Test2 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)
[2]GaryKing.org TESTING 26 June 2023

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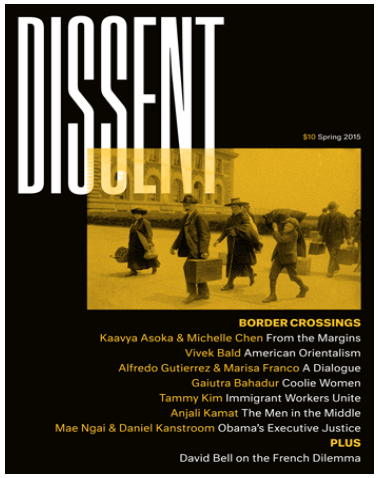

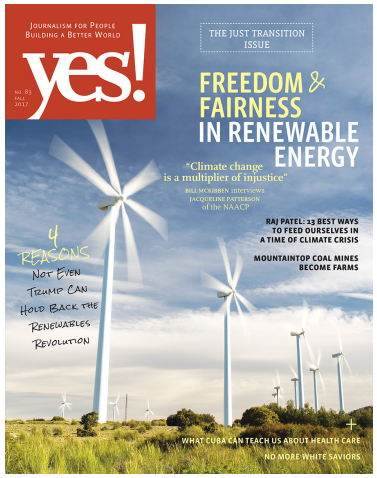

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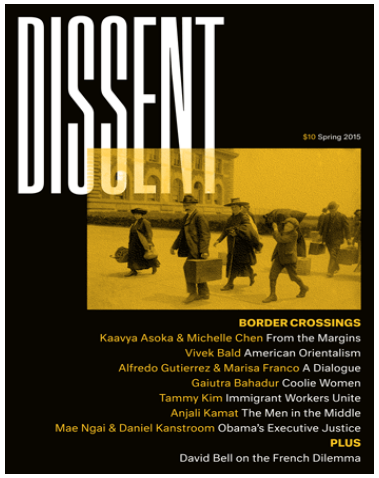

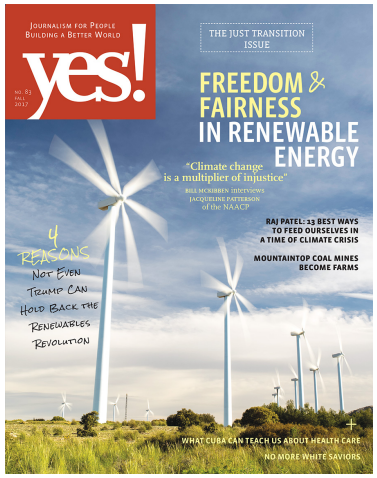

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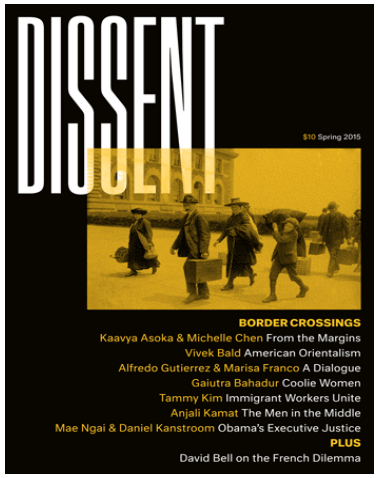

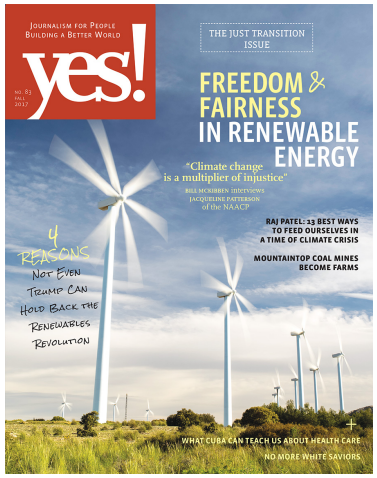

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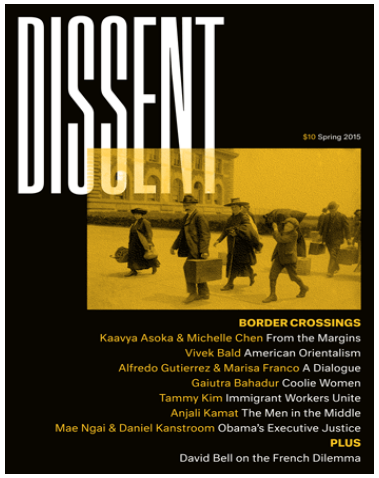

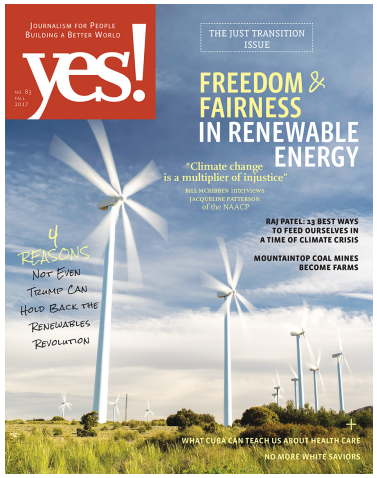

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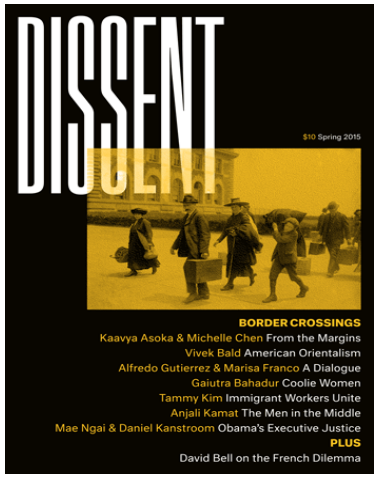

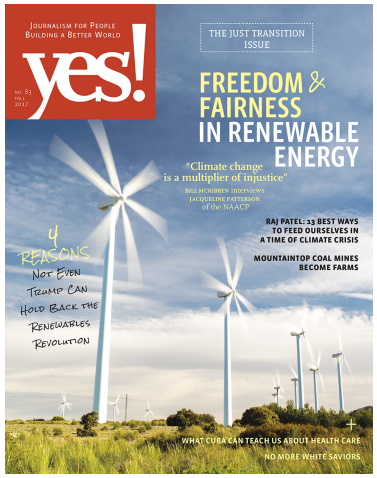

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  - Rules: (a) major national importance; (b) interest to outlets
  - race, immigration, jobs, abortion, climate, food policy, water, education policy, refugees, domestic energy production, and reproductive rights
  - Using 11 rather than 1: more representative; larger n needed

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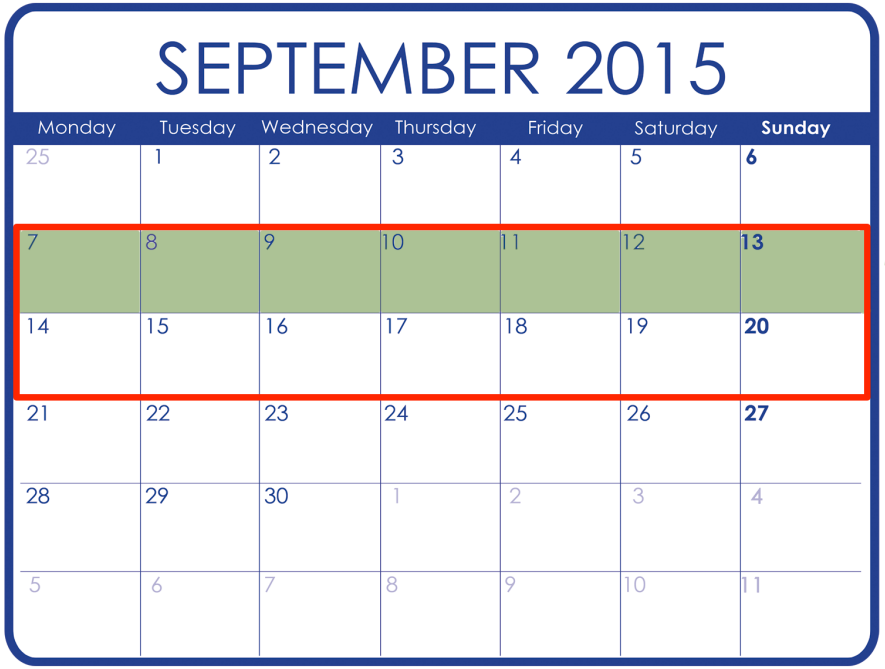

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- (Ex post: Automated text analysis & qualitative evidence: indistinguishable from normal publications & practices; no outlet received a single complaint)

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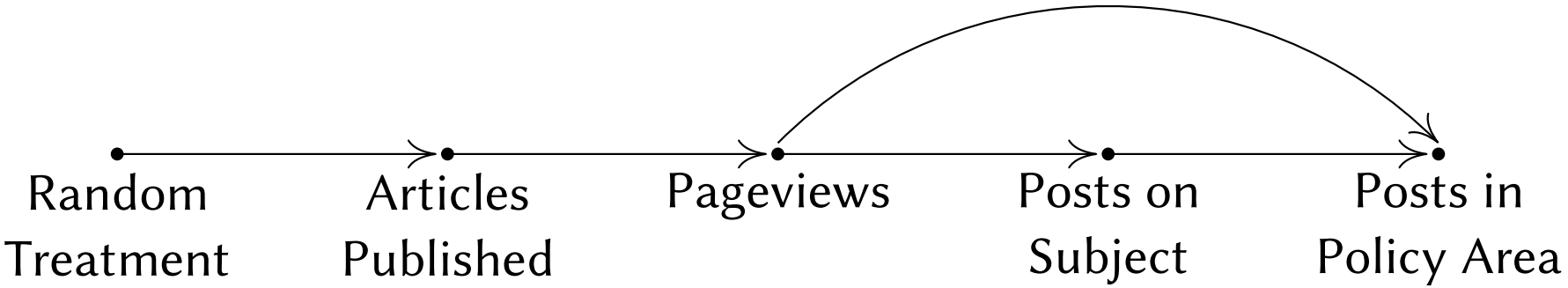

