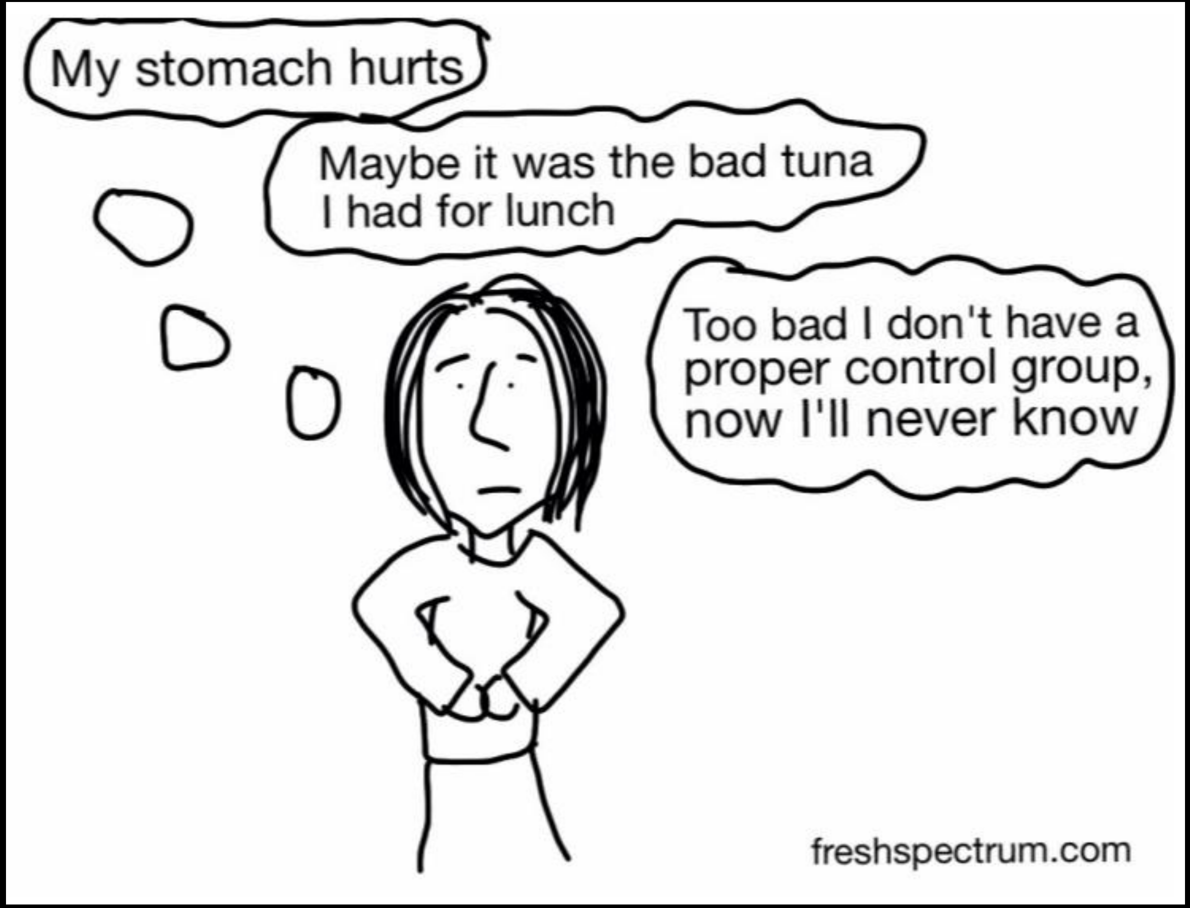


INFO 251: Applied Machine Learning

Machine Learning & Causal Inference

Today's Focus

- How can ML help answer casual questions?
  - I'll highlight a few promising areas
  - But we're still figuring this out!

  - Great background: "Machine Learning Methods Economists Should Know About", by Susan Athey and Guido Imbens. *Annual Review of Economics*

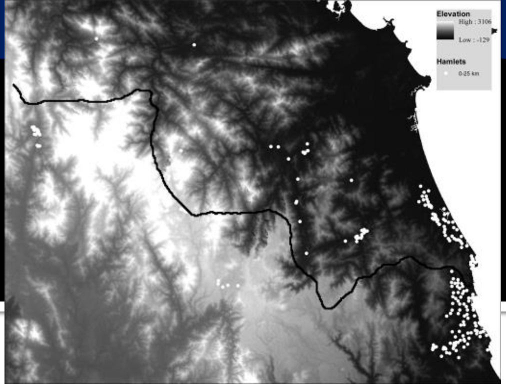
Outline

- **ML for measurement**
- Inference after selection
- Selecting among many controls
- Selecting among many instruments
- Heterogeneous treatment effects
- Other topics

ML for measurement

- One way ML can help answer causal questions is by making it possible (or easier) to observe a variable that was previously difficult to observe
- Version A: "Same question, same identification strategy, **new measurement strategy**"
  - e.g., "predicting poverty" lecture provides a method for measuring wealth in data-poor environments
    - Wealth is one of the most common/important "LHS variables"
    - Wealth is an important "RHS variable" or interaction/heterogeneity
      - Blumenstock et al., 2016. Airtime Transfers and Mobile Communications: Evidence in the Aftermath of Natural Disasters. *Journal of Development Economics*
  - Note: better measurement doesn't imply causality!!!

