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

Gary King[2]

Institute for Quantitative Social Science
Harvard University

Department of Sociology, Harvard University, 5/2/2018

[1] Based on joint work with Benjamin Schneer and Ariel White (*Science* 2017)
[2] GaryKing.org

Introduction

Research Design

Results

Supporting Analyses

Implications

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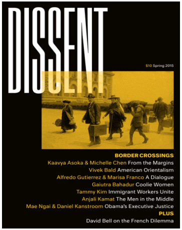

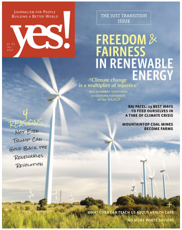

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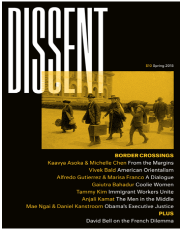

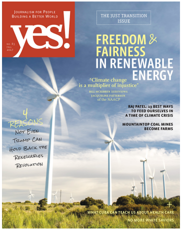

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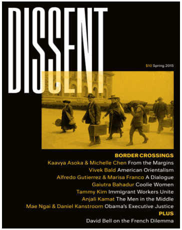

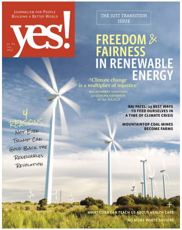

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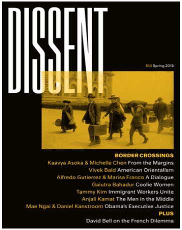

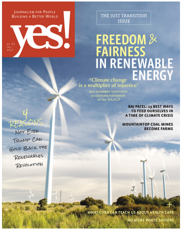

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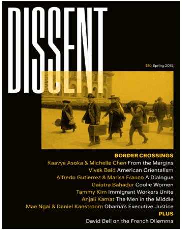

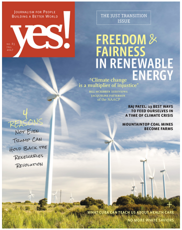

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- (Ex post: Automated text analysis & qualitative evidence: indistinguishable from normal publications & practices; no outlet received a single complaint)

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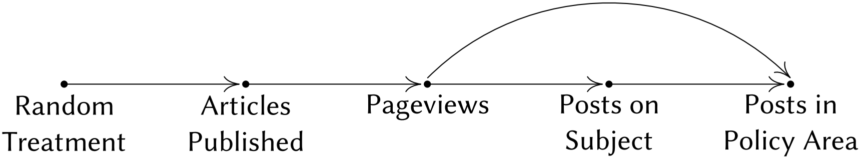

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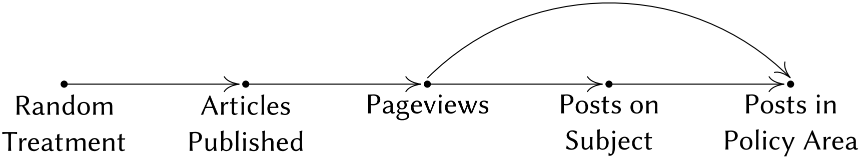

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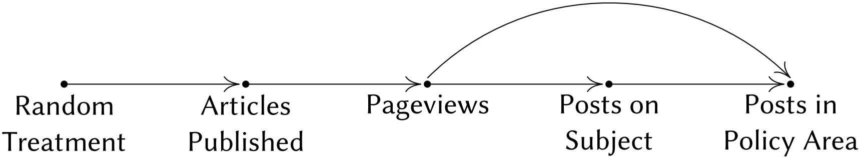

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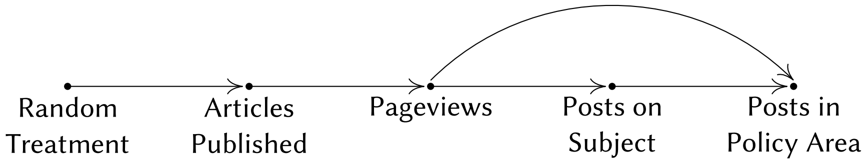

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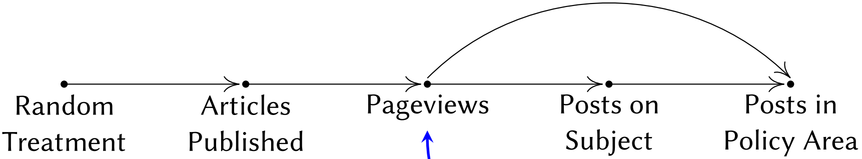