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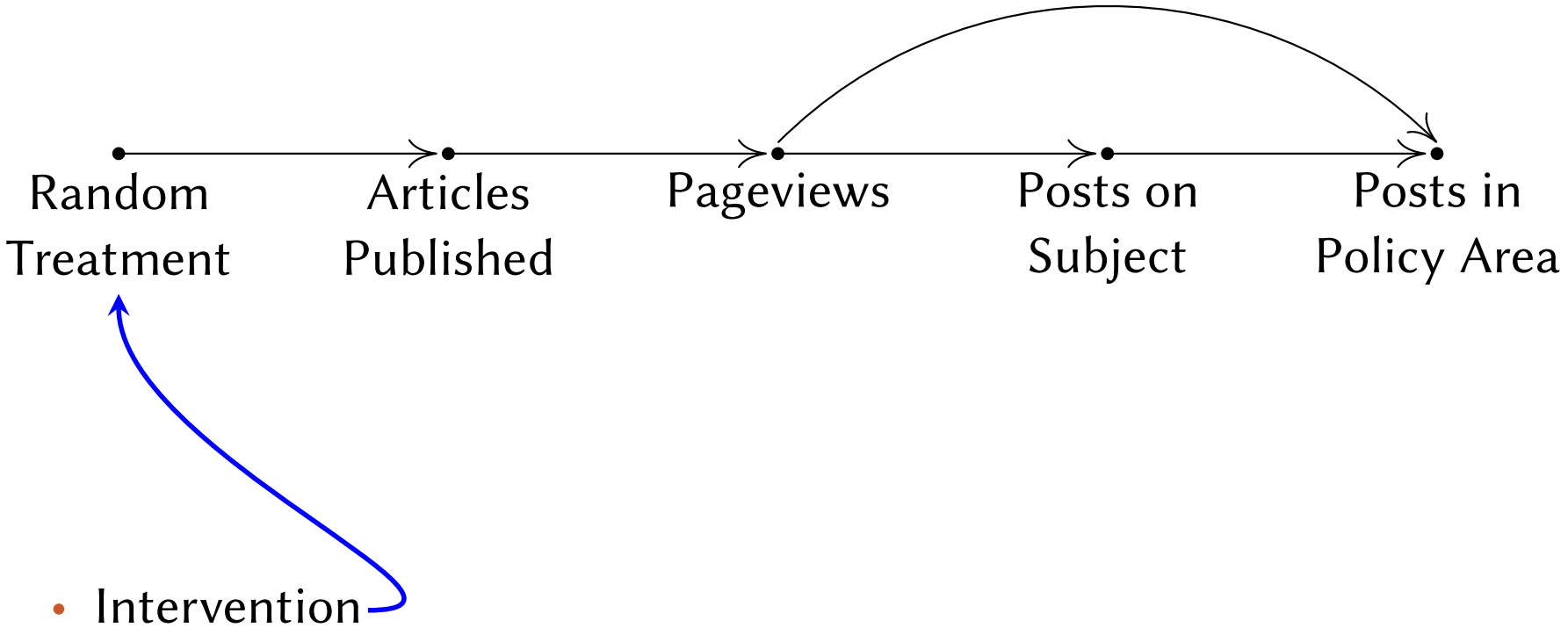

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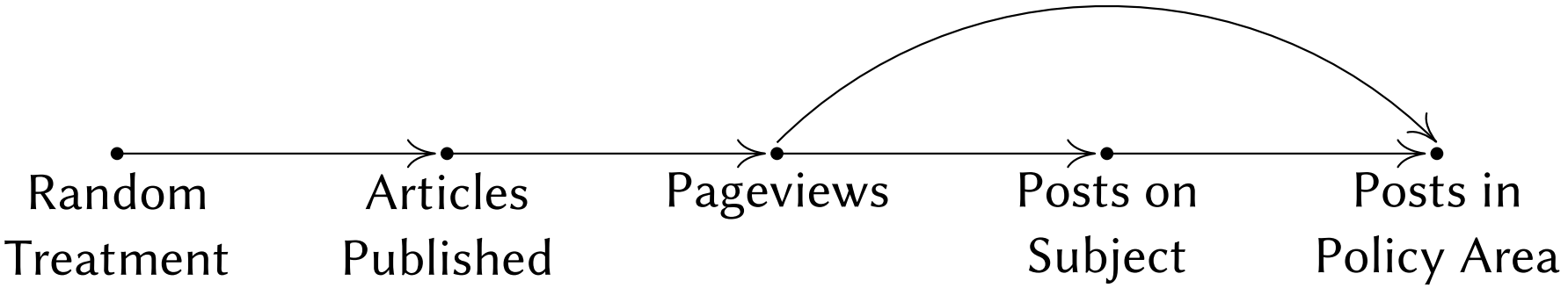

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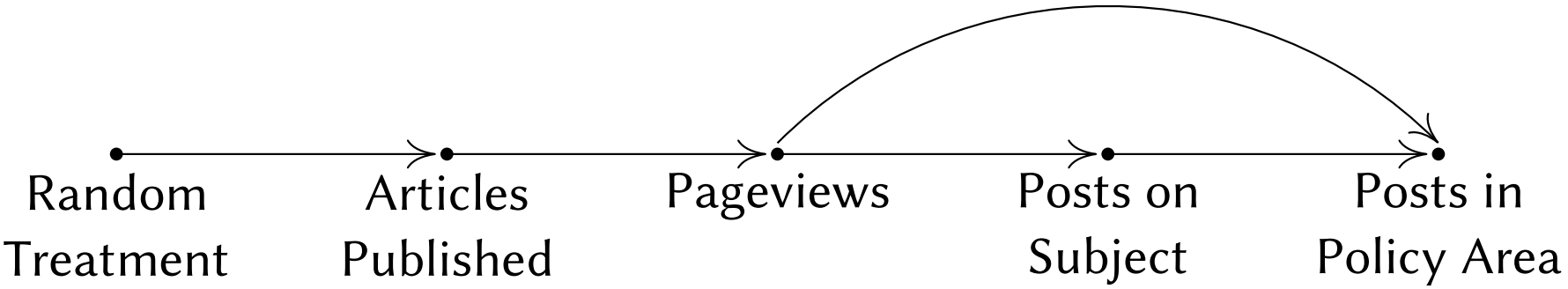

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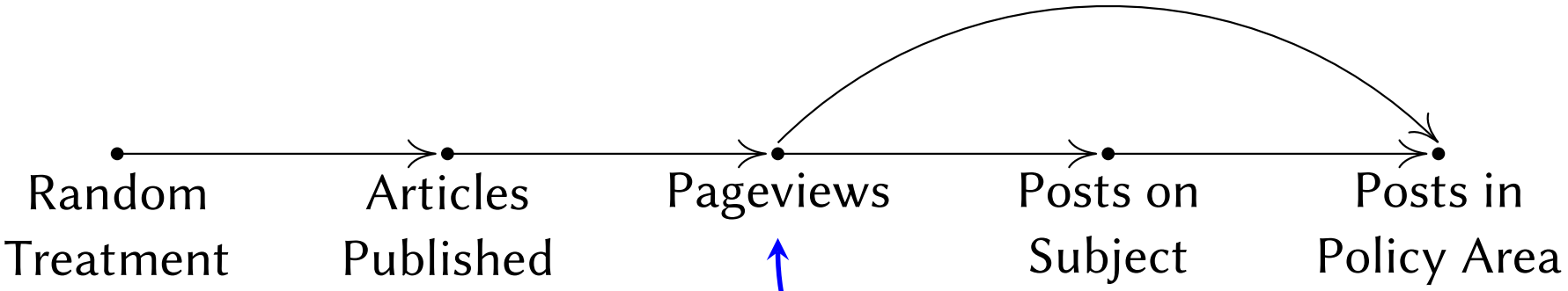

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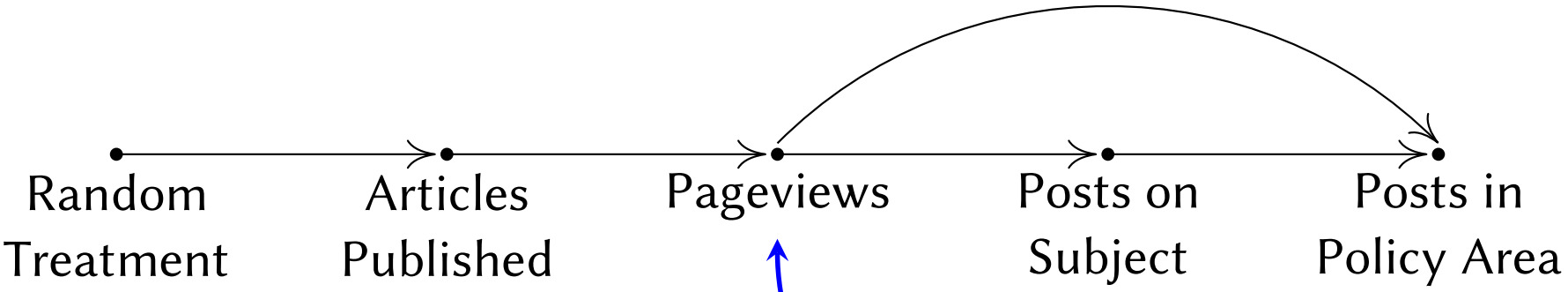

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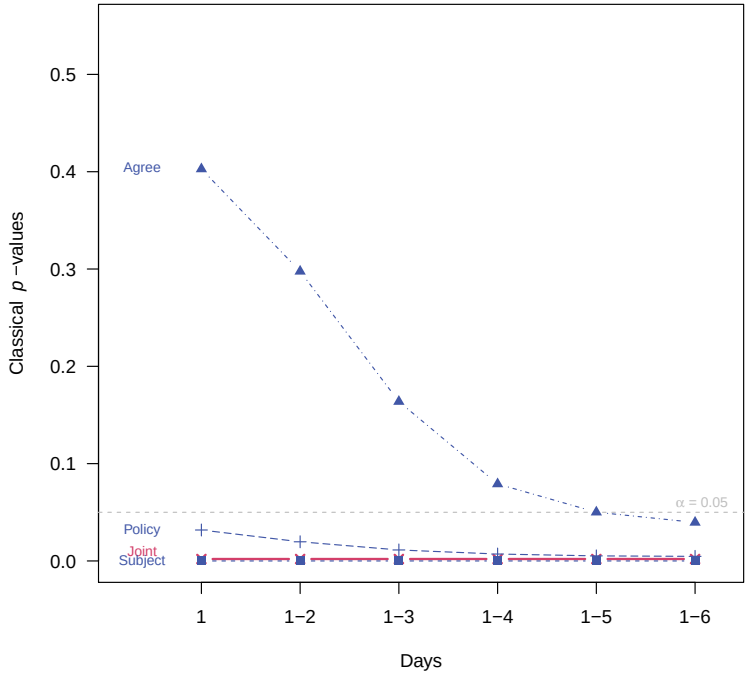