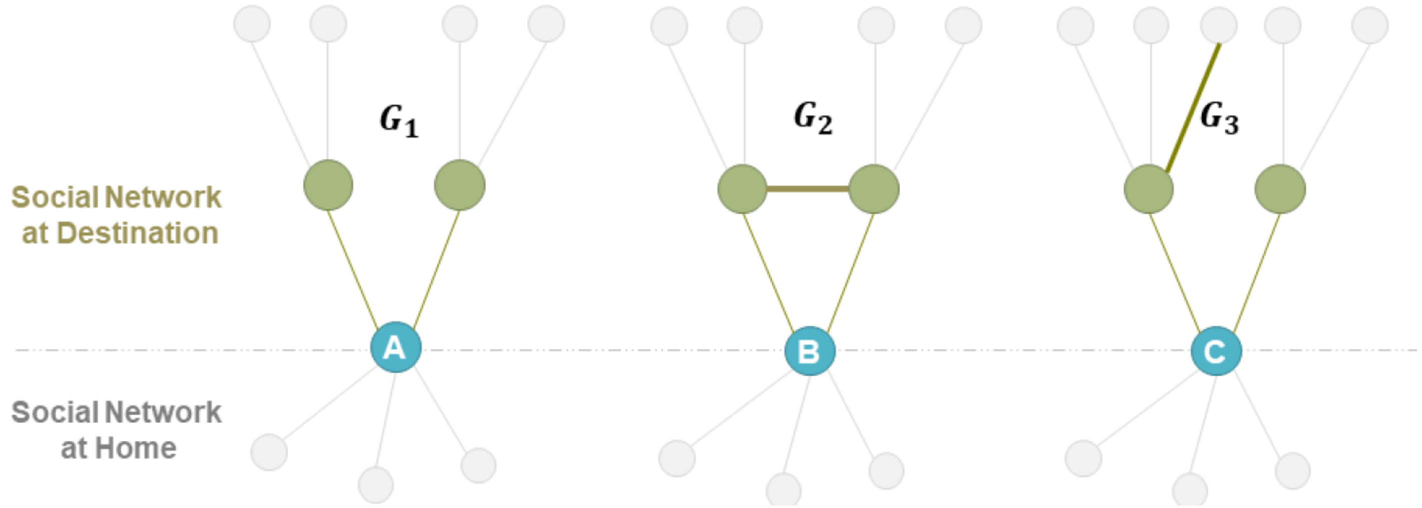
ML for measurement



- Version B: "Same question, **new identification strategy**, new measurement strategy"
  - Better measurement can facilitate new approaches to causal identification for long-standing questions
    - Spatial regression discontinuity
      - Donaldson, D., Storeygard, A., 2016. The View from Above: Applications of Satellite Data in Economics. *JEP*
      - Dell, M., Querubin, P., 2018. Nation building through foreign intervention: Evidence from discontinuities in military strategies. *QJE*
    - Event studies and temporal regression discontinuity
      - Xu, W., Li, Z., Cheng, C., Zheng, T., 2013. Data mining for unemployment rate prediction using search engine query data. *Service Oriented Computing and Applications*
      - Hall, A.S., 2018. Machine learning approaches to macroeconomic forecasting. *The Federal Reserve Bank of Kansas City Economic Review*

ML for measurement

- Version C: "**New question**, new identification strategy, new measurement strategy"
  - The combination of new measurement and new identification can make it possible to empirically analyze questions that were historically intractable
    - Blumenstock, J.E., Chi, G., Tan, X., 2025. Migration and the Value of Social Networks.



Outline

- ML for measurement
- **Inference after selection**
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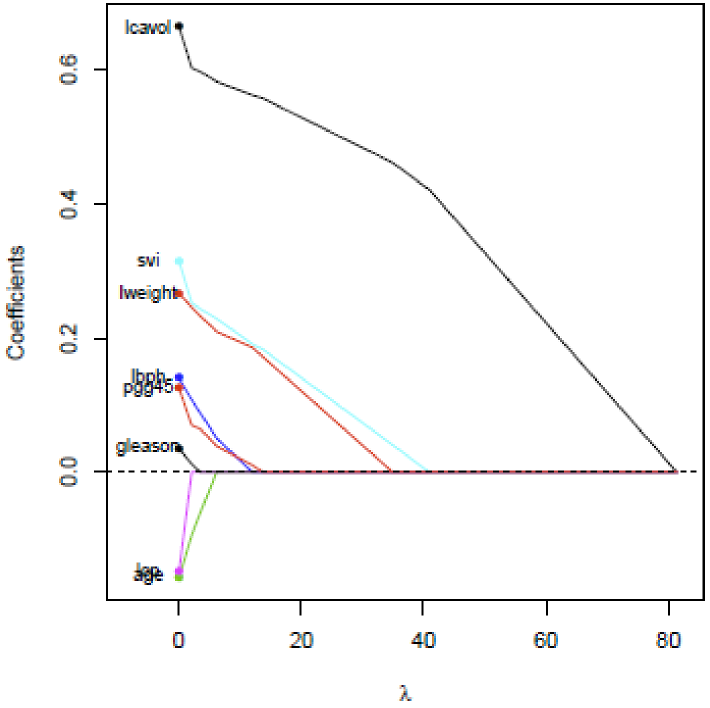
Inference after selection

- Recall LASSO

$$J(\theta) = \frac{1}{2N}\sum_{i=1}^{N}\left(\theta_0 + \theta_1 X_i + \ \ldots + \theta_k X_i^k - Y_i\right)^2 + \lambda \sum_{j=1}^{k} |\theta_j|$$

- How to interpret the θ's?
  - Regularization shrinks them
  - Biased toward zero
  - Penalized by magnitude
    - Not just on zero vs. non-zero



Inference after selection

- LASSO
  - A method for estimation of the coefficients of a sparse/penalized linear model
  - Useful for prediction and forecasting
    - Regularization helps reduce overfitting!
  - Provides a rough indication of which variables are correlated with the outcome
  - Without additional steps, bad for inference!

