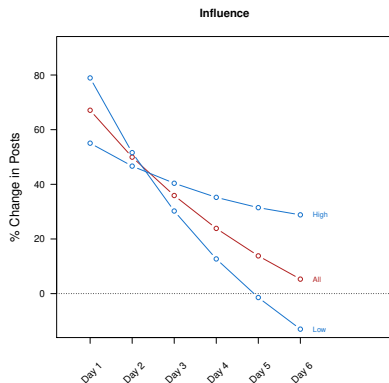
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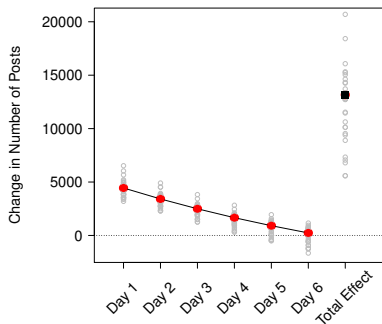


Effect on the national conversation in major policy areas is national

Causal Heterogeneity: Leave-One-Outlet-Out

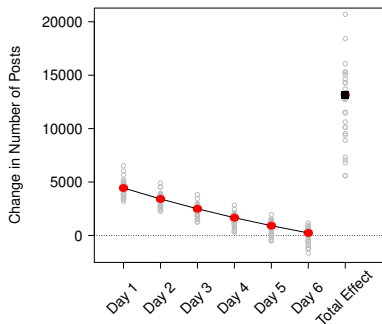
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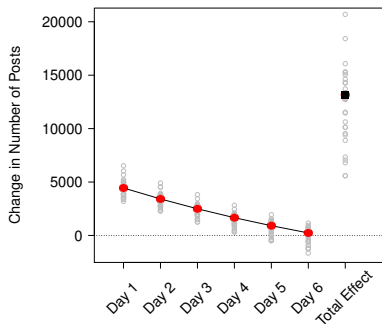
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- **Red Dots:** Original (model-based) estimates

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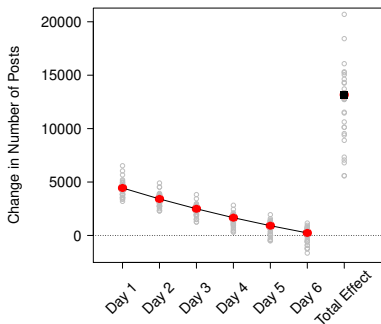
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- Open circles: same, with one outlet dropped from any packs
- **Results:** no dominant outlet; high heterogeneity

Introduction

Research Design

Results

Supporting Analyses

Implications

High Experimental Compliance

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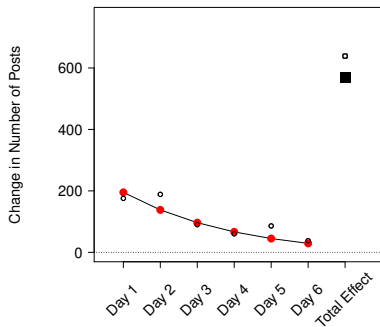
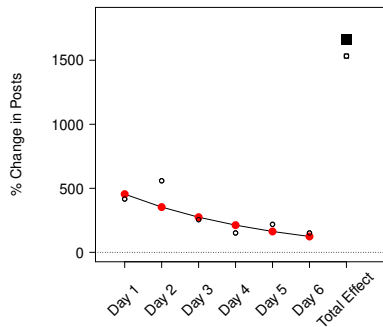
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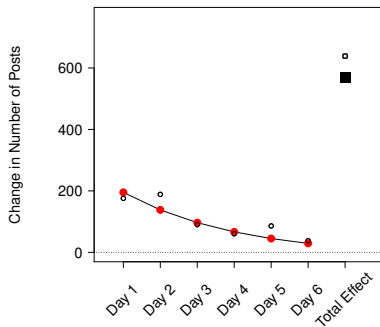
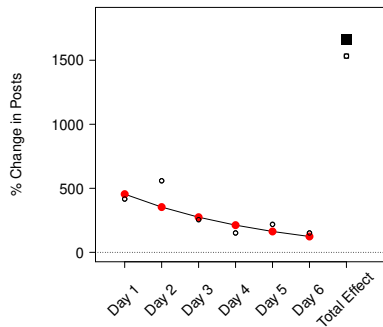
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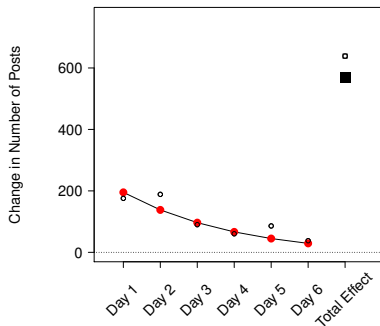
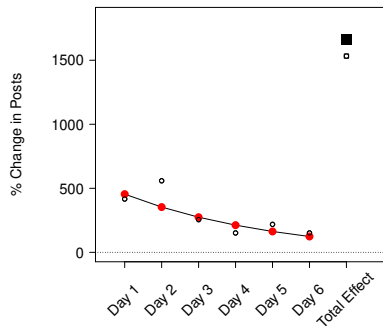


