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Causal Inference for IR and IPE with Substantive Applications

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MacMillan Center

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Climate change and IPE/IR

- Climate shocks as global negative externalities.
- IOs seek to address the consequences of climate change.
- Sparks creation/mobilization of transnational movements.
- Climate migration is a big problem for international legislation.
- Can generate conflict within and between nations!

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- Citizens learn about bad policy and decide to remove government.
- Does climate change erode citizen-state relations?

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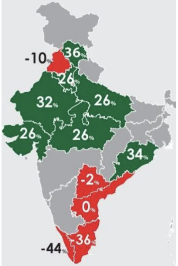

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Climate Change and Political Legitimacy

- Ex-ante and ex-post policy:
  - Security and adaptation (ex-ante): first responders; ag. policy, etc.
  - Security and relief (ex-post): property rights; govt. transfers, other.

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Climate Change and Political Legitimacy

- Climatic pressures distort citizens' opinions about government.

The effect of climate change on legitimacy

Climate change will:

- **H1.** Undermine confidence in political leaders. Why?
- **H2.** Undermine confidence in domestic-security forces. Why?
- **H3.** Enhance pro-social behavior and political mobilization. Why?

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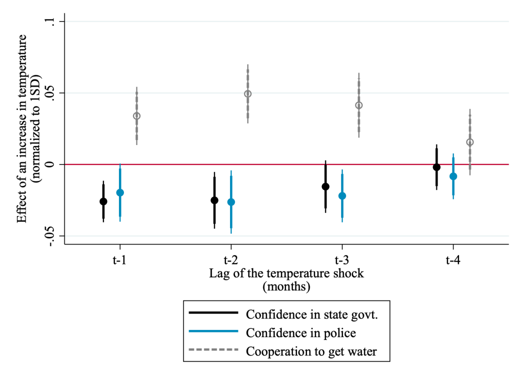
Mechanisms generalize to non-violent forms of political mobilization.

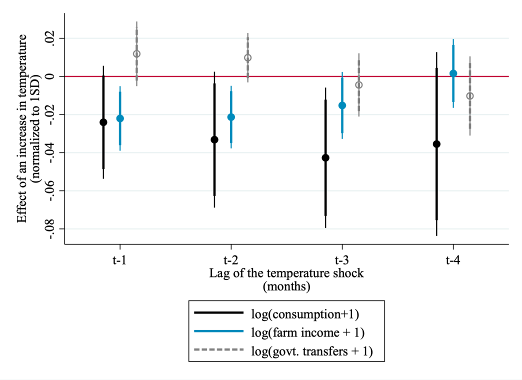
Climate change generates grievances

Impact of temperature shock on confidence in govt. institutions



Note: 90%, 95% (Conley, 500km) confidence intervals.

Impact of temperature shock on economic well-being



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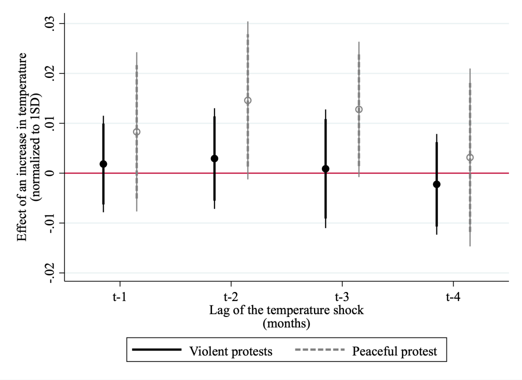
Protests

Impact of temperature shock on protest outcomes



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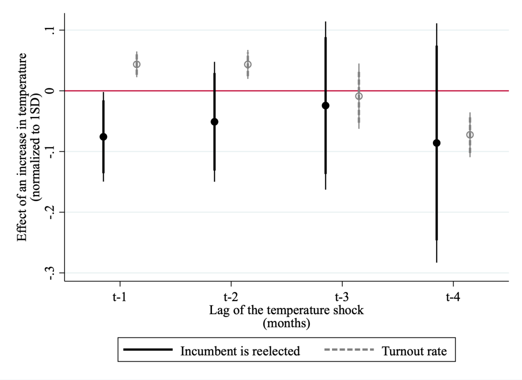
Electoral outcomes: turnout and reelection

Impact of temperature shock on elections



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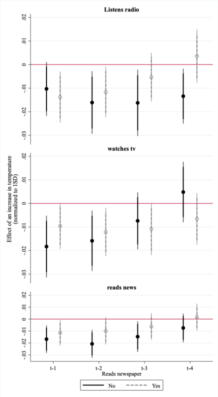
Het. impact of temperature shock confidence in govt.