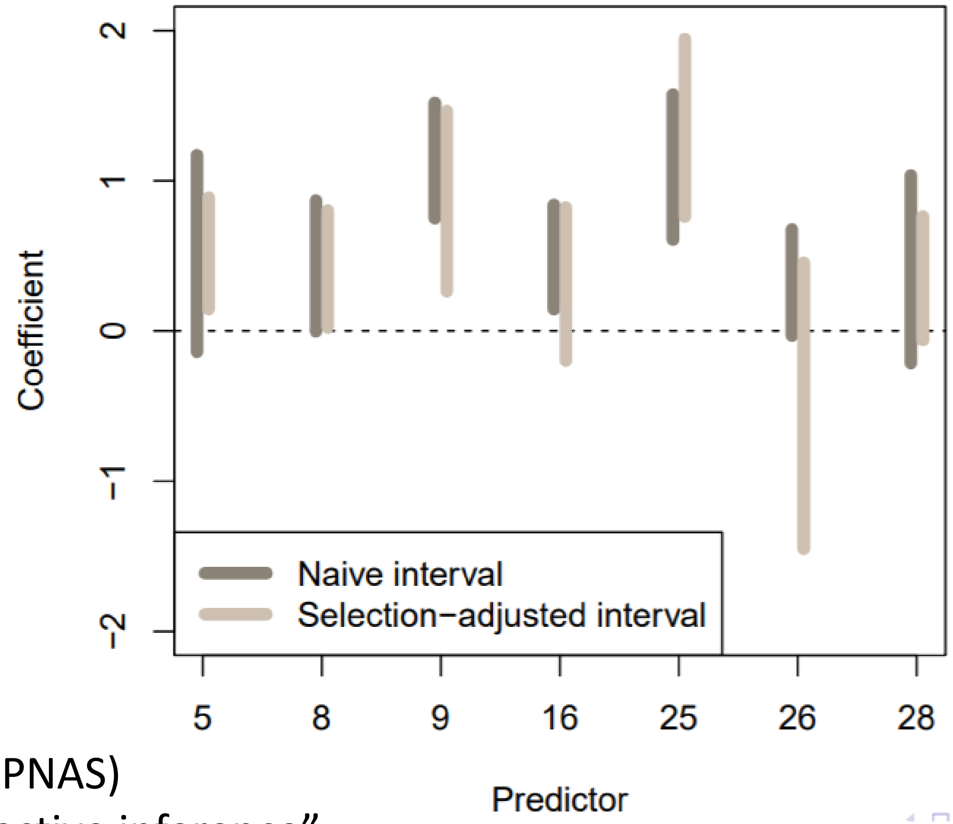
Inference after selection

- "Post LASSO"
  - What if I run LASSO for variable selection, and then run OLS on the remaining coefficients?
  - This is "cheating", since you've already looked at the data -- the resulting p-values and confidence intervals will no longer be valid
    - A "quiet scandal" in the statistical community – Leo Breiman
    - Similar to "p-hacking", but now done algorithmically!
    - Note: Under some conditions this may be okay, in particular, if "the set of variables selected by the lasso is deterministic and non-data dependent with high probability" – see Zhao et al. (2017), "In Defense of the Indefensible: A Very Naive Approach to High-Dimensional Inference"

Inference after selection

- Example

HIV data: mutations that predict response to a drug. Selection intervals for lasso with fixed tuning parameter λ.



Taylor and Tibshirani (2015 PNAS)
"Statistical learning and selective inference"

Inference after selection

- So… What to do?
  - **Data splitting**
  - Data carving
  - Randomized response
  - Exact procedures, polyhedral lemmas
  - Exponential family framework (MCMC)
  - …

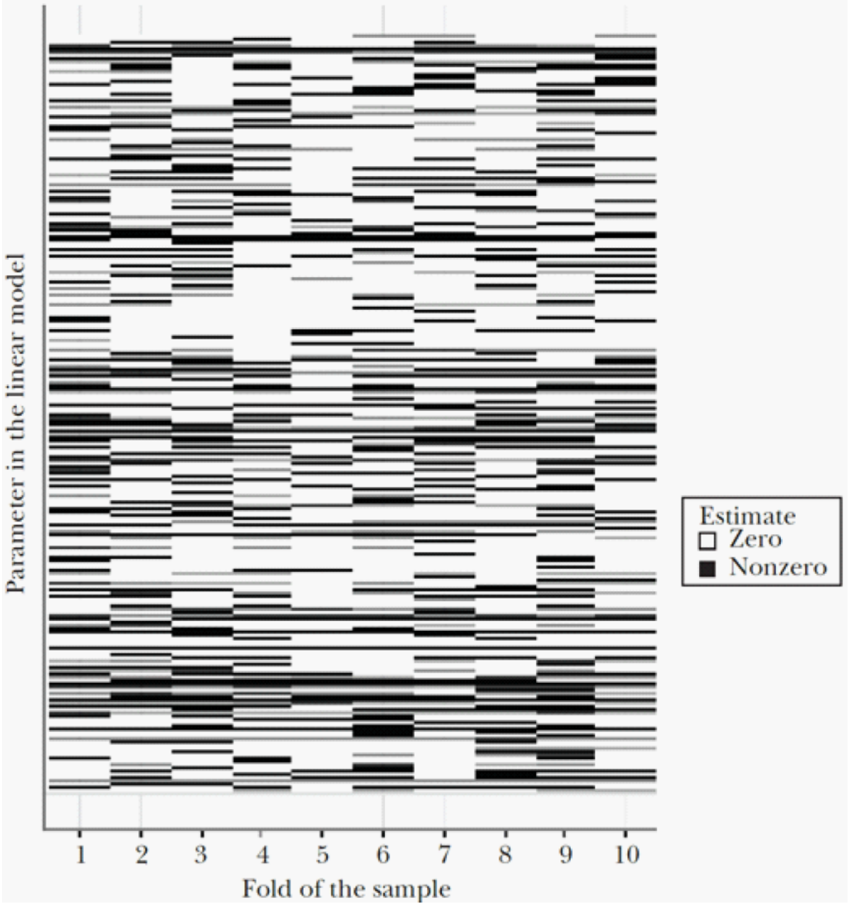
Inference after selection

- Split-sample "Post LASSO"
  1. Using half the data: Use LASSO to select **H** variables from **X**
  2. Using the other half: Run OLS of **Y** on **H**
     - This dates back to Cox, D. (1975). A note on data-splitting for the evaluation of significance levels. *Biometrika*
     - Good review article: Taylor, J. and Tibshirani, R. J. (2015). Statistical learning and selective inference. *PNAS*

  - Advantage: very easy and transparent
  - Disadvantages: you waste data, fitted model may be different between the two halves

Inference after selection

- Example of fitted model changing with folds



From Colin Cameron

Inference after selection

- Key citations:
  - Lee, Jason D., et al. "Exact post-selection inference, with application to the lasso." *The Annals of Statistics* 44.3 (2016): 907-927.
  - Taylor, Jonathan, and Robert J. Tibshirani. "Statistical learning and selective inference." *Proceedings of the National Academy of Sciences* 112.25 (2015): 7629-7634.

