Machine Learning

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A Causal Inference Refresher

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  - Simplest (yet very powerful) case$\rightsquigarrow$ $T_i \in \{0, 1\}$, $Y_i(T_i) \in \{0, 1\}$

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$$\text{ATE} = E[Y(1) - Y(0)]$$

  - Estimate with:

$$\widehat{\text{ATE}} = E[Y(1)|T = 1] - E[Y(0)|T = 0]$$

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$$\widehat{\text{ATE}} = \frac{\sum_{i=1}^{N} I(T_i = 1) Y_i}{\sum_{i=1}^{N} I(T_i = 1)} - \frac{\sum_{i=1}^{N} I(T_i = 0) Y_i}{\sum_{i=1}^{N} I(T_i = 0)}$$

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Question: how do we accurately estimate quantities like ATE?

Our Plan for the Day

- Experimental design
- Conditional average treatment effects
- Methods for estimating heterogeneous treatment effects

An Example Experiment

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Rep. Harold "Hal" Rogers (KY-05) announced today that Kentucky is slated to receive $962,500 to protect critical infrastructure- power plants, chemical facilities, stadiums, and other high-risk assets, through the U.S. Department of Homeland Security's buffer zone protection program

An Example Experiment

A federal grant will help keep the Brainerd Lakes Airport operating in winter weather. Today, Congressman Jim Oberstar announced that the Federal Aviation Administration (FAA) will award $528,873 to the Brainerd airport. The funding will be used to purchase new snow removal and deicing equipment.

An Example Experiment

Congresswoman Darlene Hooley (OR-5) and Congressmen Earl Blumenauer (OR-3), David Wu (OR-1) and Greg Walden (OR-2) joined together today in announcing $375,000 in federal funding for the Oregon Partnership to combat methamphetamine abuse in Oregon.

An Example Experiment

What information in credit claiming messages affect evaluations?

Rewarding Actions and Type of Expenditure, Not Money

Experiment: vary the recipient of money and the action reported in credit claiming statement (and many other features)

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Treatments: type

1) Planned Parenthood
2) Parks
3) Gun Range
4) Fire Department
5) Police
6) Roads

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Experiment: vary the recipient of money and the action reported in credit claiming statement (and many other features)
Treatments: type, stage

1) Will request
2) Requested
3) Secured

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1) $50 Thousand
2) $20 Million

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Treatments: type, stage, money, collaboration

1) Alone
2) w/ Senate Democrat
3) w/ Senate Republican

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Treatments: type, stage, money, collaboration, partisanship

1) Democrat
2) Republican

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Control Condition:

> Advertising press release

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Example Treatment:

Headline: Representative [blackbox] secured $50 Thousand to purchase safety equipment for local firefighters

Body: Representative [blackbox] (Democrat) and Senator [blackbox], a Democrat, secured $50 Thousand to purchase safety equipment for local firefighters.

Rep. [blackbox] said "This money will help our brave firefighters stay safe as they protect our businesses and homes"

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Example Treatment:
Headline: Representative [blackbox] will request $20 million for medical equipment at the local Planned Parenthood.
Body: Representative [blackbox] (Democrat), will request $20 million for medical equipment at the local Planned Parenthood.
Rep. [blackbox] said "This money would help provide state of the art care for women in our community."

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Mechanics$\rightsquigarrow$ Mechanical Turk sample (Findings are replicated in representative samples, using real representatives/senators)

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$$\text{MATE}_{\mathrm{T}_j = k} \quad = \quad \int \mathrm{E}[Y(\mathrm{T}_j = k, \mathbf{T}_{-j}) - Y(0)] \mathrm{dF}_{\mathbf{T}_{-j} | \mathrm{T}_j = k}$$

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- Separate systematic differences from noise $\rightsquigarrow$ data and assumptions

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    - LASSO, Find It (Imai and Ratkovic, 2013)$\rightsquigarrow$ sparsity

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  - LASSO, Find It (Imai and Ratkovic, 2013)$\rightsquigarrow$ sparsity
  - Ridge, KRLS (Hainmueller and Hazlett, 2013)$\rightsquigarrow$ flexible surface, dense