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Legibility as state capacity

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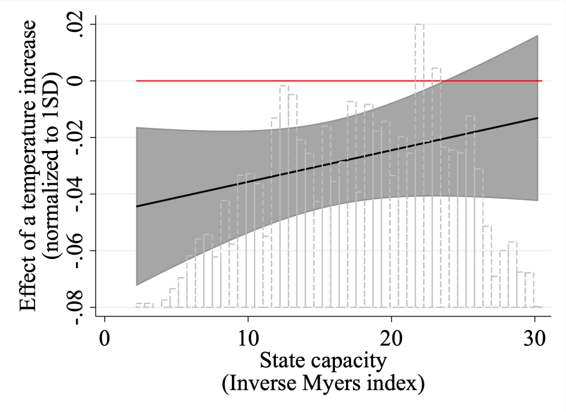

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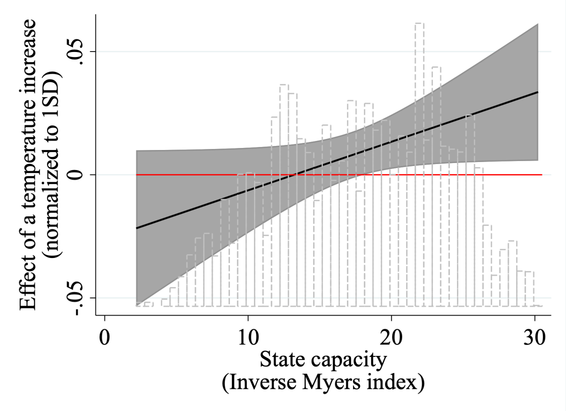
Legibility as state capacity

Het. impact of temperature shock on govt. transfers



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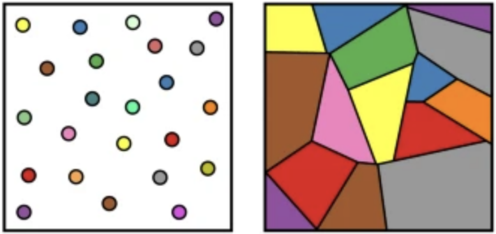
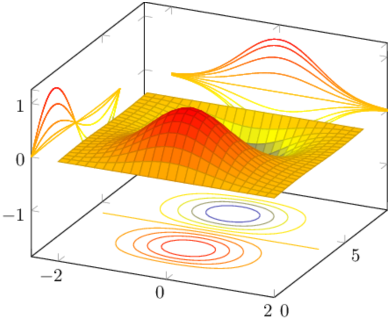
Theory and heterogeneous effects

Conditional relationships



- Eq. outcomes can be different conditional on parameter space.
- May be non-linear as a function of another dimension.
- Cross partials: $\partial U^2/\partial L \partial P \Rightarrow \partial Y^2/\partial D \partial X$.

Conditional relationships



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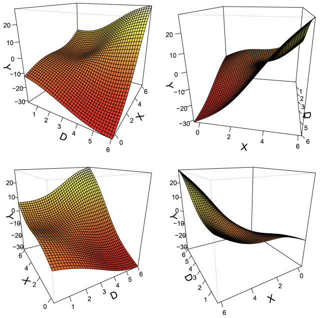

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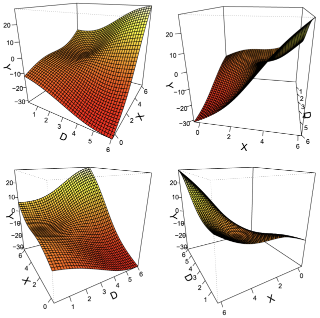

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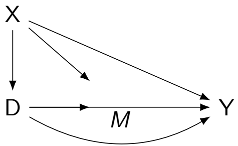
Theoretical mechanism activation



- Parameter (X) indicates activation of behavioral mechanism (M).
- Absence of effect can reflect strategic adjustment. Why?
- When can we rule out violation of sequential ignorability?
- Theory is necessary to understand het. treatment effects.

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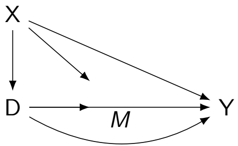

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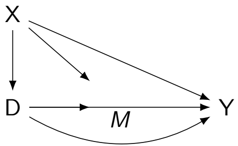

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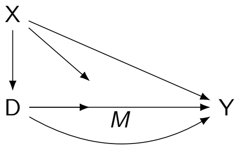

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Theoretical mechanism activation (II)

$$
\begin{tikzcd}
 & & v_i\text{: Valence} \arrow[dr] & & \\
 & & & y_{1i}\text{: Utility} \arrow[r] & y_{2i}\text{: Vote choice} \\
\omega\text{: Shock} \arrow[rr] & {} & \beta_i(\overline{\theta})\text{: Posterior} \arrow[ur] & & \\
 & \pi_i(\overline{\theta})\text{: Prior} \arrow[u] & & &
\end{tikzcd}
$$

- Effect from mechanism must be direct so HTE is identified.