Outline

- Motivation
- ML for measurement
- Inference after selection
- **Selecting among many controls**
- Selecting among many instruments
- Heterogeneous treatment effects
- Other topics

Selecting among many controls

- "Selection on observables" design [recap]

$$Y_i = \alpha + \beta T_i + \gamma X_i + \epsilon_i$$

  - We are interested in unbiased estimates of β
  - We assume treatment assignment is exogenous after conditioning on control variables
    - After controlling for X, T is "as good as random"
    - $E[\epsilon_i | T_i, X_i] = 0$
- Note:
  - This is a strong assumption, but very common in applied settings

Selecting among many controls

$$Y_i = \alpha + \beta T_i + \gamma X_i + \epsilon_i$$

- Typically, in such models, $k<<N$
- What happens when $k>>N$?
  - Standard OLS will perfectly fit training data
  - LASSO can shrink β (as well as γ) - possibly to zero

Selecting among many controls

$$Y_i = \alpha + \beta T_i + \gamma X_i + \epsilon_i$$

- Why not just exclude β from LASSO penalty?
  - Use LASSO to select **H** variables from **X**
  - Then estimate $Y_i = \alpha + \beta T_i + \delta \boldsymbol{H_i} + \epsilon_i$
  - Issue: LASSO designed for *prediction*, not *inference*
  - Example: what if a variable in X is highly correlated with T?
    - From the standpoint of *prediction*, it should be dropped
    - From the standpoint of *inference*, it should be kept!
    - Can create *omitted variable bias* if real relationship exists ($\gamma \neq 0$)
      - E.g., Y = wages; T = education; X = parental wealth

Selecting among many controls

- Option 1: "Regularized regression adjustment"
  - Assumes that T_i is randomly assigned
  - (Also requires other iid/Gaussian assumptions - see citations)
- Example (Ludwig et al 2018):
  - Use cross-validation to predict Y from X, call this $\hat{f}(X_i)$
  - Control for $\hat{f}(X_i)$: $Y_i = \alpha + \beta T_i + \gamma \hat{f}(X_i) + \epsilon_i$

Selecting among many controls

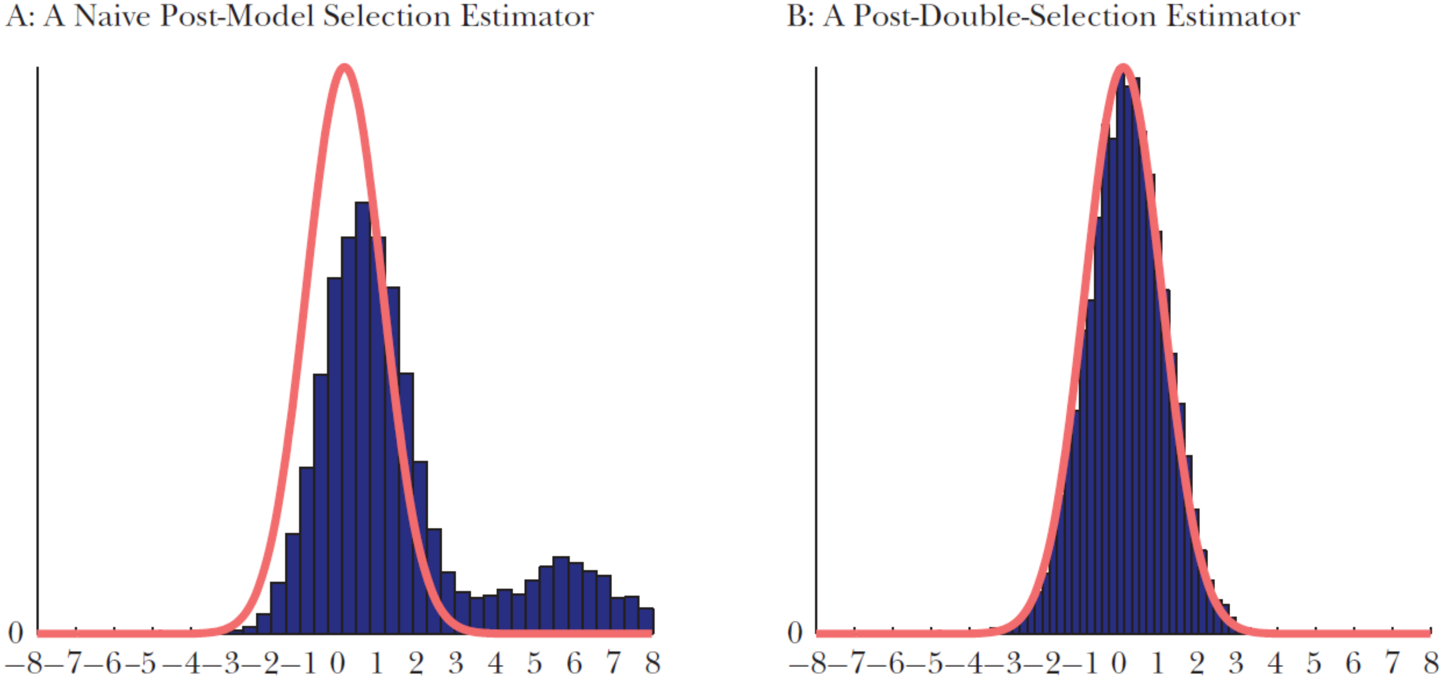
- Key Citations
  - Bloniarz, A., Liu, H., Zhang, C.-H., Sekhon, J.S., Yu, B., 2016. Lasso adjustments of treatment effect estimates in randomized experiments. PNAS 113, 7383–7390.
  - Ludwig, J., Mullainathan, S., Spiess, J., 2019. Augmenting pre-analysis plans with machine learning, in: AEA Papers and Proceedings. pp. 71–76.
  - Wager, S., Du, W., Taylor, J., Tibshirani, R.J., 2016. High-dimensional regression adjustments in randomized experiments. PNAS 113, 12673–12678.