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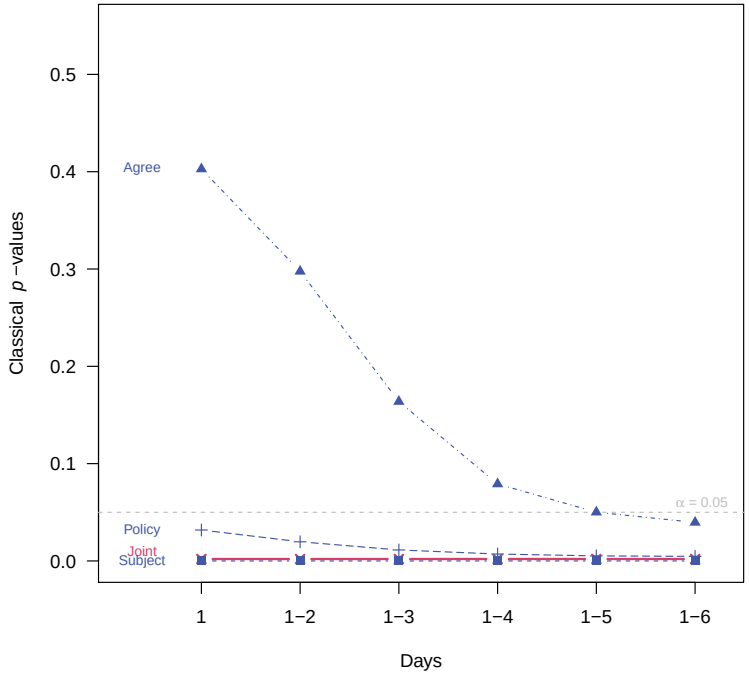

- Frequentist validation: extensive [non]parametric tests

Main Causal Effect: Public Expression in Policy Areas

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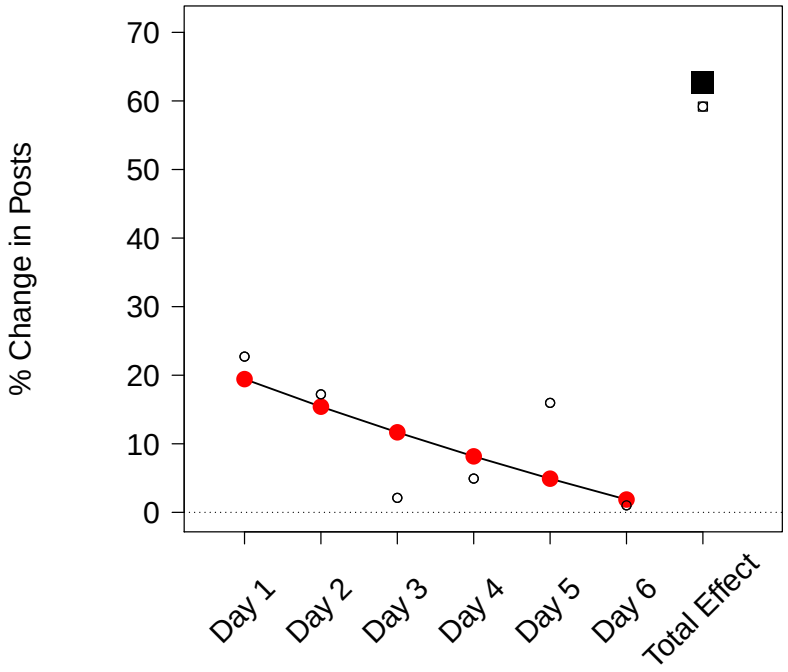

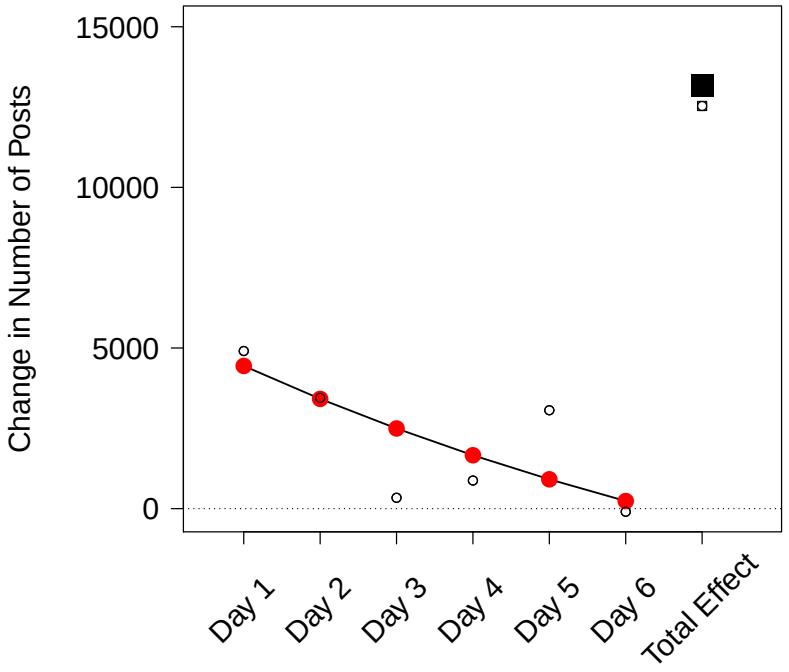

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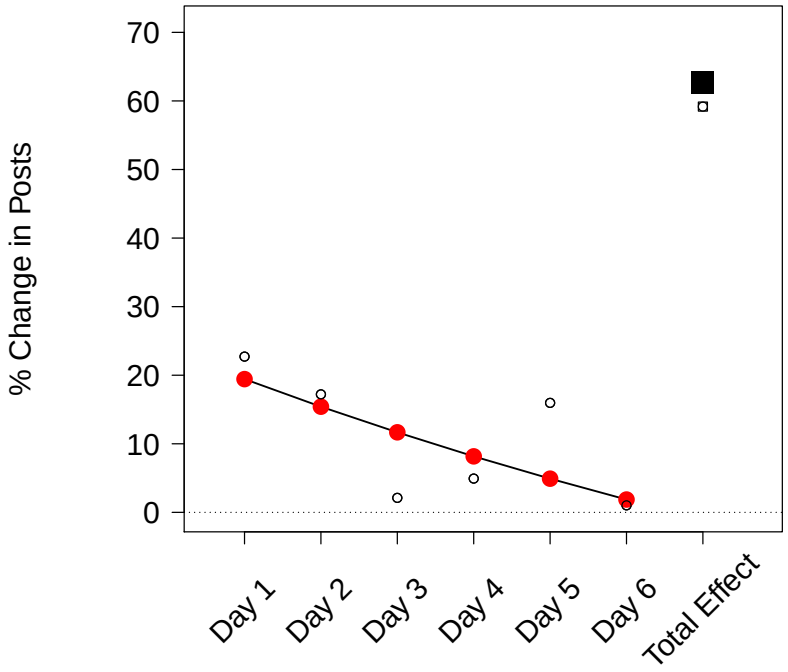

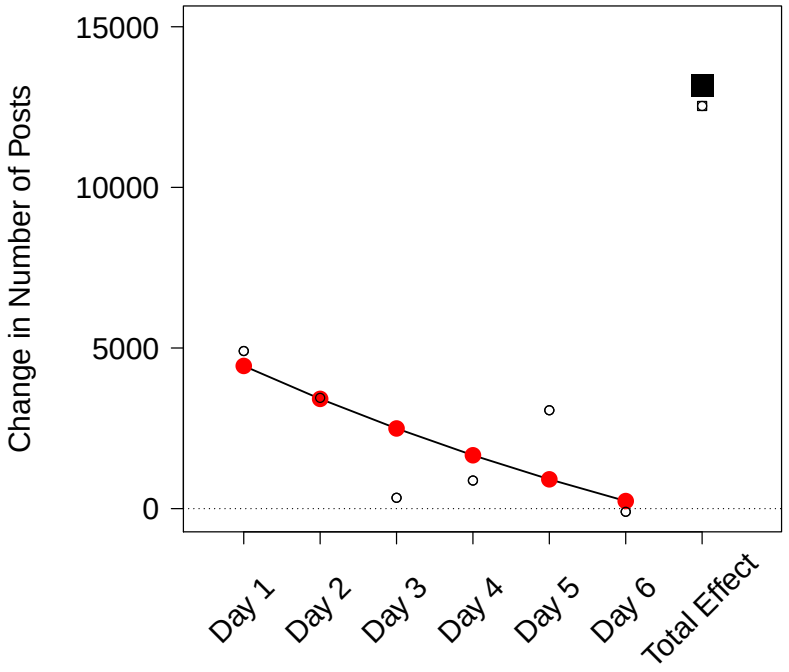

- Red Dots: model-based estimate (assumes linearity over days)

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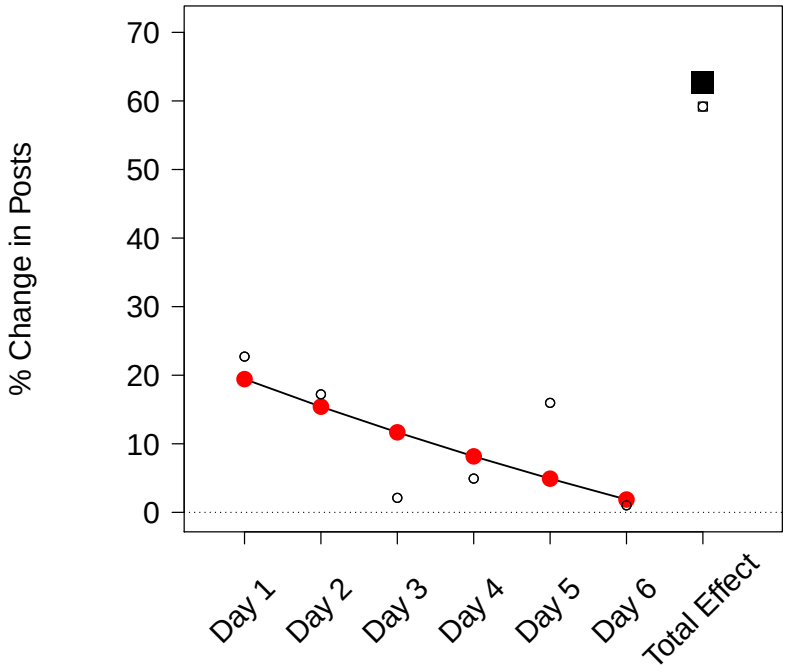