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$$\text{MCATE}_{\text{T}_j=k,\mathbf{x}} = \text{E}[Y(\text{T}_j = k)|\mathbf{x}] - \text{E}[Y(0)|\mathbf{x}]$$

$$\widehat{\text{MCATE}}_{\text{T}_j=k,\mathbf{x}} = \frac{\sum_{i=1}^{N} Y_i I(\text{T}_j = k, \mathbf{x}_i = \mathbf{x})}{\sum_{i=1}^{N} I(\text{T}_j = k, \mathbf{x}_i = \mathbf{x})} - \frac{\sum_{i=1}^{N} Y_i I(\text{T}_i = 0, \mathbf{x}_i = \mathbf{x})}{\sum_{i=1}^{N} I(\text{T}_i = 0, \mathbf{x}_i = \mathbf{x})}$$

- Curse of Dimensionality: highly variable estimates, (sometimes) empty strata
- Separate systematic differences from noise $\rightsquigarrow$ data and assumptions
  Heterogeneous treatment effect methods
  - LASSO, Find It (Imai and Ratkovic, 2013)$\rightsquigarrow$ sparsity
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  - Model m to estimate some function $g_m(\text{T}_j = k, \boldsymbol{x})$

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Create ensemble: weighting methods by (unique) out of sample predictive performance

Weighted Ensemble to Measure Credit Claiming Rate

- Suppose we have M ($m = 1, \ldots, M$) models.

Weighted Ensemble to Measure Credit Claiming Rate

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  - Result $\widehat{\pi}_m$ for each method

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    - (Alternatively) Estimate weights from mixture model (EBMA) (Raftery et al 2005; Montgomery, Hollenback, Ward 2012)$\rightsquigarrow$ EM, Gibbs, Variational Approximation

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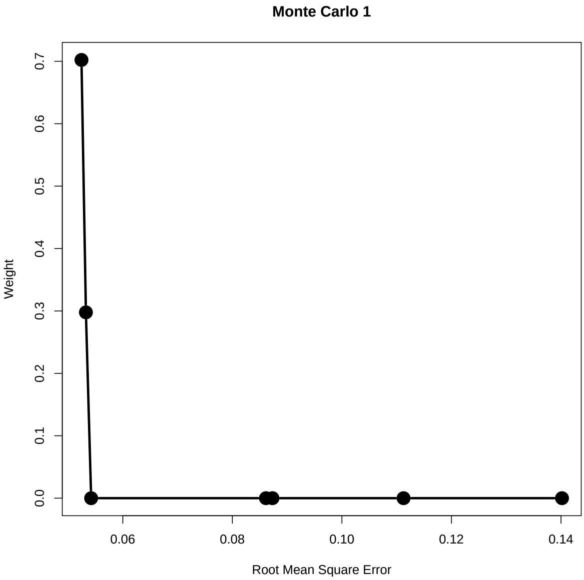
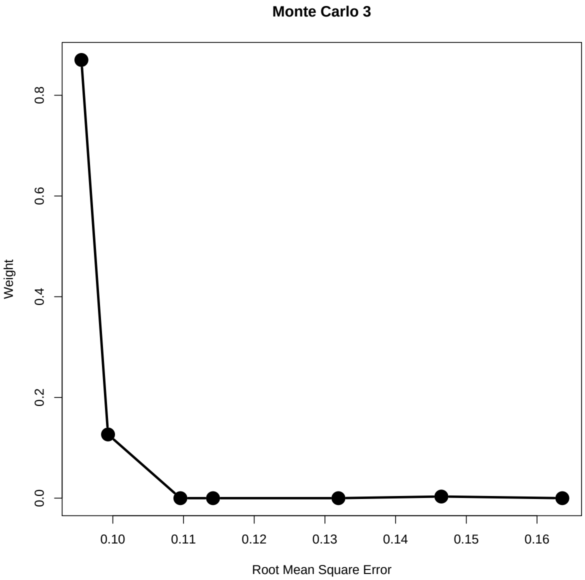
- Estimate weights ($\widehat{\pi}_m$)
- Estimate $\widehat{g}_m(\text{T}_j = k, \mathbf{x})$ $\rightsquigarrow$ Apply all M models to entire data set
- Generate effects of interest (perhaps weighting to other population) $\mathbf{x}_{\text{new}}$

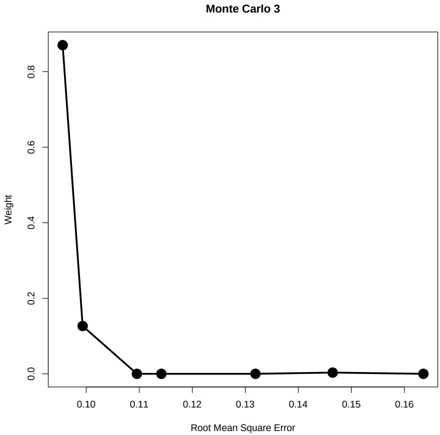
Monte Carlo Evidence



Monte Carlo Evidence



Monte Carlo Evidence



Ensembles outperform constituent methods $\rightsquigarrow$ ensembles place weight on better performing method