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Research Design

Results

Supporting Analyses

Implications

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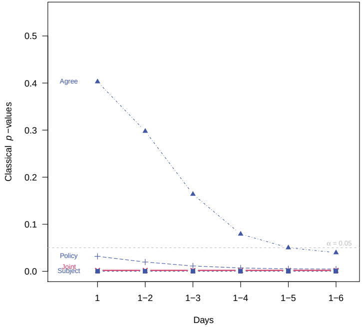

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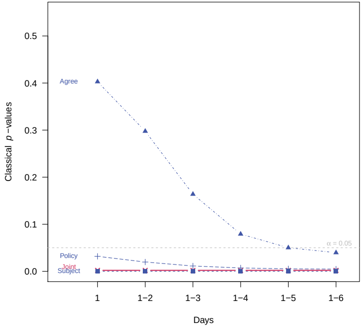

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Main Causal Effect: Public Expression in Policy Areas

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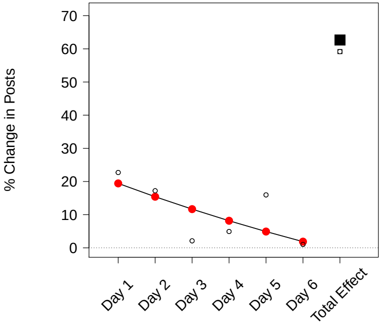

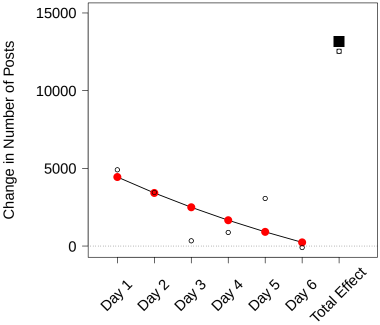

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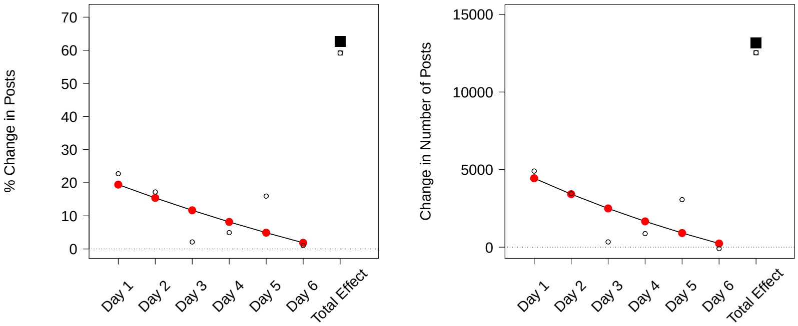

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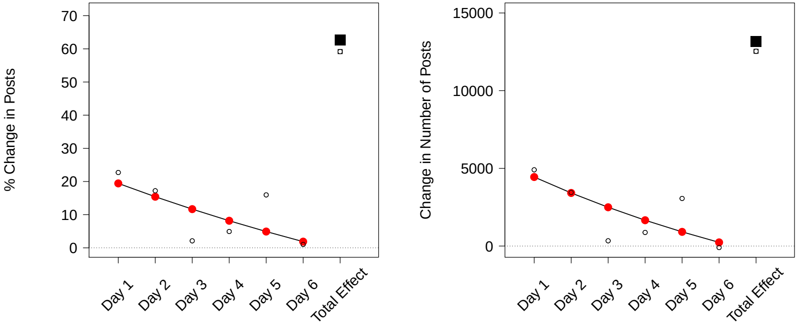

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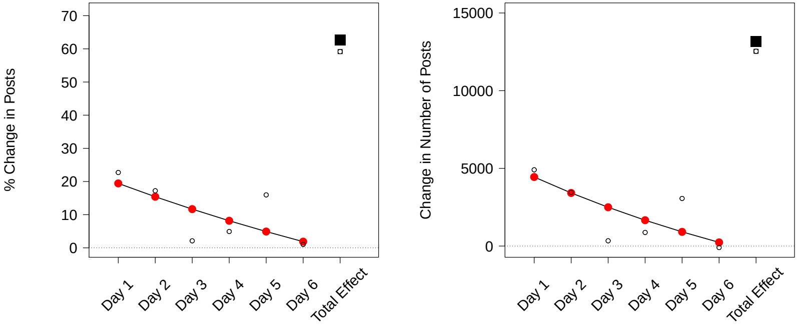