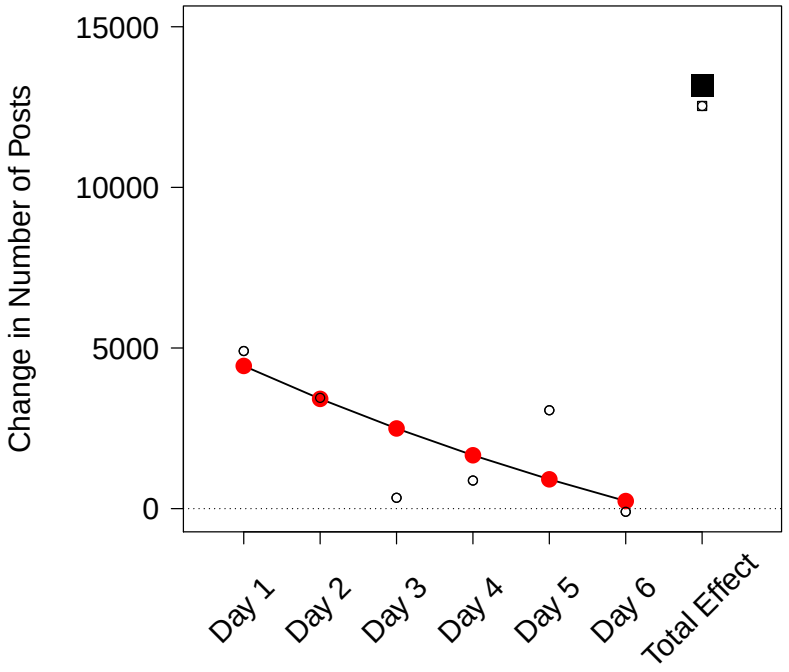

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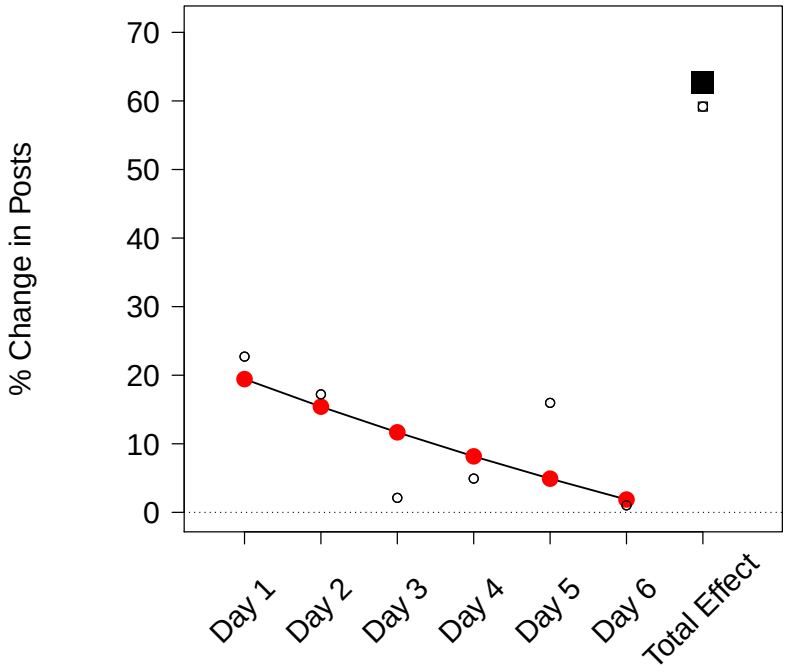

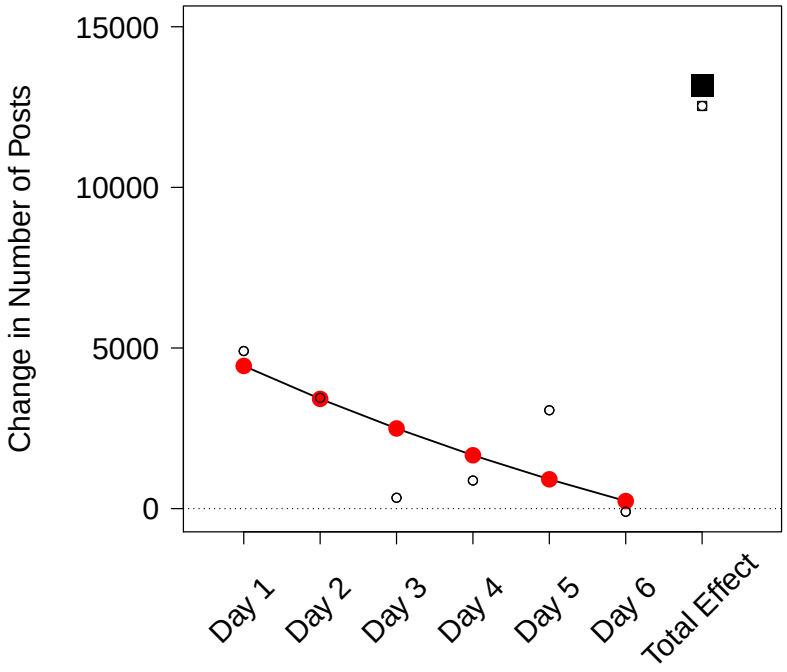

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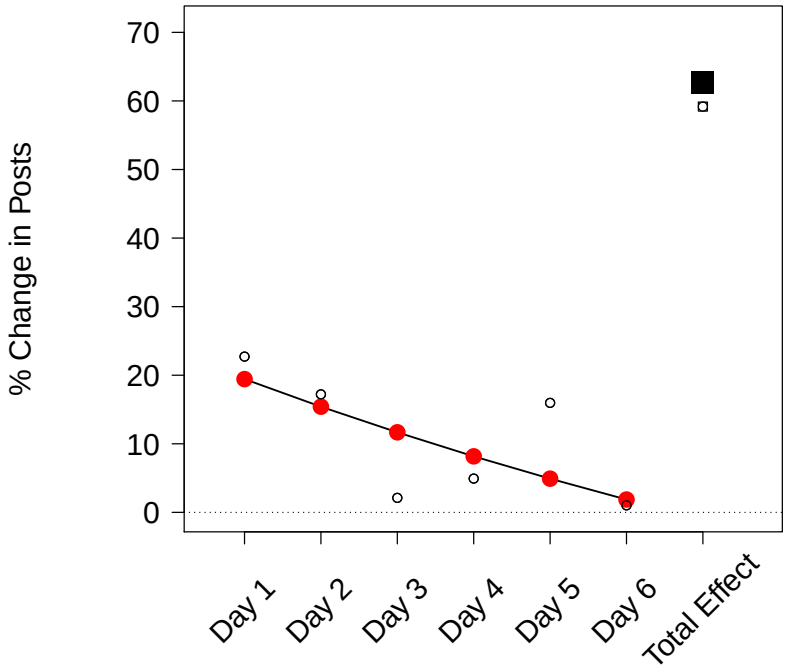

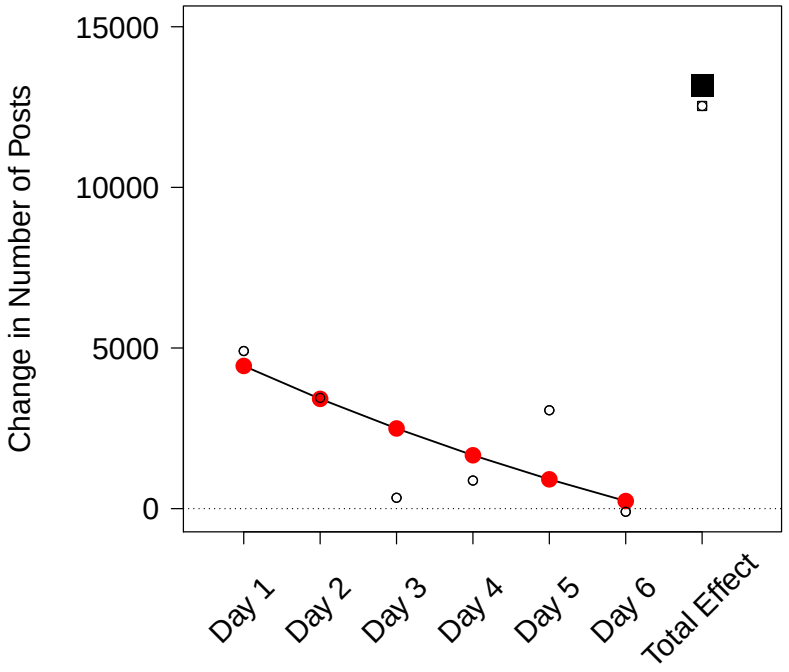

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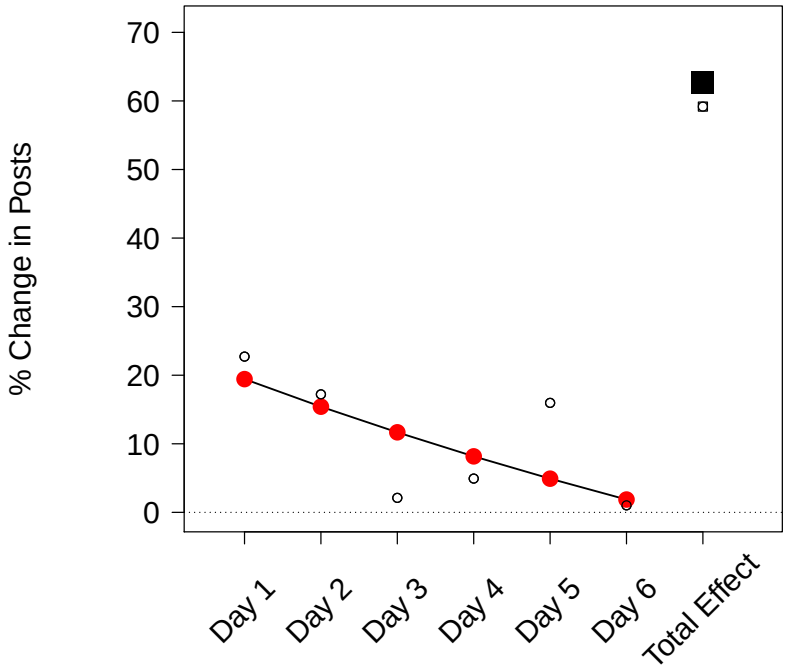