Theoretical mechanism activation (II)

Definition 3. *Given treatment Z, let variable $\widetilde{Y}(Z)$ be a (potential) outcome. If*

1. *There exists another variable $Y(Z)$ that causally precedes $\widetilde{Y}$; and*
2. *$\widetilde{Y} = h(Y)$ where $h(\cdot)$ is not an affine function;*

then we call $\tilde{Y}$ an ***indirectly-affected outcome****. Otherwise, $\widetilde{Y}$ is a* ***directly-affected outcome****.*

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Theoretical mechanism activation (II)

Outcome type	Notation	Examples
Directly affected by mechanism	Y	Utility, attitudes
Indirectly affected by mechanism	$h(Y)$	Behavior/choice, survey responses

- Effect from mechanism must be direct so HTE is identified.

Theoretical mechanism activation (II)

	Outcome variable is: Directly affected by mechanism j	Indirectly affected by mechanism j
$\exists$ HTEs wrt X_k:	$X_k \in \mathbf{X}^{MIV}$ $\Longrightarrow M_j$ is active.	$X_k \in \mathbf{X}^{R}$ M_j active or inactive
$\nexists$ HTEs wrt X_k:	$X_k \notin \mathbf{X}^{MIV}$ **and/or** $\nexists$ MIV for mechanism j M_j active or inactive	$X_k \in \mathbf{X}$ (vacuous) M_j active or inactive

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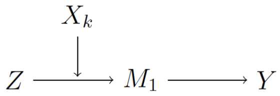

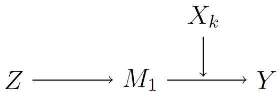

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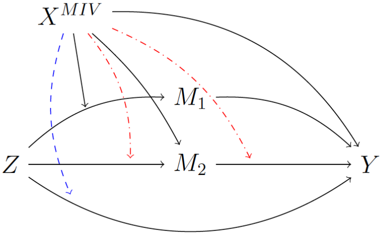

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Heterogeneous treatment effects

$$Y_{it} = \alpha + \beta_1 D_{it} + \beta_2 X_{it} + \beta_3 D \times X_{it} + \mu_i + \gamma_t + \varepsilon_{it}.$$

- β_1 is the effect of the treatment conditional on $X = 0$:

$$E(Y_{it}|D_{it} = 1, X_{it} = 0) - E(Y_{it}|D_{it} = 0, X_{it} = 0)$$

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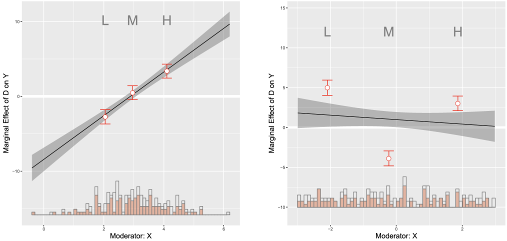
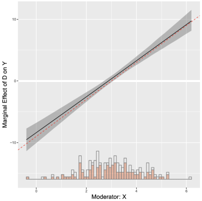
Parametric vs. non-parametric

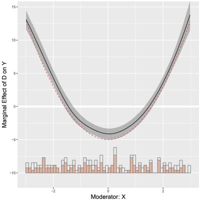


- Is there a theoretical reason to estimate non-parametric?

Parametric vs. non-parametric



(a) Linear Marginal Effect



(b) Nonlinear Marginal Effect

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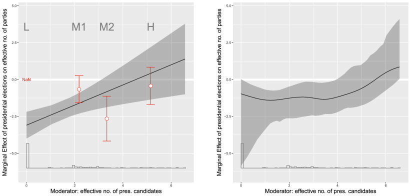

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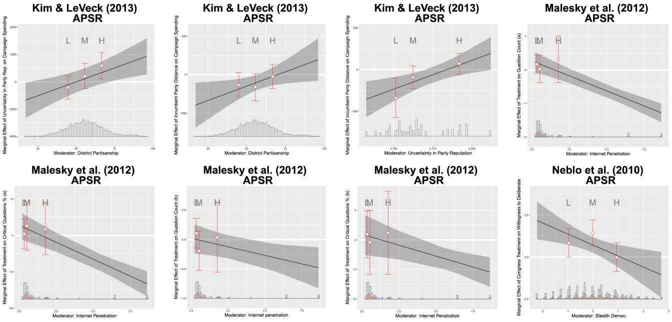