Selecting among many controls

- Option 2: "Double Selection" (aka Post-double selection LASSO):
  1. Use LASSO to select H features from regressing Y on X
  2. Use LASSO to select K features from regressing T on X
     - If T is truly randomly assigned, K will be empty
     - In practice, K is almost never empty
  3. Regress Y on T and the union of H and K

- Key citation: Belloni, Chernozhukov, Hansen (*Review of Economic Studies*), "Inference on Treatment Effects after Selection amongst High- Dimensional Controls."

Selecting among many controls

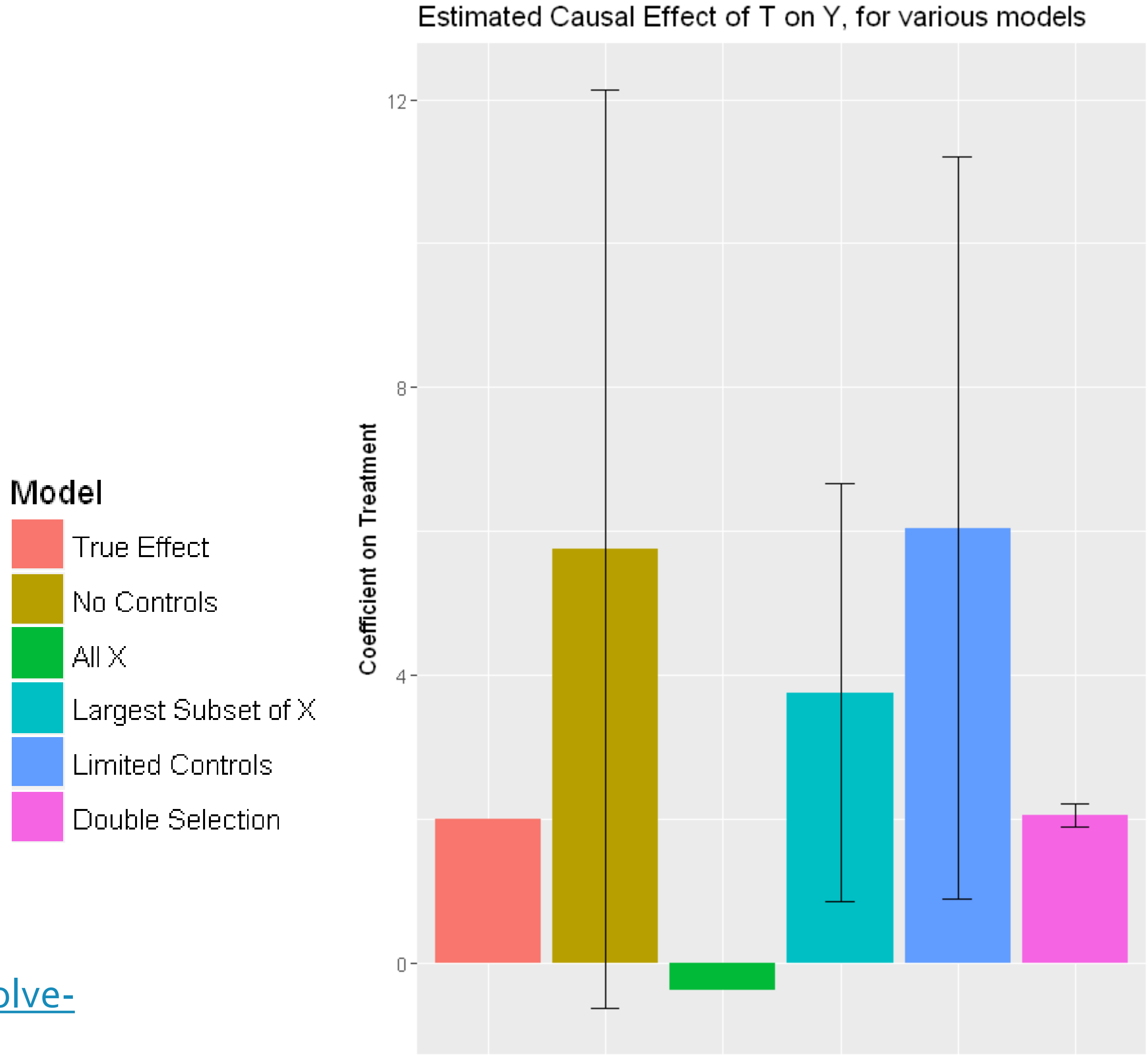


Source: Belloni, Chernozhukov, and Hansen (forthcoming).

Notes: The left panel shows the sampling distribution of the estimator of α based on the first naive procedure described in this section: applying LASSO to the equation $y_i = d_i + x_i' \theta_y + r_{yi} + \zeta_i$ while forcing the treatment variable to remain in the model by excluding α from the LASSO penalty. The right panel shows the sampling distribution of the "double selection" estimator (see text for details) as in Belloni, Chernozhukov, and Hansen (forthcoming). The distributions are given for centered and studentized quantities.