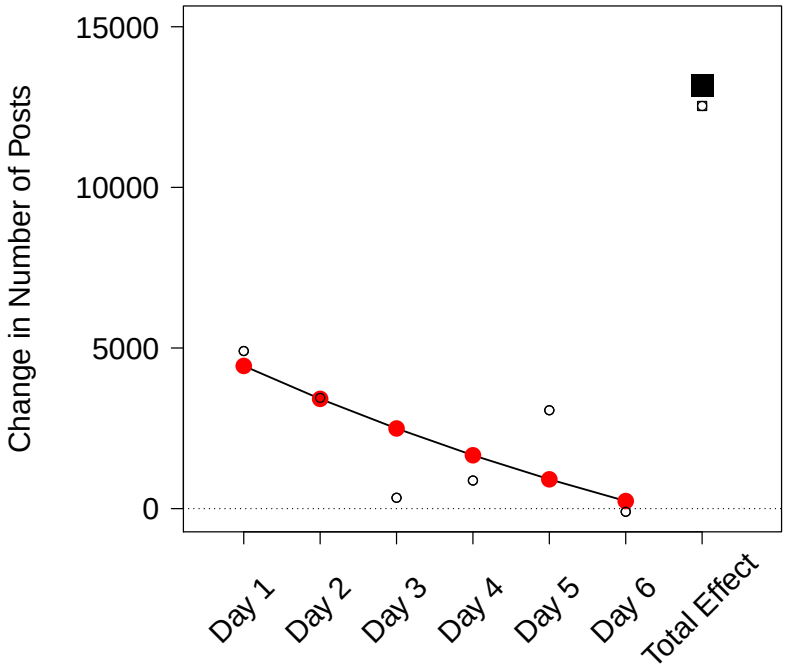

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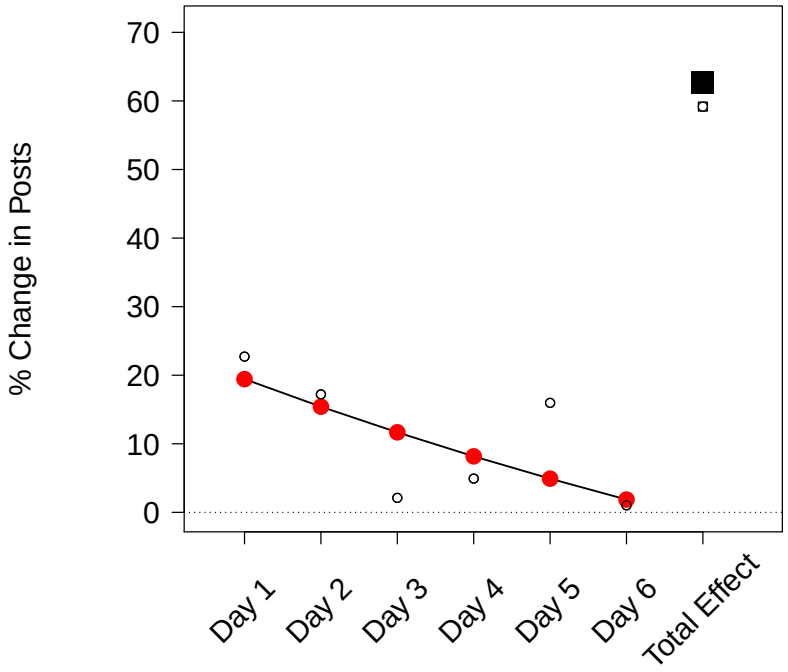

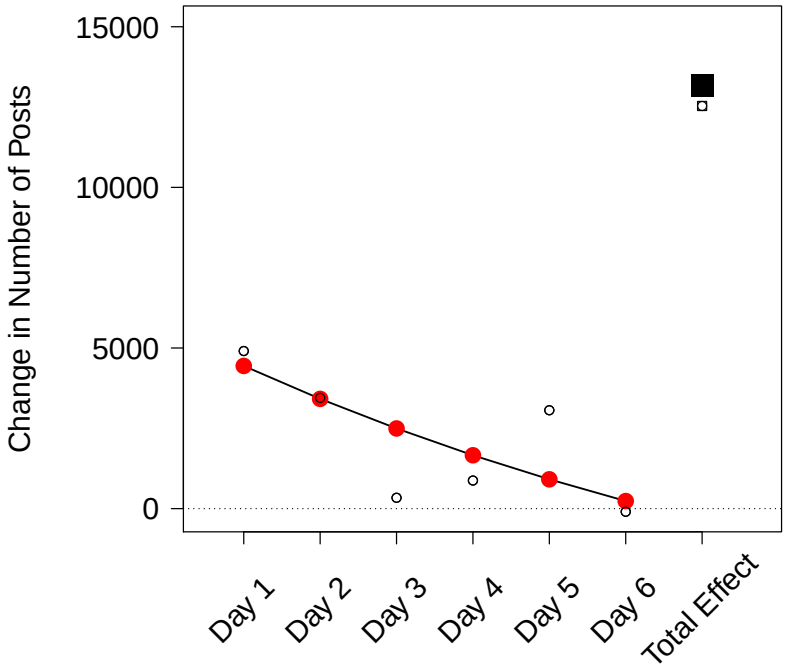

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Causal Effect: Indistinguishable Across Subgroups

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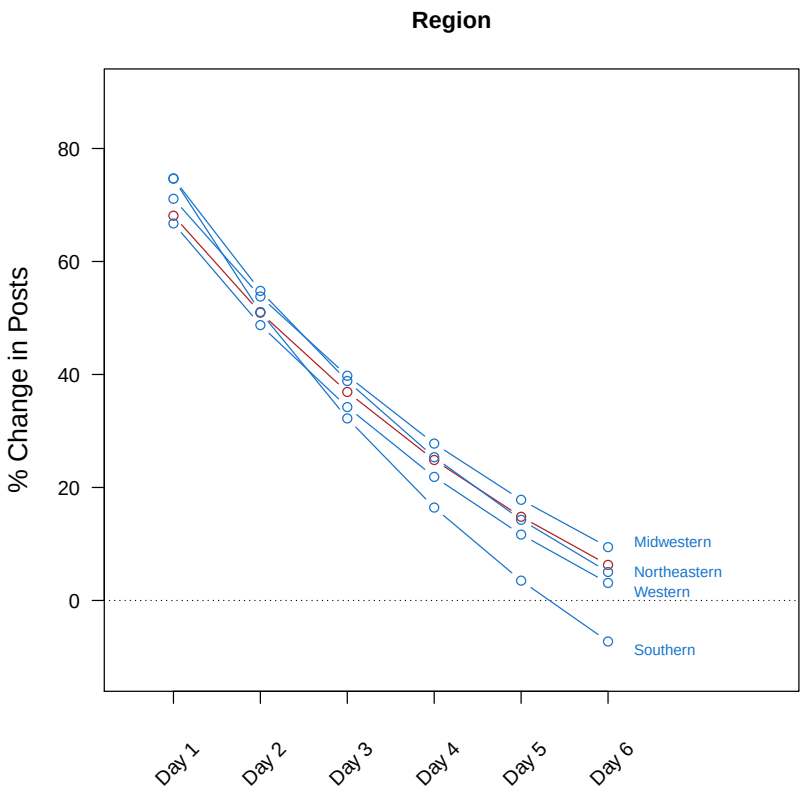

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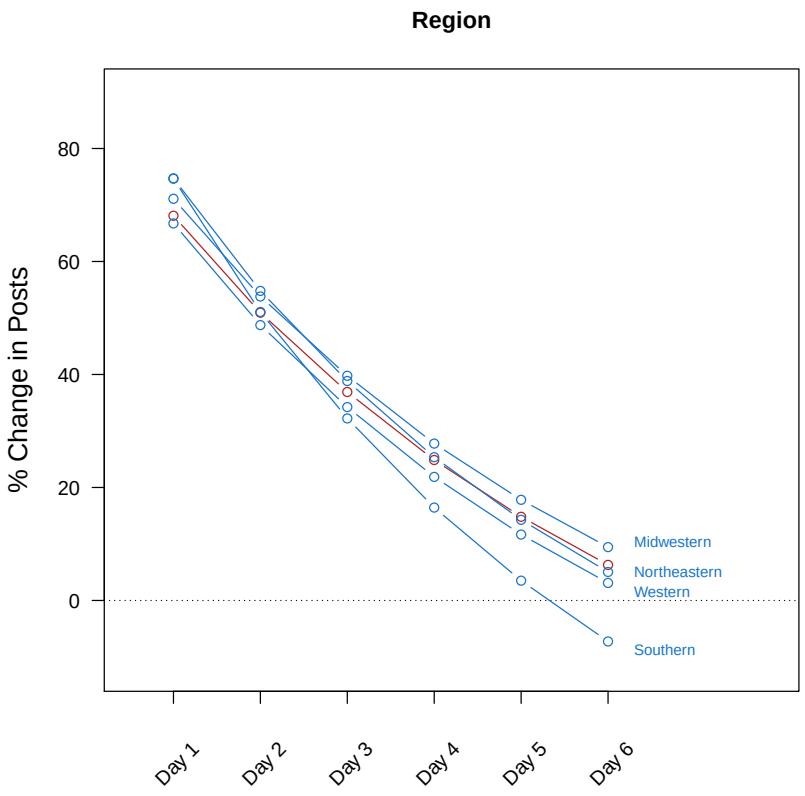

Effect on the national conversation in major policy areas is national

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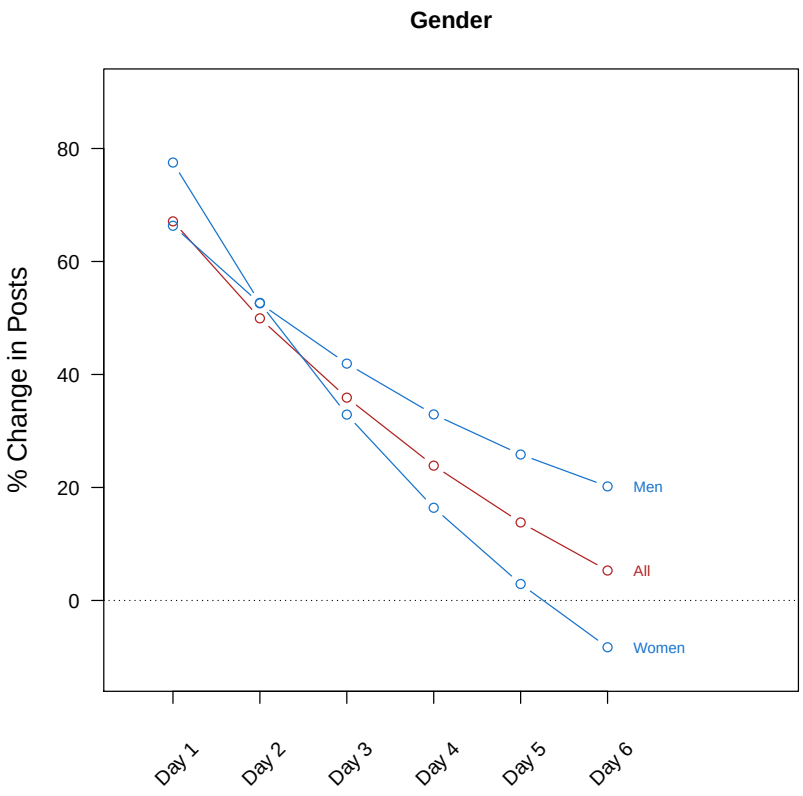