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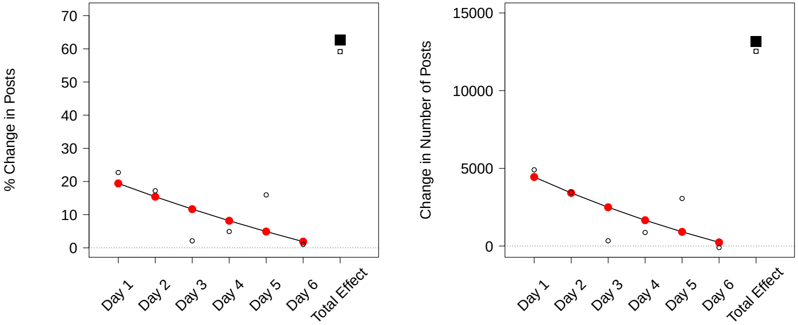

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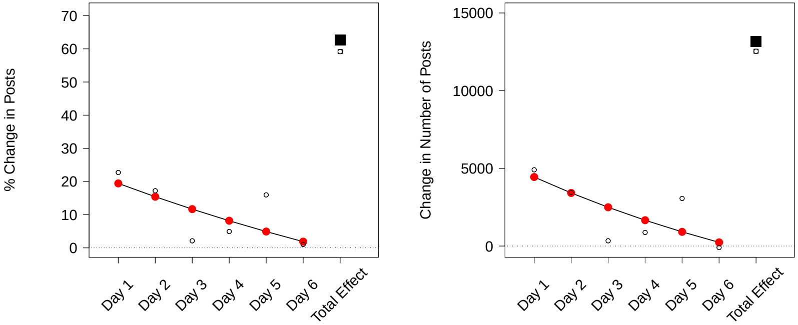

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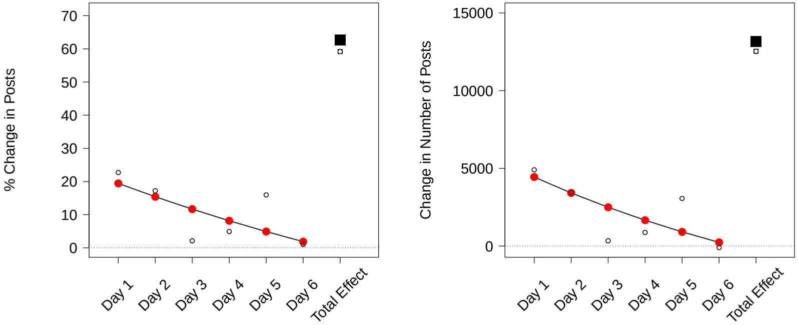

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Causal Effect: Indistinguishable Across Subgroups

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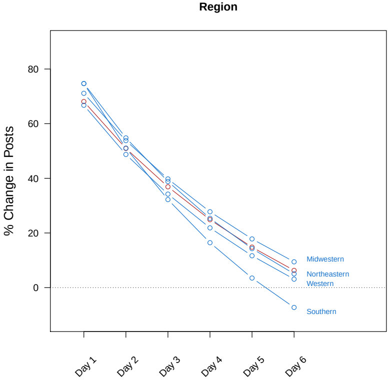

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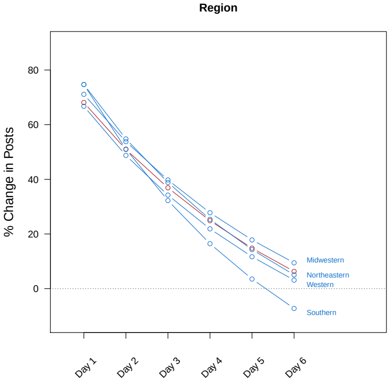

Effect on the national conversation in major policy areas is national

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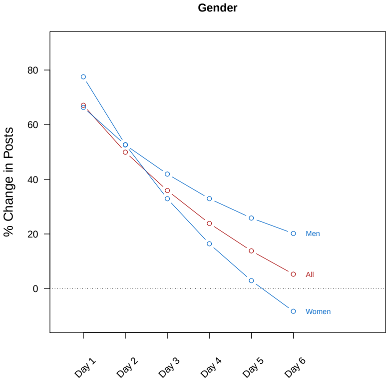