Selecting among many controls

- Simulation



https://medium.com/teconomics-blog/using-ml-to-resolve-experiments-faster-bd8053ff602e

Selecting among many controls

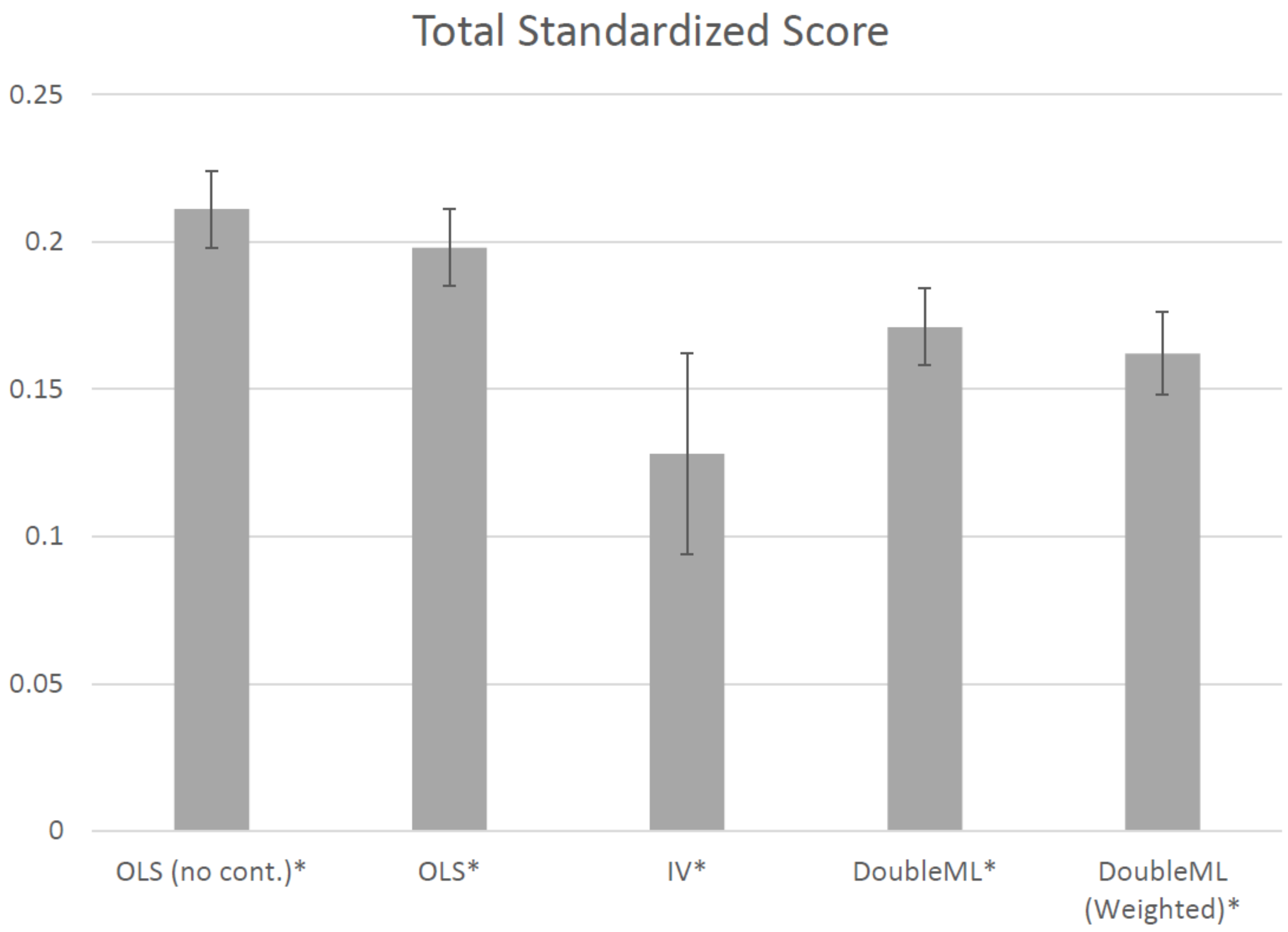
- Option 3: "Double Machine Learning"
  1. Start with double selection to obtain H and K
  2. Compute residuals Y* from regressing* Y on H
  3. Compute residuals T* from regressing* T on K
  4. Regress Y* on T*. This is the causal estimate

- Key citation: Chernozhukov et al (2018 *Econometrics Journal*), "Double/debiased machine learning for treatment and structural parameters"
  - Slightly more general than double selection
  - *Can be used on wider range of ML models (not just LASSO)

Selecting among many controls

- DML example: Duflo, Dupas, Kramer (2011 *AER*)
  - Effects of secondary schooling on labor market outcomes
    - RCT in Ghana provided secondary school scholarships to 682 randomly selected students
  - 2011 paper: scholarship is instrument for schooling
  - Re-analysis: Compares IV to OLS and DML

Selecting among many controls



Outline

- Motivation
- ML for measurement
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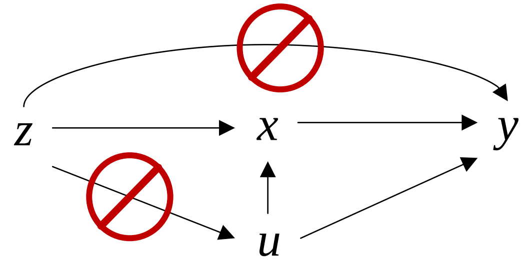
- Selecting among many controls
- **Selecting among many instruments**
- Heterogeneous treatment effects
- Other topics

Selecting among many instruments

- Recall instrumental variables:
  - You want to estimate: $Y_i = \alpha + \beta X_i + u_i$
  - Assume you have a valid instrument Z_i
    - Instrument relevance: $\mathrm{corr}(\mathrm{Z_i}, \mathrm{X}_i) \neq 0$
    - Instrument exogeneity: $\mathrm{corr}(\mathrm{Z_i}, \mathrm{u}_i) = 0$
  - Stage 1: $\mathrm{X_i} = b_0 + b_1 Z_i + v_i$
  - Stage 2: $\mathrm{Y_i} = \alpha + \beta \widehat{X}_i + u_i$



Selecting among many instruments

- Often, we struggle to find any instruments
- Sometimes, there are many potential instruments to choose between
  - Example: Tech firm running millions of randomized experiments, some of which might affect X
    - X = leaving a review; Y = subsequent purchases
- What to do?
  - Idea: **Use LASSO to select first stage instruments**