Returning to Example Experiment

Recall: experiment to assess effects of credit claiming on approval $\rightsquigarrow$ 1,074 participants (MTurk)

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Positive weight on three methods:

1) LASSO (0.62)

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Positive weight on three methods:

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2) KRLS (0.24)

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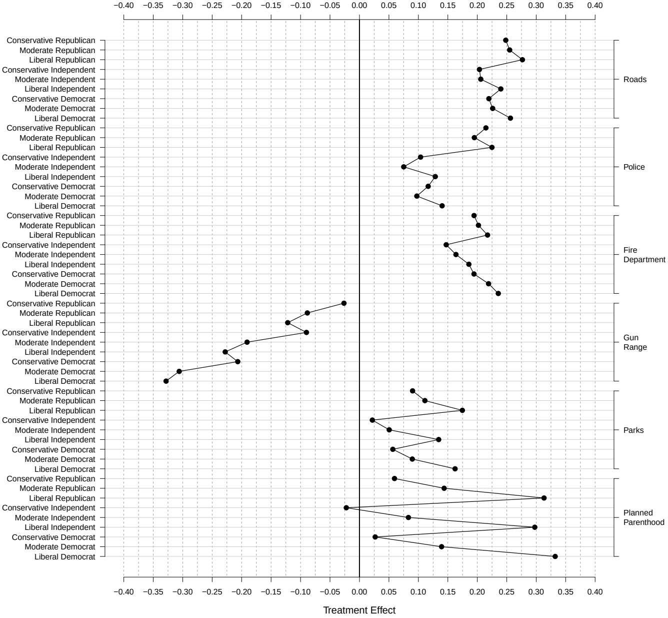
Positive weight on three methods:

