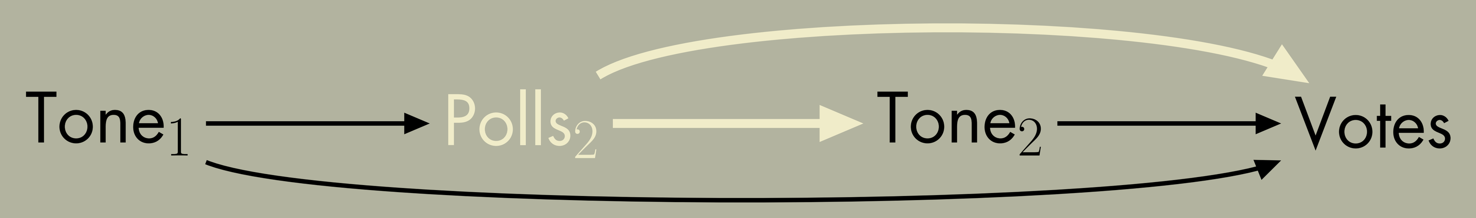
Dynamic Causal Inference and Negative Advertising

Matthew Blackwell | Harvard University | mblackwell@iq.harvard.edu

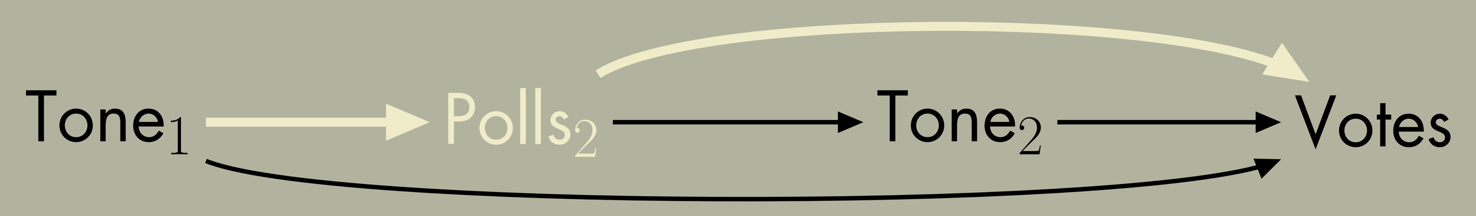
Dynamic Selection

Dynamic selection hinders the estimation of campaign effects because it creates two pernicious forms of bias that "conditional methods" such as matching and regression cannot simultaneously correct.