Selecting among many instruments

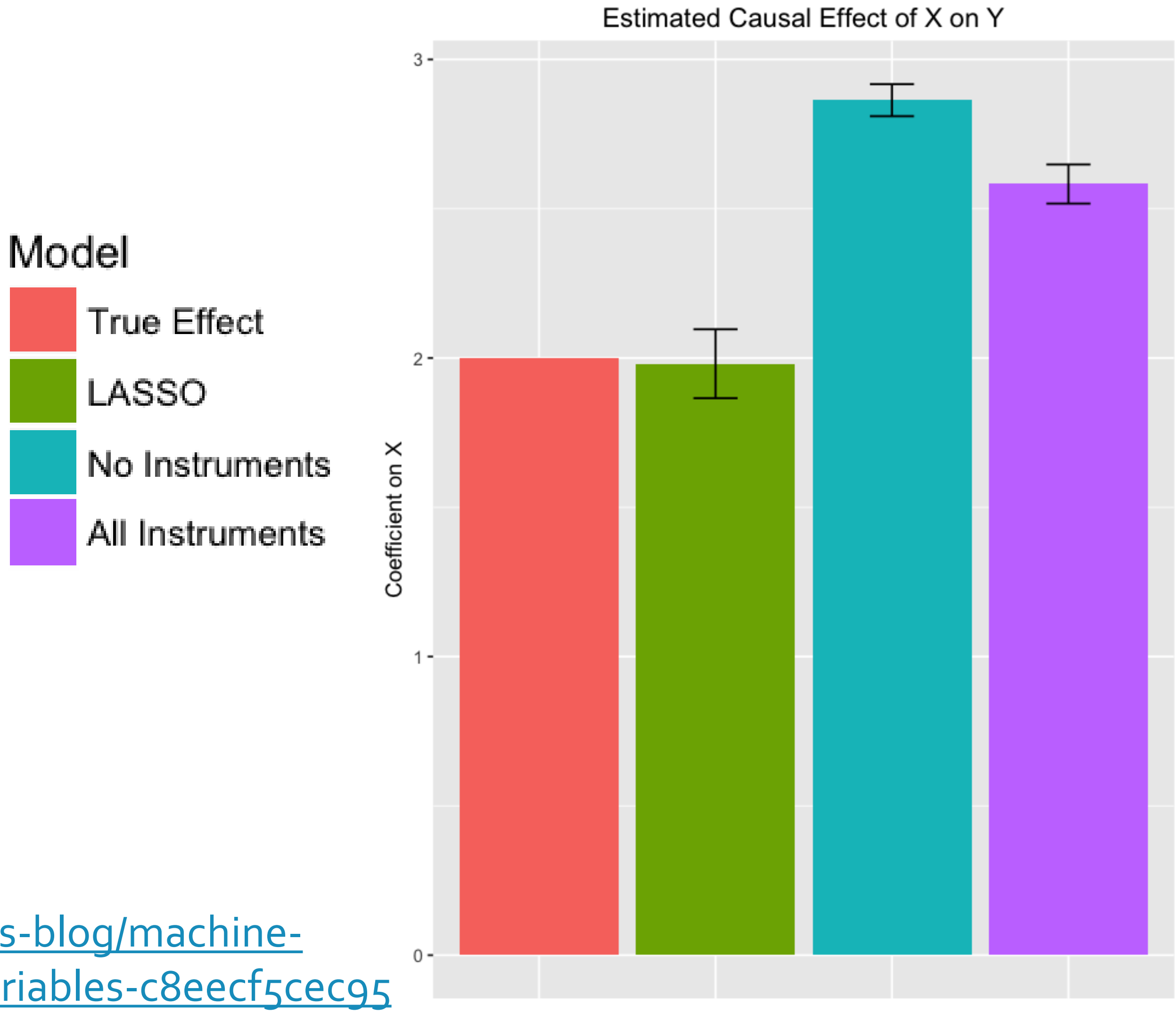
- Belloni et al (2012 *Econometrica*)
  - Provides a set of formal conditions under which conventional inference from two-stage least squares, based on instruments selected by LASSO, is valid for learning about β
  - Intuition: The variable selection part of the problem is limited to the first-stage equation, which is a pure predictive relationship
  - "The second-stage estimate is *orthogonal* or *immune* to variable selection errors where instruments… are mistakenly excluded from estimation."

Selecting among many instruments

- Belloni et al (2012 *Econometrica*)
  1. Call M the full set of possible instruments. Run LASSO of X on M → yields Z instruments
  2. Use standard IV of Y on X, using Z as instrument for X

Selecting among many instruments

- Simulation



https://medium.com/teconomics-blog/machine-learning-meets-instrumental-variables-c8eecf5cec95

Selecting among many instruments

- Key References
  - Belloni, Chen, Chernozhukov, and Hansen (2012 *Econometrica*), "Sparse models and methods for optimal instruments with an application to eminent domain".
  - Jason Hartford, Greg Lewis, Kevin Leyton-Brown, Matt Taddy (2017): "Deep IV: A Flexible Approach for Counterfactual Prediction." ICML.

Selecting among many instruments

- For another applied example, see:

Dissecting the Effect of Credit Supply on Trade: Evidence from Matched Credit-Export Data

Daniel Paravisini, Veronica Rappoport, Philipp Schnabl, Daniel Wolfenzon

The Review of Economic Studies, Volume 82, Issue 1, January 2015, Pages 333–359,

- Idea: "credit supply" for a firm can depend on many different factors; they use LASSO to select relevant factors

Outline

- Motivation
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- **Heterogeneous treatment effects**
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Heterogeneous treatment effects

- Recap of heterogeneous TE's (Lecture 4)
- How to simultaneously measure the effect of a treatment *T* **and** a non-experimental control variable *X* **and** a differential effect of treatment by control variable on an outcome *Y* in a regression setting?

$$Y_i = \alpha + \beta T_i + \gamma X_i + \boldsymbol{\delta(T_i * X_i)} + \epsilon_i$$

- When might this happen in practice?
  - Treatment effect is different for different types (X_i)
  - Some types of people respond to medicine, others don't
  - Some types of people respond to cookies, others don't