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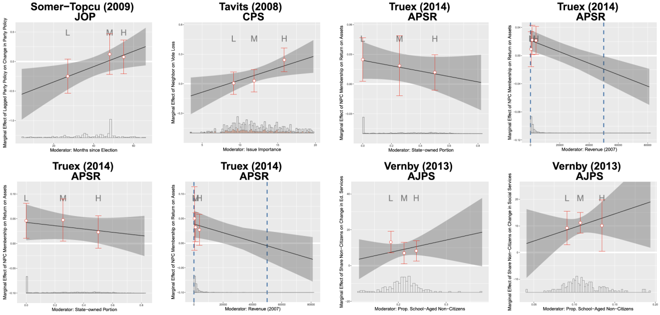

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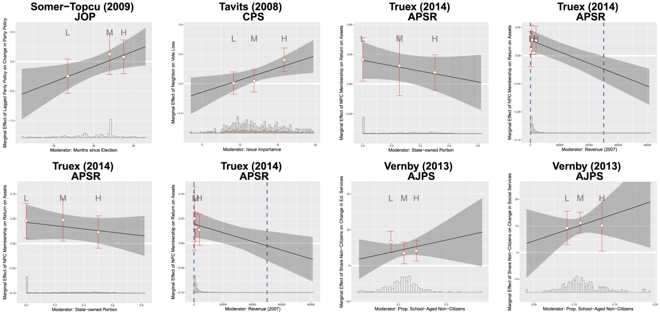

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- The distribution of the moderator does matter!
- Robustness to binning, but how many bins?

Heterogeneity robust treatment effects

Convex weighting

$$y = \alpha + \tau d + X\beta + u,$$

- Recall: effective weights $\neq$ regression weights.
- ATE on treated (ATT) + ATE on untreated (ATU).
- Weighting is inversely proportional to group size.
  - Standard regression can be inappropriate.
- Common support and IPW are relevant.

Convex weighting

$$\tau_{ATE} = \rho \times \tau_{ATT} + (1 - \rho) \times \tau_{ATU}.$$

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Convex weighting

$$w_1 = \frac{(1-\rho)\times V[p(X)|d=0]}{\rho\times V[p(X)|d=1]+(1-\rho)\times V[p(X)|d=0]}$$

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$$\tau - \tau_{ATE} = \delta \times (\tau_{ATU} - \tau_{ATT}) .$$

$$\delta = \rho - w_1$$

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Negative weights

$$\beta_{fe} = E\left(\sum_{(g,t):D_{g,t}=1} W_{g,t} \Delta_{g,t} \right)$$

- Weights can be negative if treated units are also controls.
  - A (treatment) control must exist in every period for a joiner (leaver).
- If $|ATE| / SD(weights) \cong 0$, direction of estimate can be opposite.
- $E(\varepsilon_{g,t}) \neq 0$, thus $w_{g,t} < 0$.
  - $Pr(w < 0)$ larger for periods/groups with more treated units.

Negative weights

ASSUMPTION 5 (Common Trends): *For* $t \geq 2$, $E(Y_{g,t}(0) - Y_{g,t-1}(0))$ *does not vary across* g.

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$$D_{g,t} = \alpha + \gamma_g + \lambda_t + \varepsilon_{g,t}.$$

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  - A (treatment) control must exist in every period for a joiner (leaver).
- If $|ATE| / SD(weights) \cong 0$, direction of estimate can be opposite.
- $E(\varepsilon_{g,t}) \neq 0$, thus $w_{g,t} < 0$.
  - $Pr(w < 0)$ larger for periods/groups with more treated units.

Yale

Negative weights

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Heterogeneity robust estimation

$$\text{DID}_\text{M} = \sum_{t=2}^{T} \left(\frac{N_{1,0,t}}{N_S} \text{DID}_{+,t} + \frac{N_{0,1,t}}{N_S} \text{DID}_{-,t} \right).$$

- $DID_{+,t}$ accounts for the evolution between joiners and controls.
- $DID_{-,t}$ is similar but for treated and leavers.
- We should observe the same in first differences. Why?
- We should observe the same in cross -sections. Why?

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Additional things to consider (Callaway & Sant'Anna)

$$\hat{\theta} = \sum_{g \in \mathcal{G}} \sum_{t=2}^{\mathcal{T}} \widehat{w}(g,t)\widehat{ATT}_{dr}^{nev}(g,t;0),$$

- Is there anticipation of treatment (eq. outcome)?
- Staggered treatment assignment (e.g., followers)? .
- Treatment effect varies with length of exposure (e.g., dynamics)?
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- With iterated expectations + IPW, we can explore these questions.

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Next class...

Observed impacts from international competition!