Omitted variable bias on the one hand



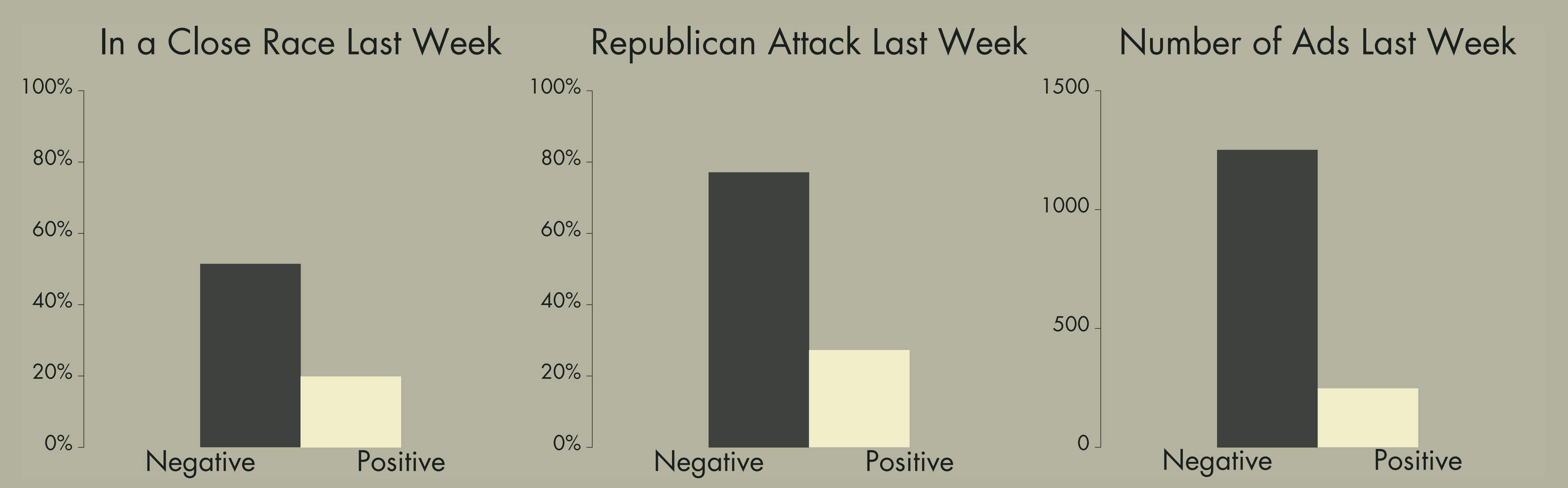
Post-treatment bias on the other



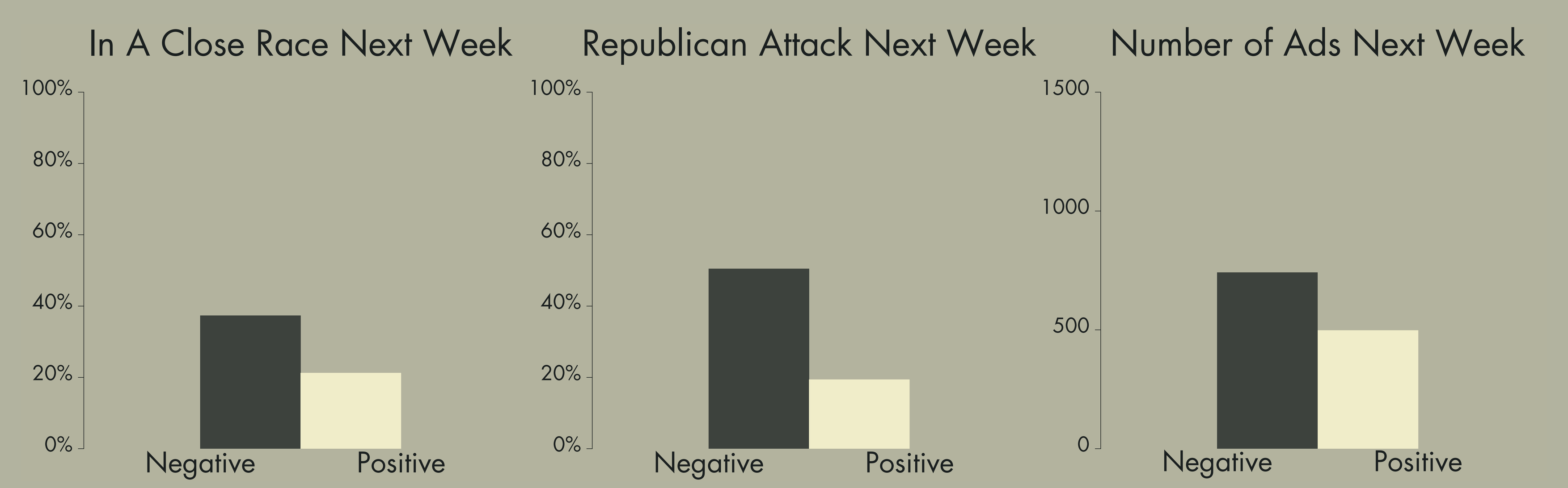
To remove both biases, I utilize an inverse-probability of treatment weighting (IPTW) approach to estimate the effectiveness of going negative in competitive U.S. Senate and Gubernatorial elections from 2000–2006.