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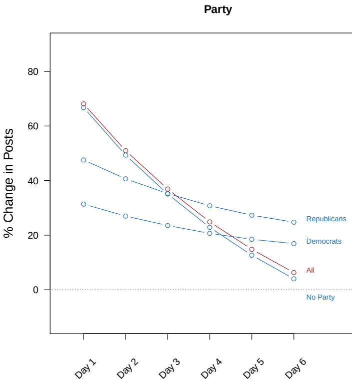

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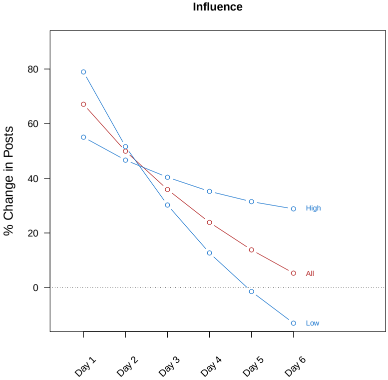

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Causal Heterogeneity: Leave-One-Outlet-Out

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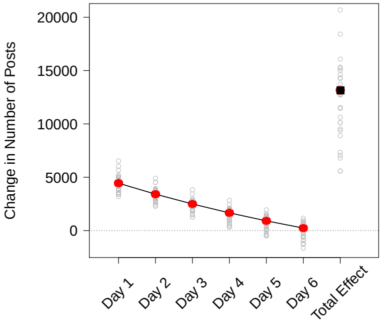
Jackknife Estimation on Policy Area Effects



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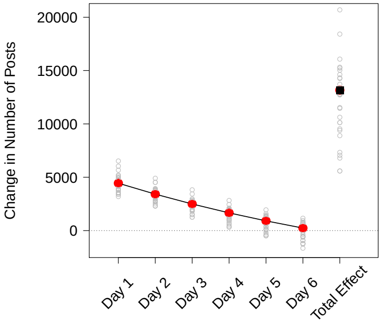

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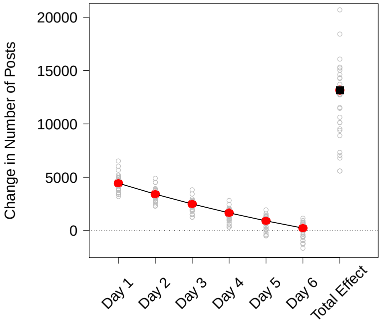

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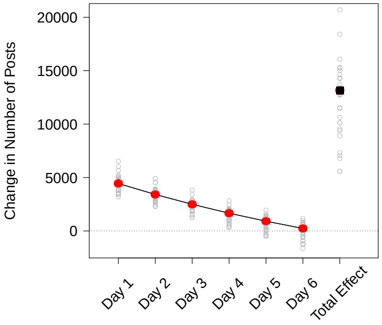

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- Results: no dominant outlet; high heterogeneity

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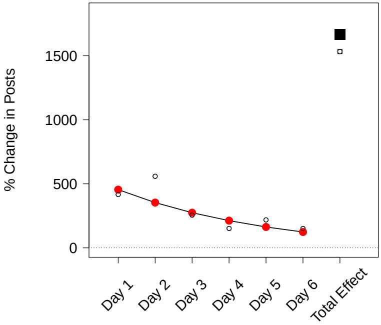

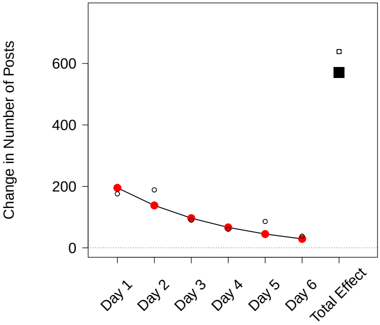

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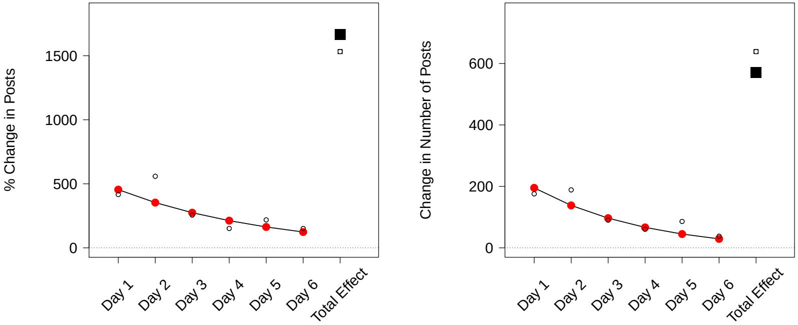