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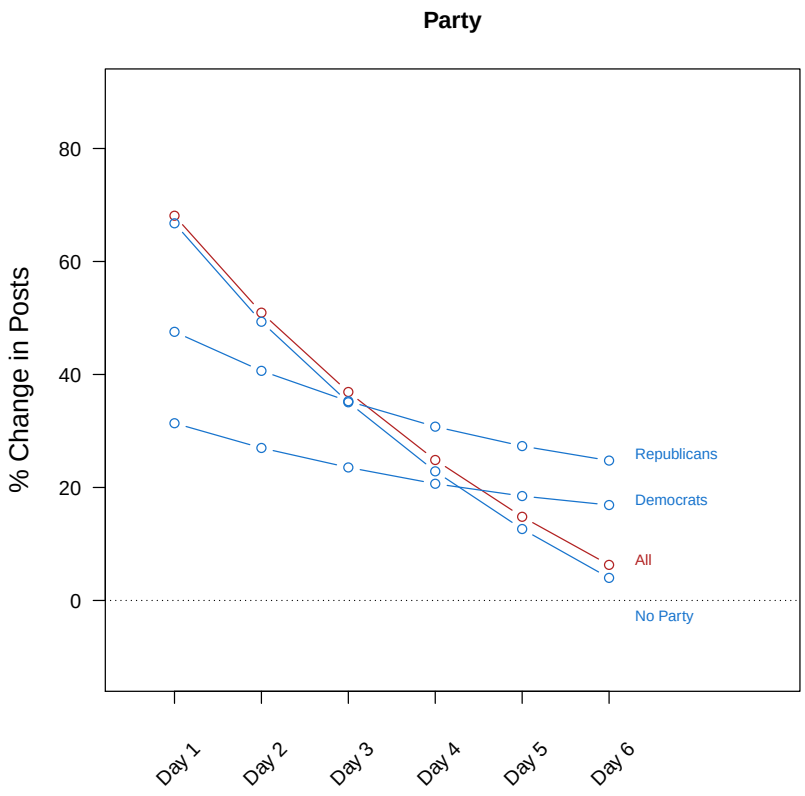

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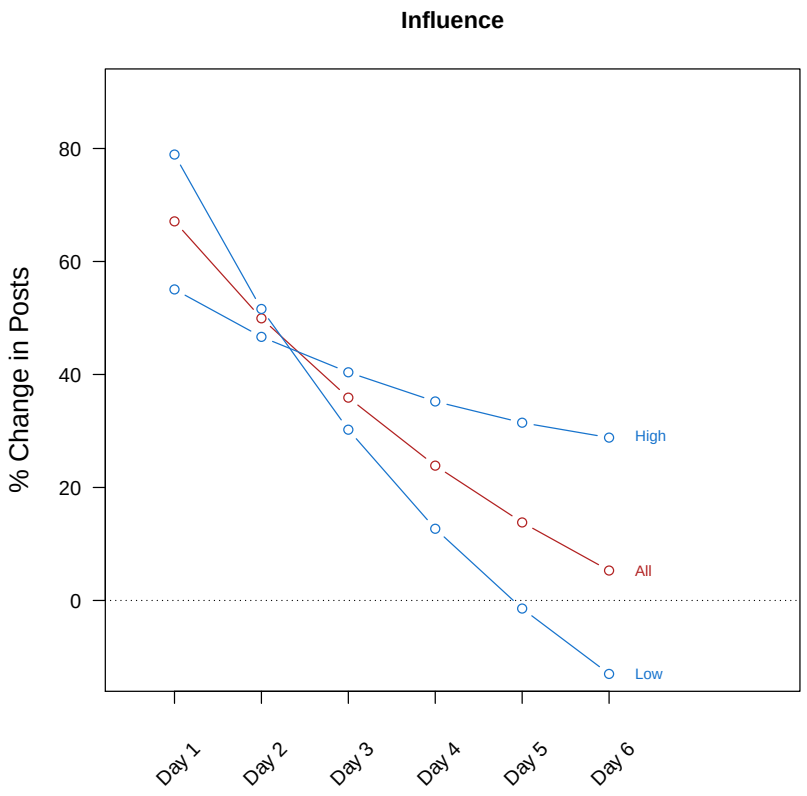

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Causal Heterogeneity: Leave-One-Outlet-Out

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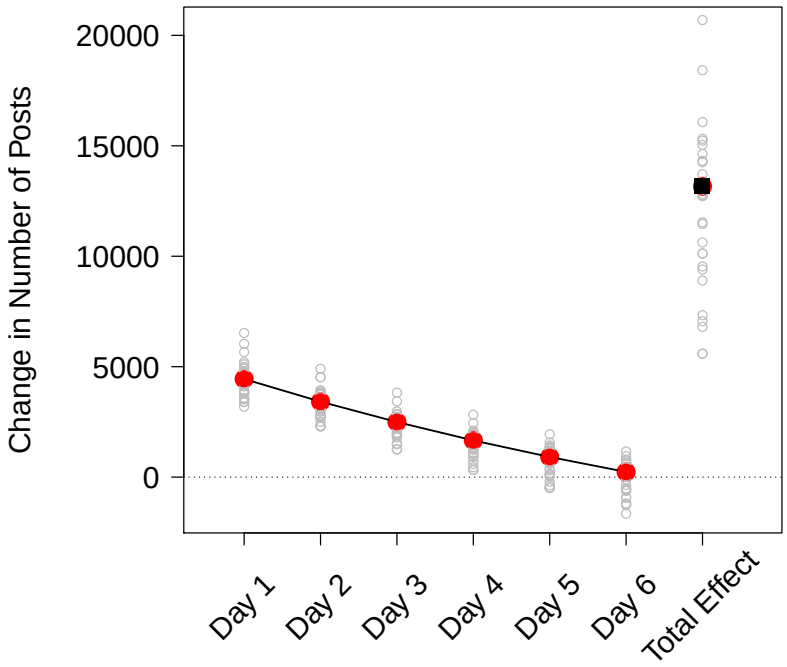

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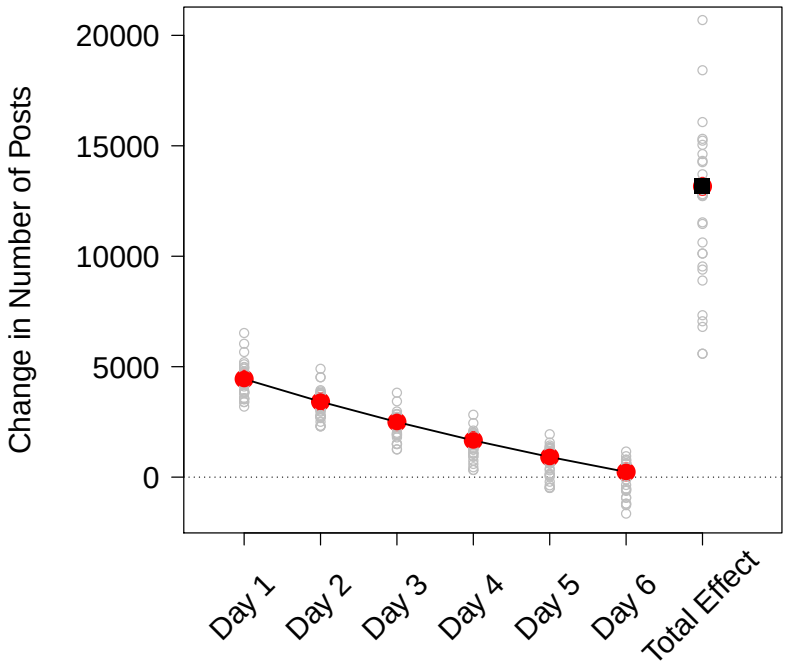

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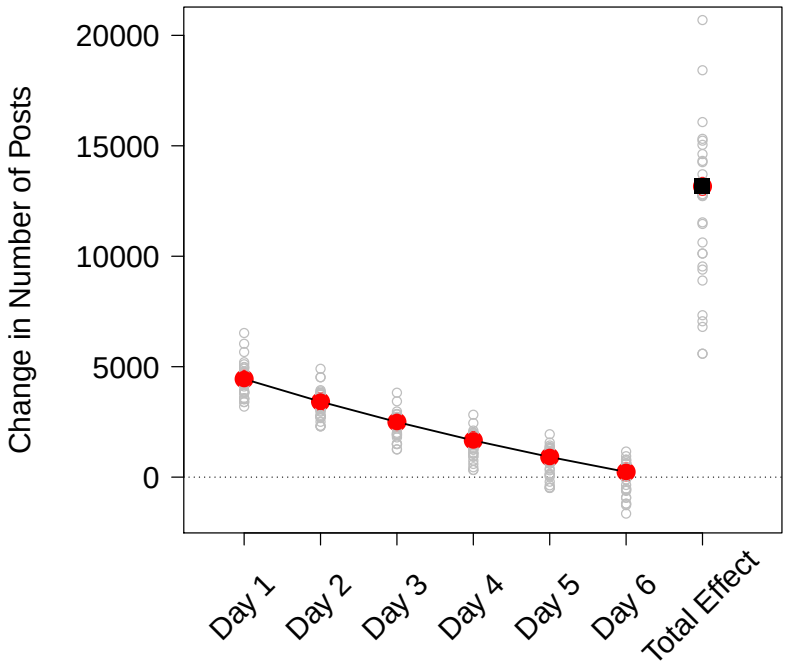

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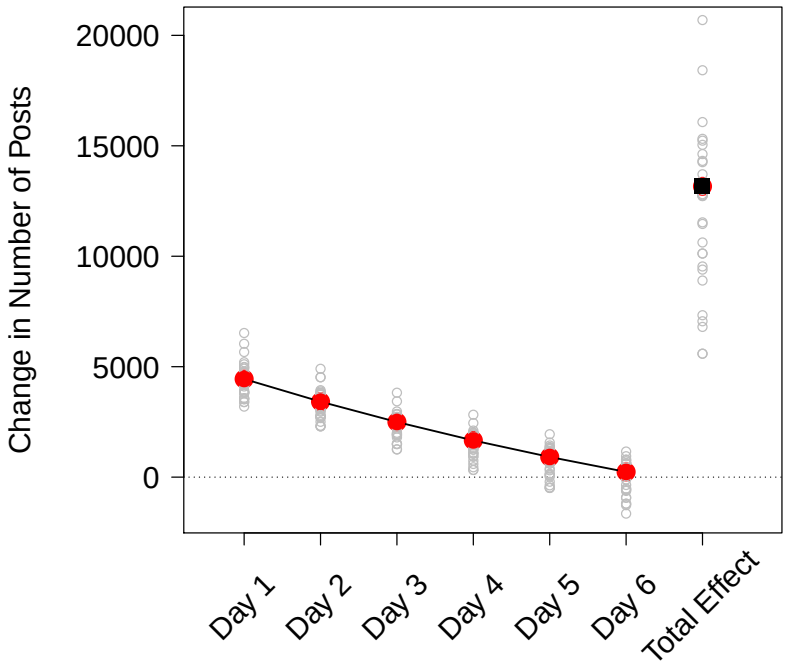