Dynamic Imbalances

Campaigns affect tone



Tone affects the campaign



Outcome Model

Notation

- $A_t = 1$ if >10% of ads are negative in week t
- $\underline{A}$ = entire history of campaign tone [e.g (1,0,1,0)]
- $\underline{A}_{\text{late}}$ = tone history, October–November
- $\underline{A}_{\text{early}}$ = tone history, Primary–September

I model the marginal mean of the potential outcome under a given tone history, $Y(\underline{A})$:

$$\mathbb{E}[Y(\underline{A})] = \beta_0 + \beta_1 \cdot \mathsf{sum}(\underline{A}_{\text{late}}) + \beta_2 \cdot \mathsf{sum}(\underline{A}_{\text{early}}).$$

This breaks up the effect of tone across stages of the campaign. Unfortunately,

$$\mathrm{E}[Y(\underline{A})] \neq \mathrm{E}[Y|\underline{A}]$$

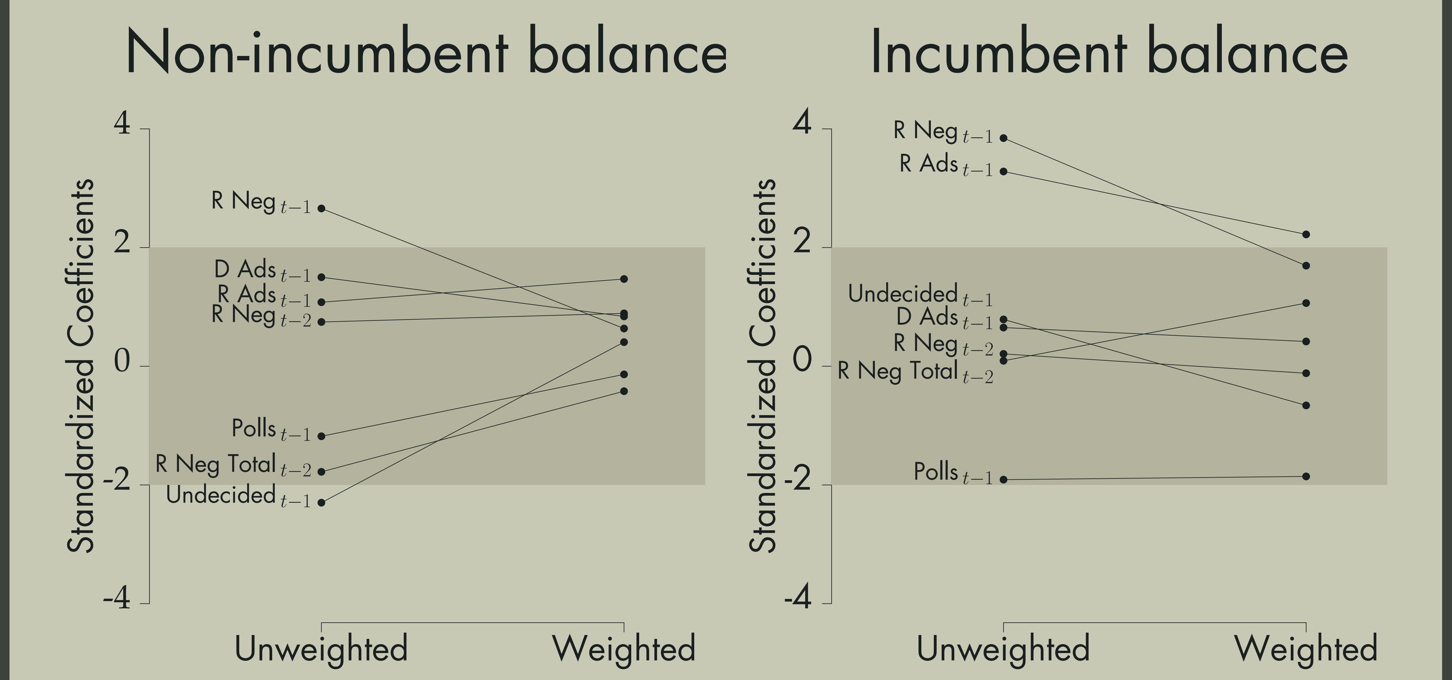
due to the **omitted variables** $\underline{X}$, but controlling for these using regression or matching induces **post-treatment bias**.