1) LASSO (0.62)
2) KRLS (0.24)
3) Find it (0.14)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Conservative Republican
Moderate Republican
Liberal Republican
Conservative Independent
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Conservative Democrat
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Roads
Police
Fire Department
Gun Range
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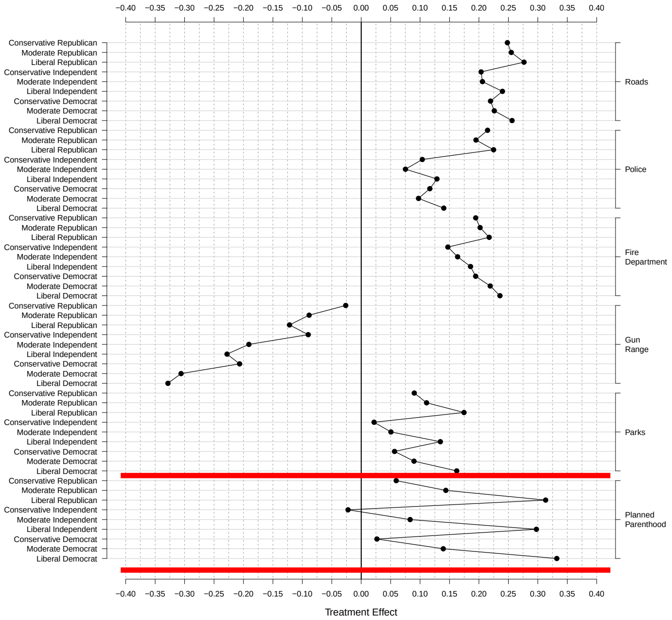
Treatment Effect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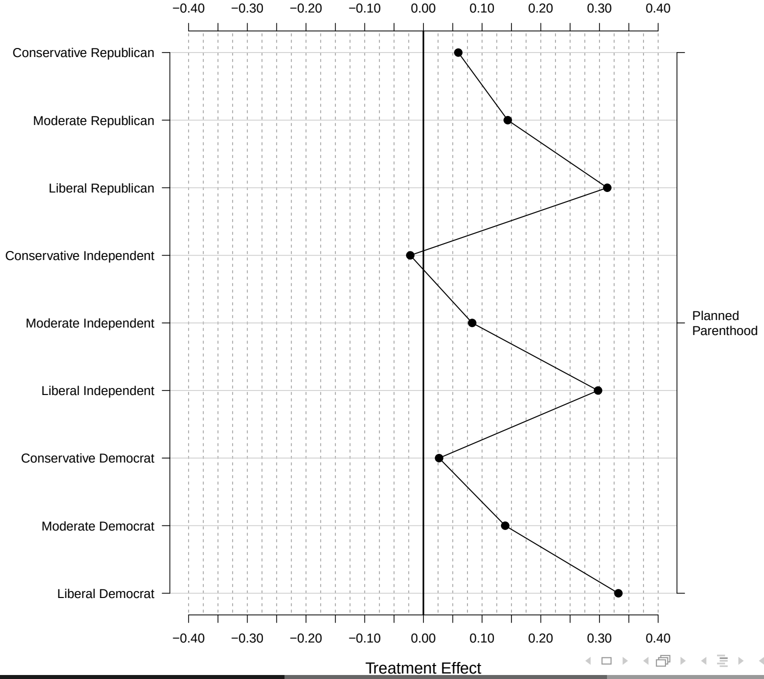
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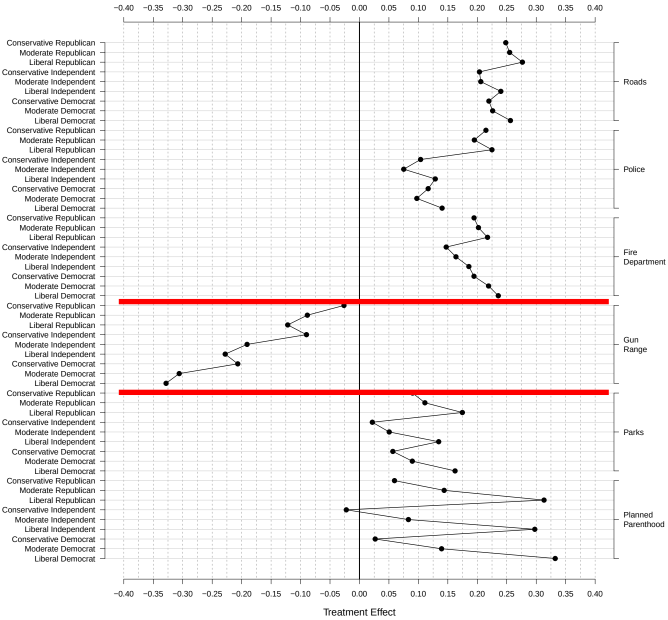
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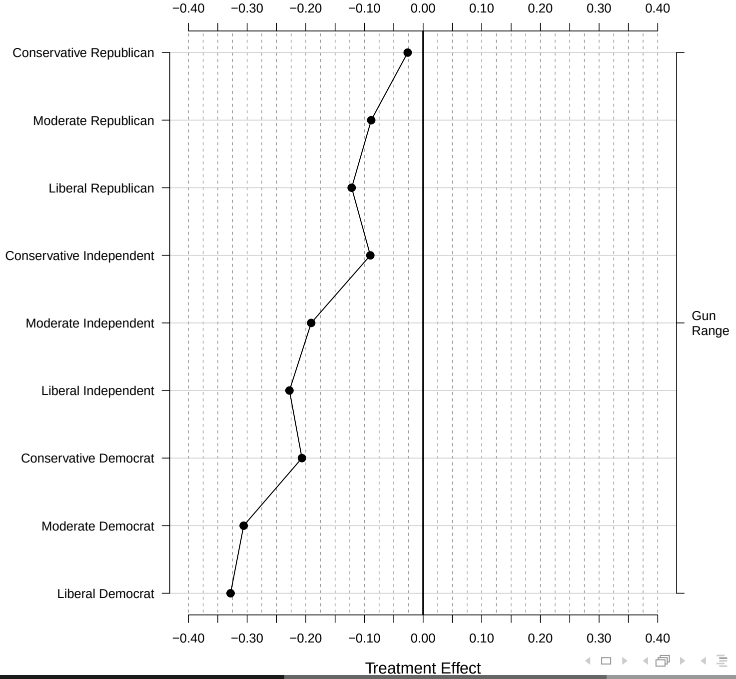
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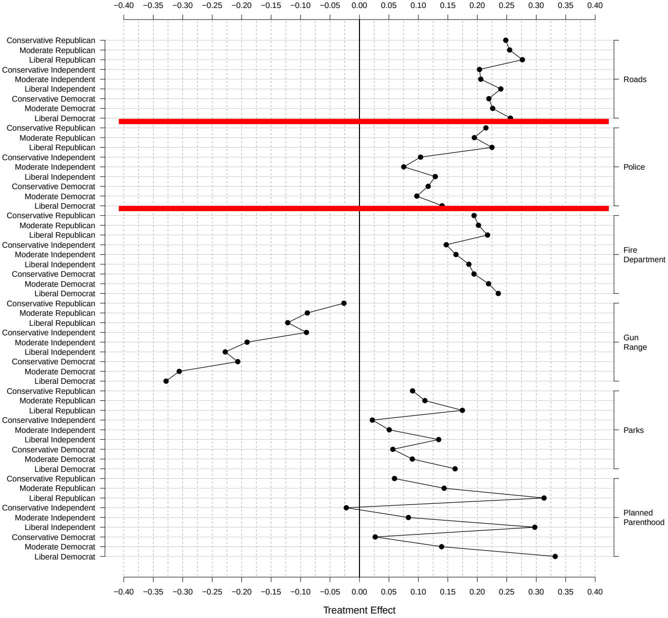
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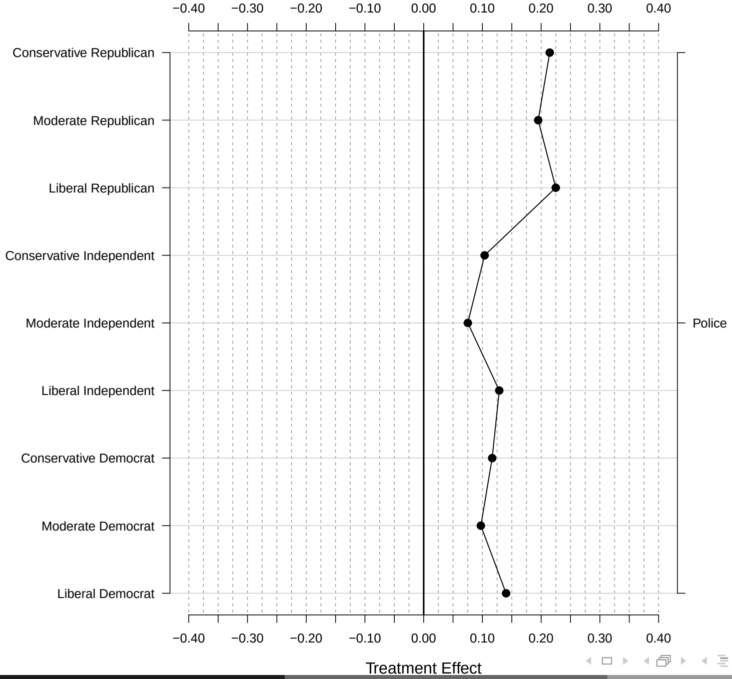