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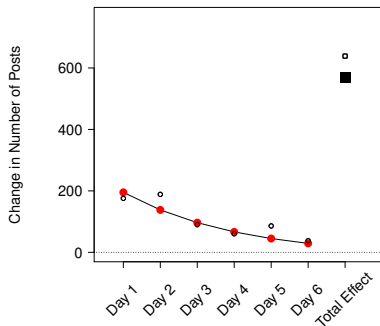
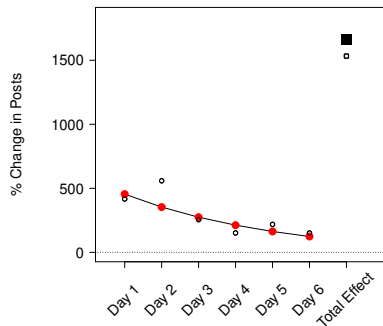
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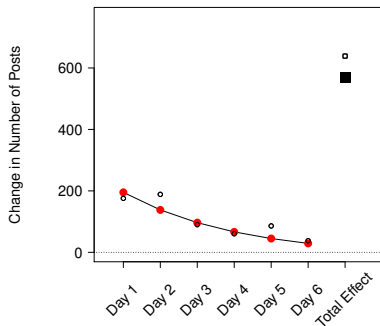
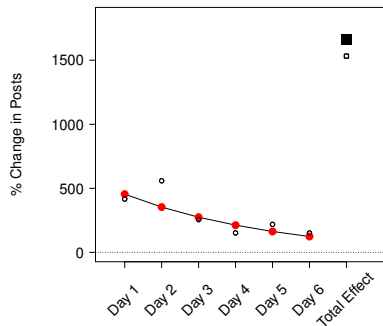
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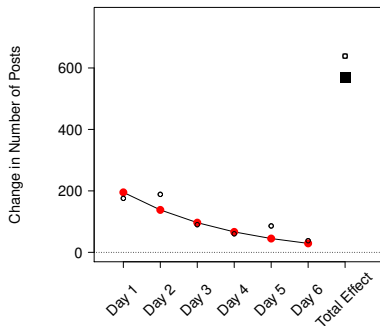
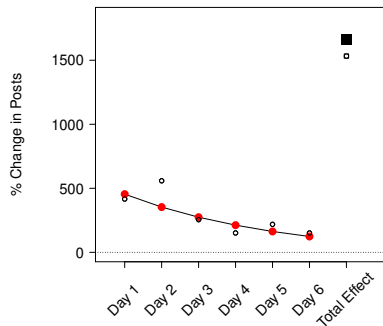
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For more information:

GaryKing.org/media

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- (perhaps with policy fixed effects)