Weighting Model

To remove the omitted variable bias, we run the above model with the following weights:

$$W_i = \frac{1}{\prod_t p(A_t|\underline{A}_{t-1}, \underline{X}_t; \hat{\alpha})},$$

- $\underline{A}_{t-1}$ is the history of tone until t and $\underline{X}_t$ is the covariate history up until time t.
- $p(A_t|\underline{A}_{t-1}, \underline{X}_t; \hat{\alpha})$ is the predicted probability of the observed tone at time t, given the past, using a pooled logit with estimated parameters $\hat{\alpha}$.
- After reweighting, we can check the imbalance using a novel diagnostic, the **history-adjusted imbalance**:



Key Assumptions

Assumption 1 (Consistency). *For any treatment regime, observed outcomes are equal to the potential outcome under the treatment history actually observed. Formally, if unit i has a treatment history consistent with history $\underline{A}$, then $Y_i = Y_i(\underline{A})$.*

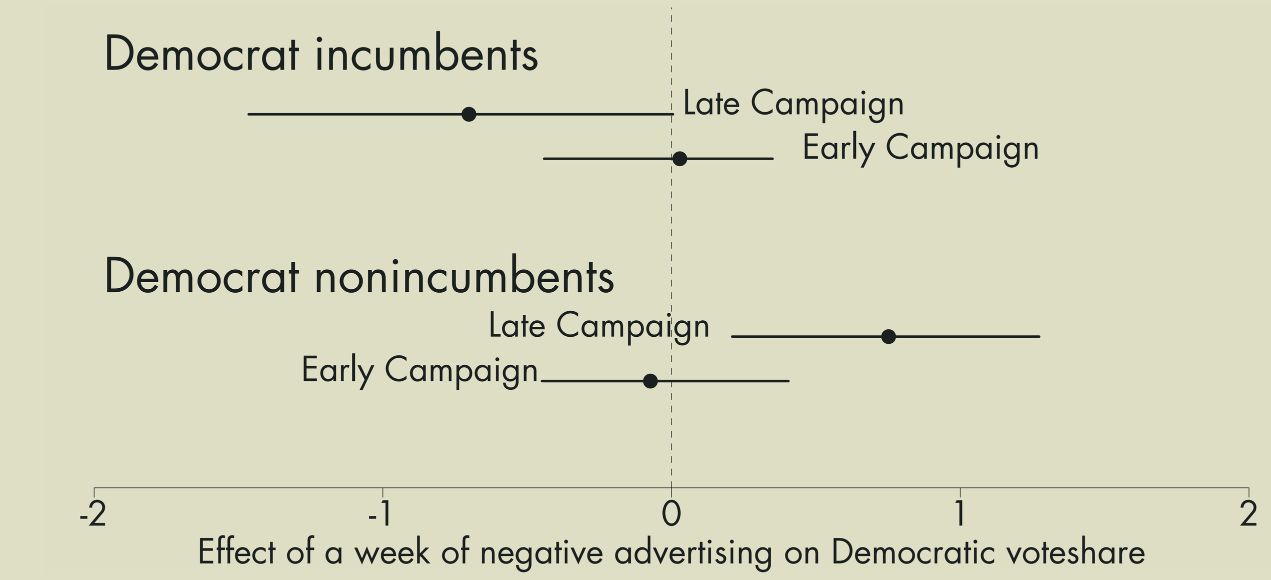
Assumption 2 (Sequential Ignorability). *For any treatment regime $\underline{A}$, time t, treatment assignment is independent of the potential outcome conditional on observed information available at t. Formally,*

$$Y(\underline{A}) \perp\!\!\!\perp A_t | \underline{A}_{t-1}, \underline{X}_t, \forall t.$$

These extend SUTVA and ignorability to the time-varying context.

Results

Here is how going negative affects the Democratic share of the two-party vote for incumbents and non-incumbents:



Sensitivity Analysis

I use an approach to sensitivity analysis that re-estimates the model under various assumptions about the amount of unobserved confounding in a given week of the campaign by varying a single parameter:

$$\alpha = \mathrm{E}[Y(\underline{a})|\underline{x}_t, \underline{a}_{t-1}, a_t = 1] - \mathrm{E}[Y(\underline{a})|\underline{x}_t, \underline{a}_{t-1}, a_t = 0]$$