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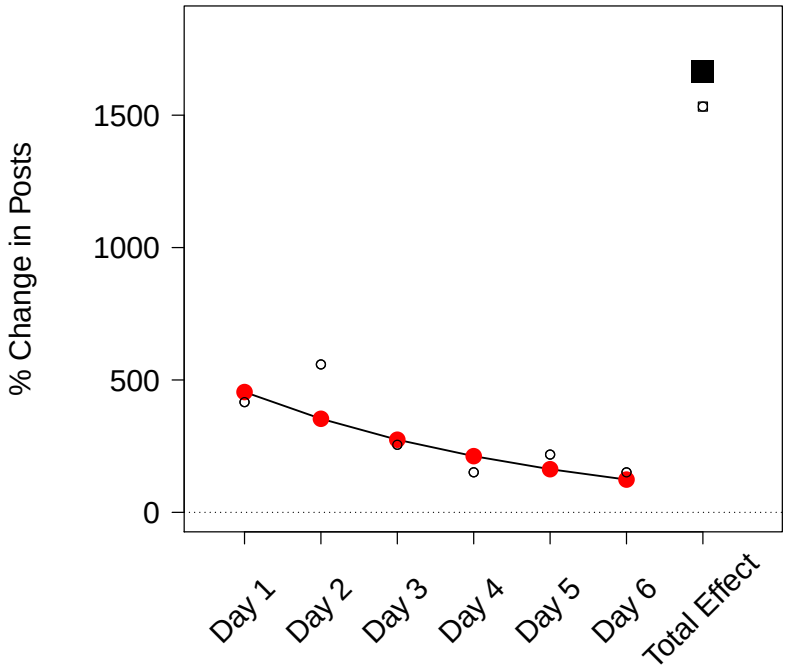

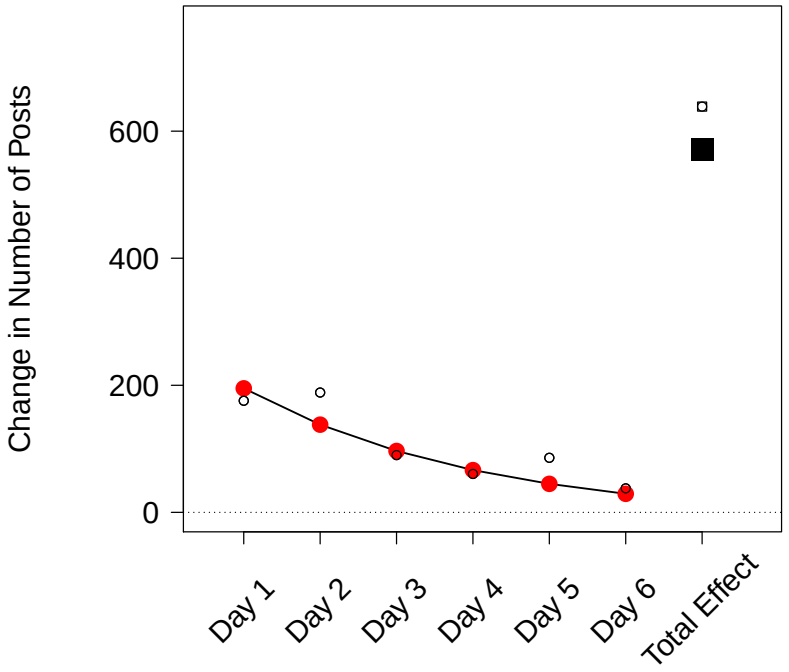

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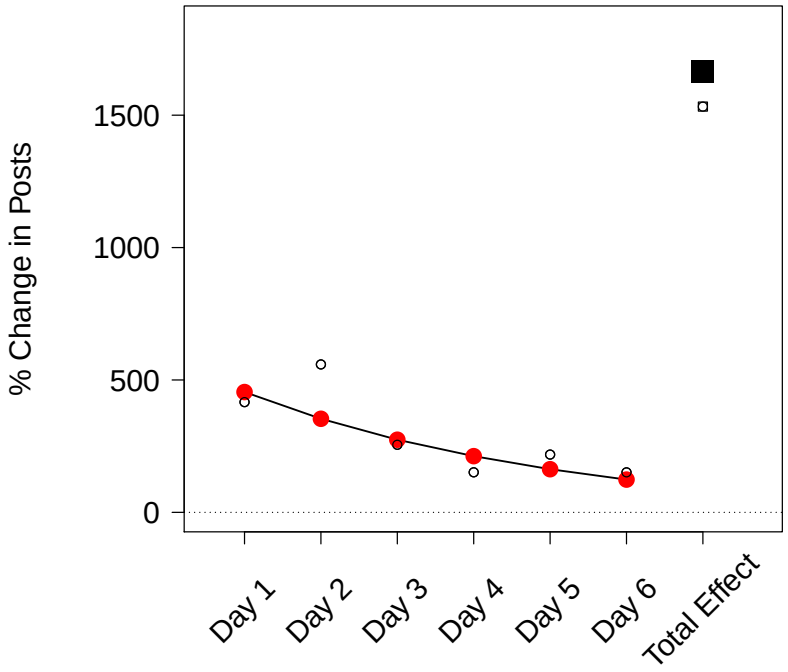

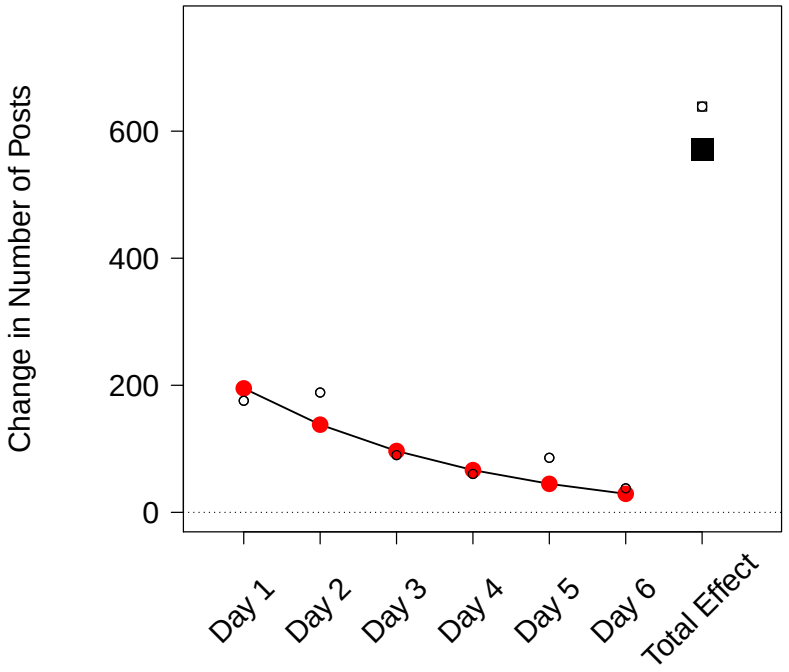

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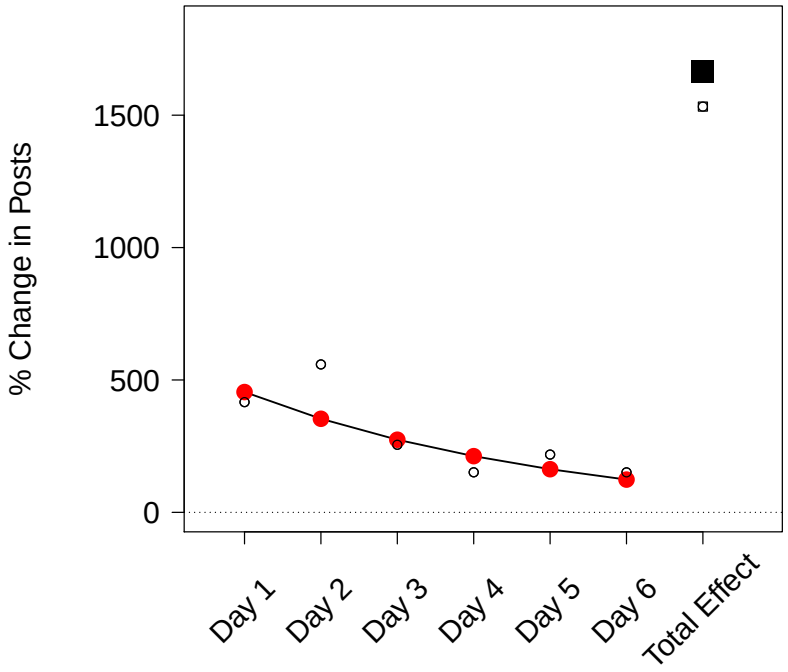