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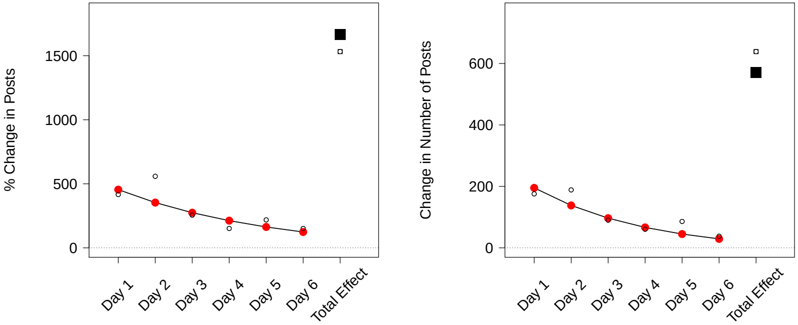

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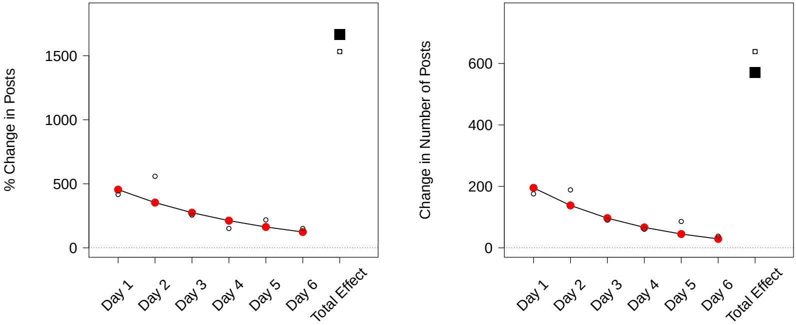

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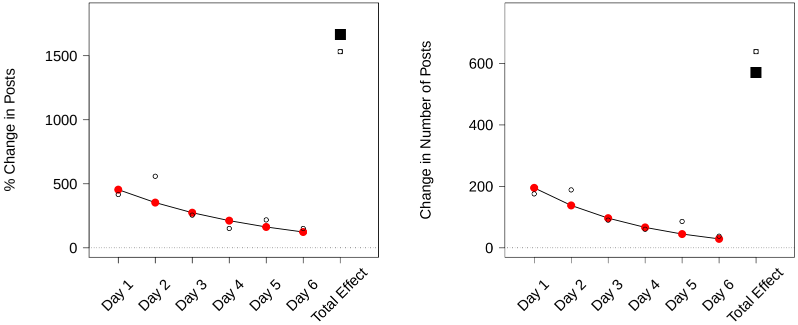

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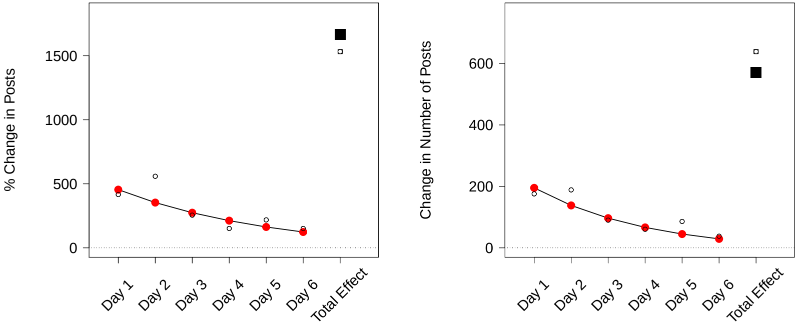

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  - Treatment articles: representative of all on complexity, type

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For more information:

GaryKing.org/media

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Estimation Approaches

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  - Transform outcome variable for normality & homoskedasticity: $z_{ped} = \ln(y_{ped} + 0.5)$
  - The Model: $E(z_{ped}|T_{ped}) = \beta^0 + \beta_p + \eta_d + \gamma_d T_{ped}$
    - β^0: constant term
    - β_p: fixed effects for the 11 policy areas
    - Assume linearity over days: $\eta_d = \eta^0 + \eta^1 d$ and $\gamma_d = \gamma^0 + \gamma^1 d$
    - Assume *conditional* independence over p, e, d
- Model-Free Approach:
  - Drop linearity & conditional independence assumptions
  - Regress z_{ped} on T_{ped} separately for each d
  - Equivalent to difference in means for each day

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- Model-Free Approach:
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  - Regress z_{ped} on T_{ped} separately for each d
  - Equivalent to difference in means for each day
  - (perhaps with policy fixed effects)