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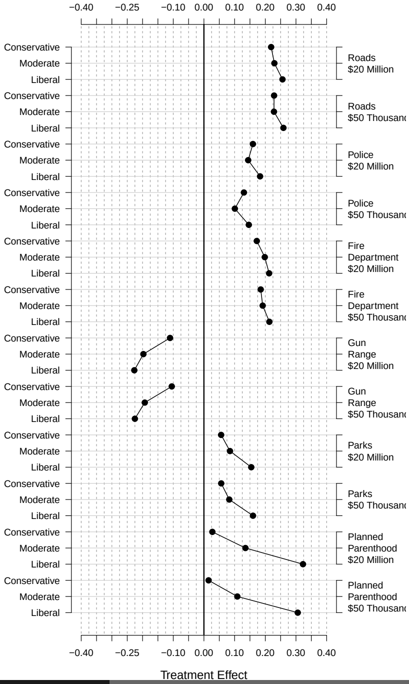

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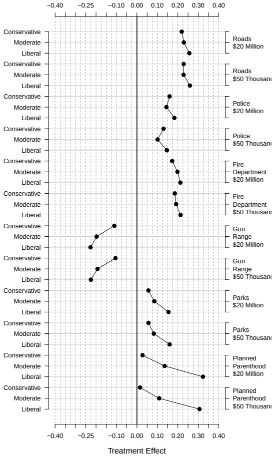

$\leadsto$ Constituents evaluate expenditures using qualitative information, rather than numerical facts

Estimating Heterogeneous Treatment Effects and the Effects of Heterogeneous Treatments

Issues with experimental design

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Wednesday's lecture will introduce discovery methods