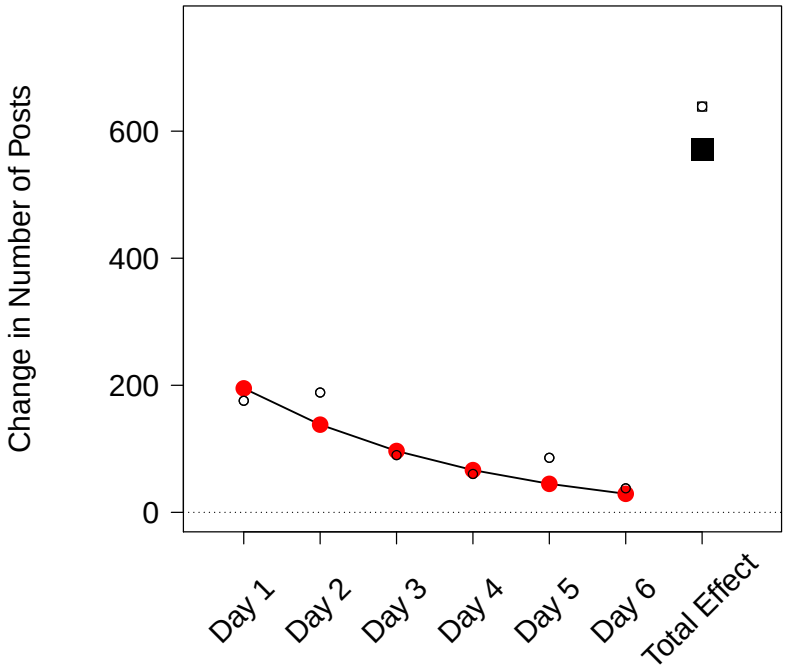

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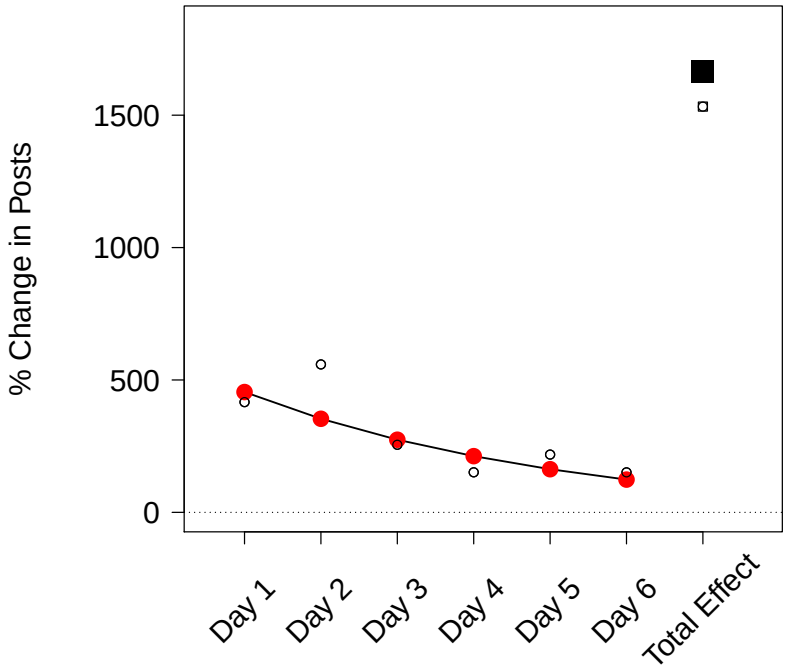

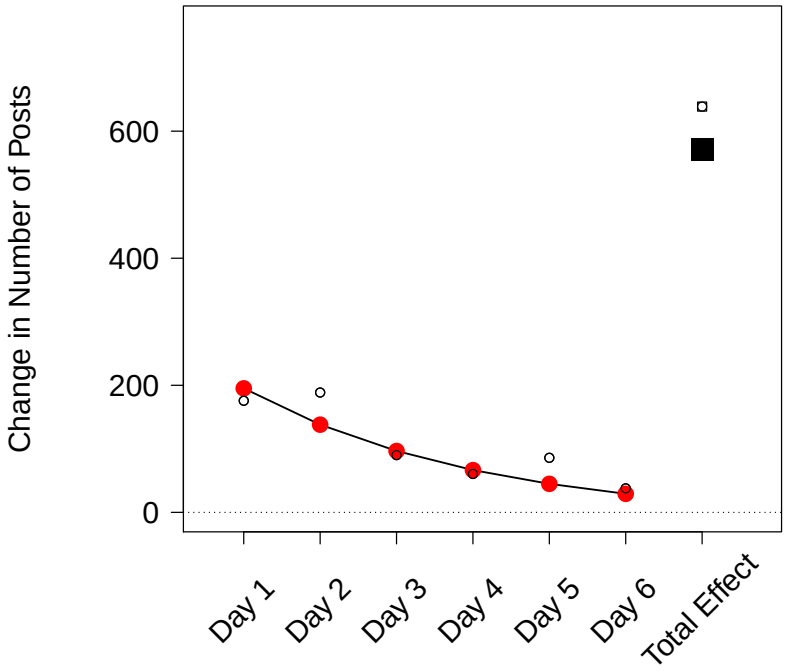

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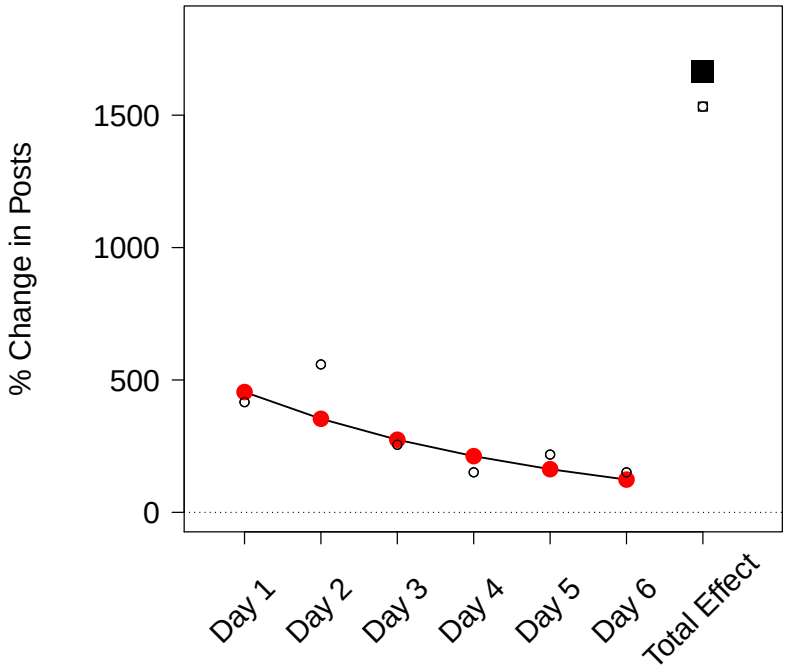

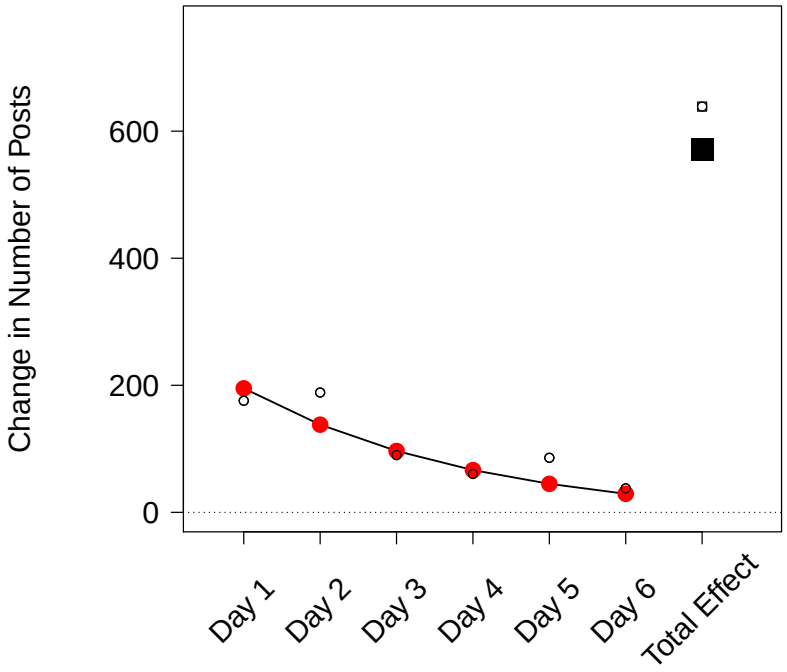

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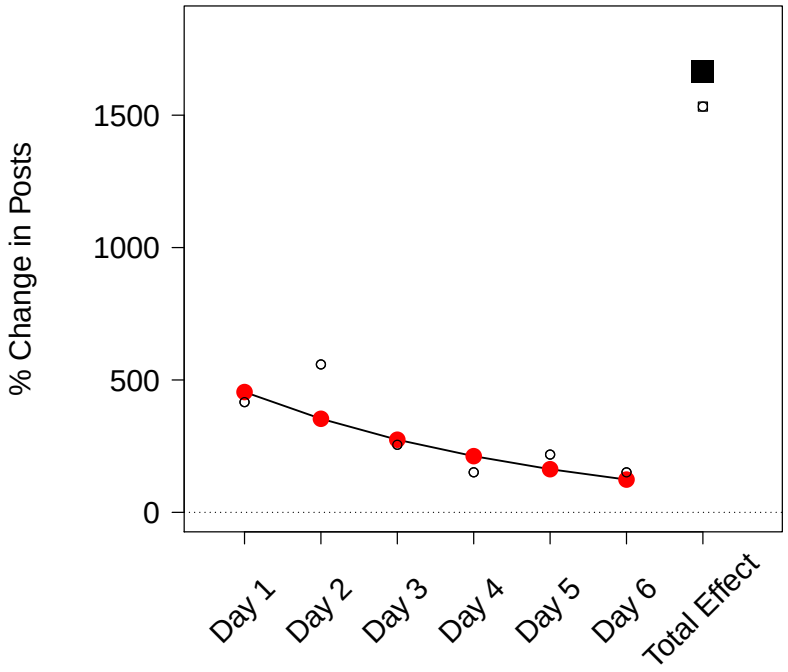

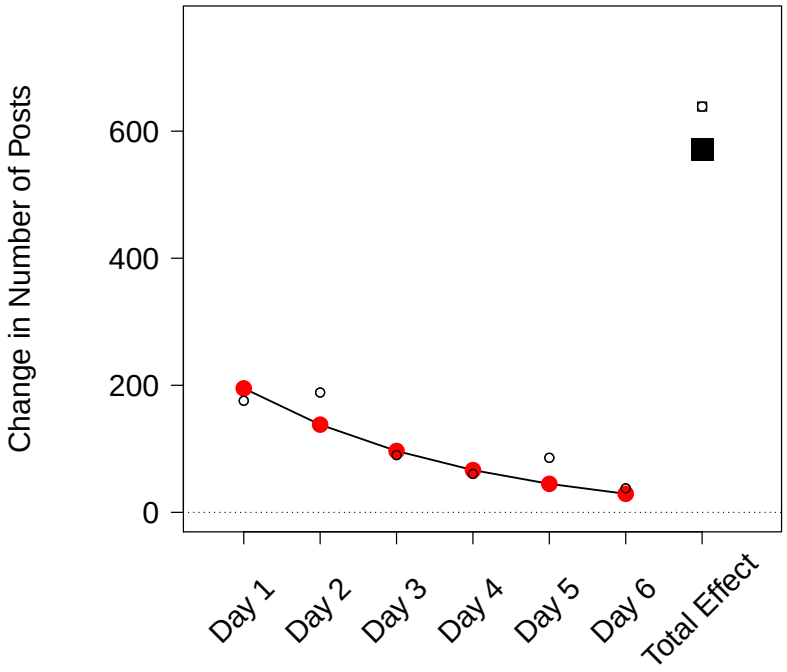

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For more information:
GaryKing.org/media

Notation and Quantities of Interest

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  - (perhaps with policy fixed effects)