Heterogeneous treatment effects

- This begs the question: which “types” X_i are likely to exhibit heterogeneity?
- Typically don’t to test all possible X_i (why?)
  - With many variables in X, data are sparse, overfitting likely
  - Biased confidence intervals / p-values
    - With *k* variables, this amounts to *k* statistical tests
    - At very least, would require multiple testing corrections
    - When *k* approaches *N*, need enormous/precise effects

Heterogeneous treatment effects

- Causal Tree (Athey and Imbens, 2016 *PNAS)*
  - Similar to a regression tree, with key differences:

1. Split sample into two halves randomly: the "structure" sample and "estimation" sample
2. Build regression tree on structure sample, *optimizing splits for treatment effect heterogeneity* (instead of purity of dependent variable)
   - More on this on next slide
3. Use estimation sample to estimate treatment effects in each leaf
   - The estimate in each leaf is the average treatment effect for samples with those characteristics

Heterogeneous treatment effects

- Causal Tree (Athey and Imbens, 2016 *PNAS*)
  - What is the splitting criterion that optimizes for treatment effect heterogeneity?
  - In principle, we want to split to obtain more precise estimates of the average treatment effects
  - Problem: this typically requires that we observe true treatment effects, but of course we don't observe unit-level treatment effects
  - Instead, reweight Y by propensity score [details]:

$$Y_i^* = Y_i \cdot \frac{T_i - p(X)}{p(X) \cdot (1 - p(X))}$$

Heterogeneous treatment effects

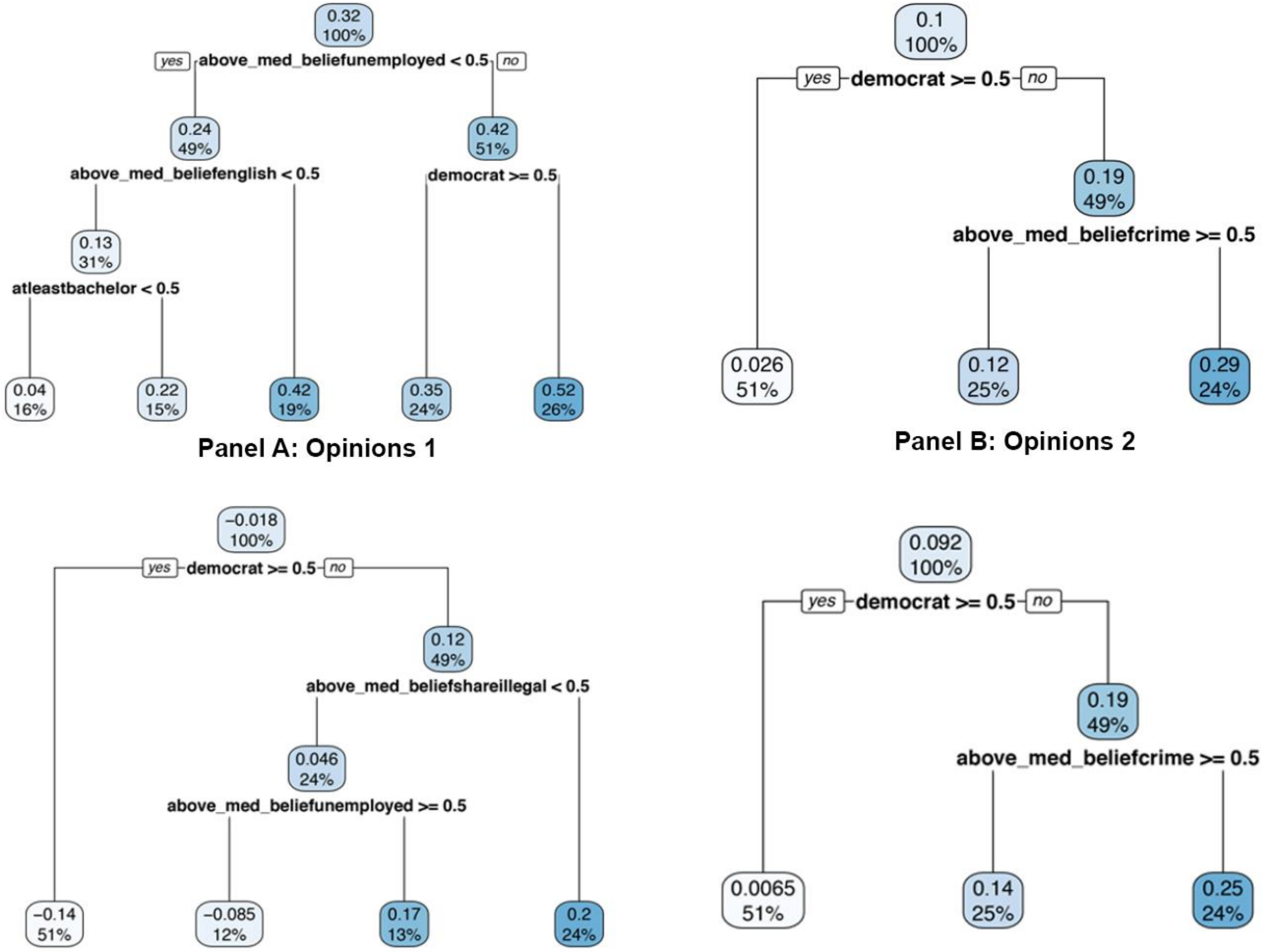
- Causal Tree (Athey and Imbens, 2016 *PNAS)*
  - Advantages:
    - Easy to implement and understand
    - A tree is "honest" if each training observation is only used to either estimate either estimate decide where to split, or estimate local treatment effect, but not both
  - Disadvantages:
    - As with any single tree, the structure is data-dependent, sensitive to outliers, and somewhat arbitrary
    - The tree doesn't immediately answer the most common question: Which dimensions of heterogeneity are most important?

Example

Does Information Change Attitudes Towards Immigrants?

Representative Evidence from Survey Experiments*

Alexis Grigorieff[†] Christopher Roth[‡] Diego Ubfal[§]



Panel A: Opinions 1

Panel B: Opinions 2

Panel C: Petition

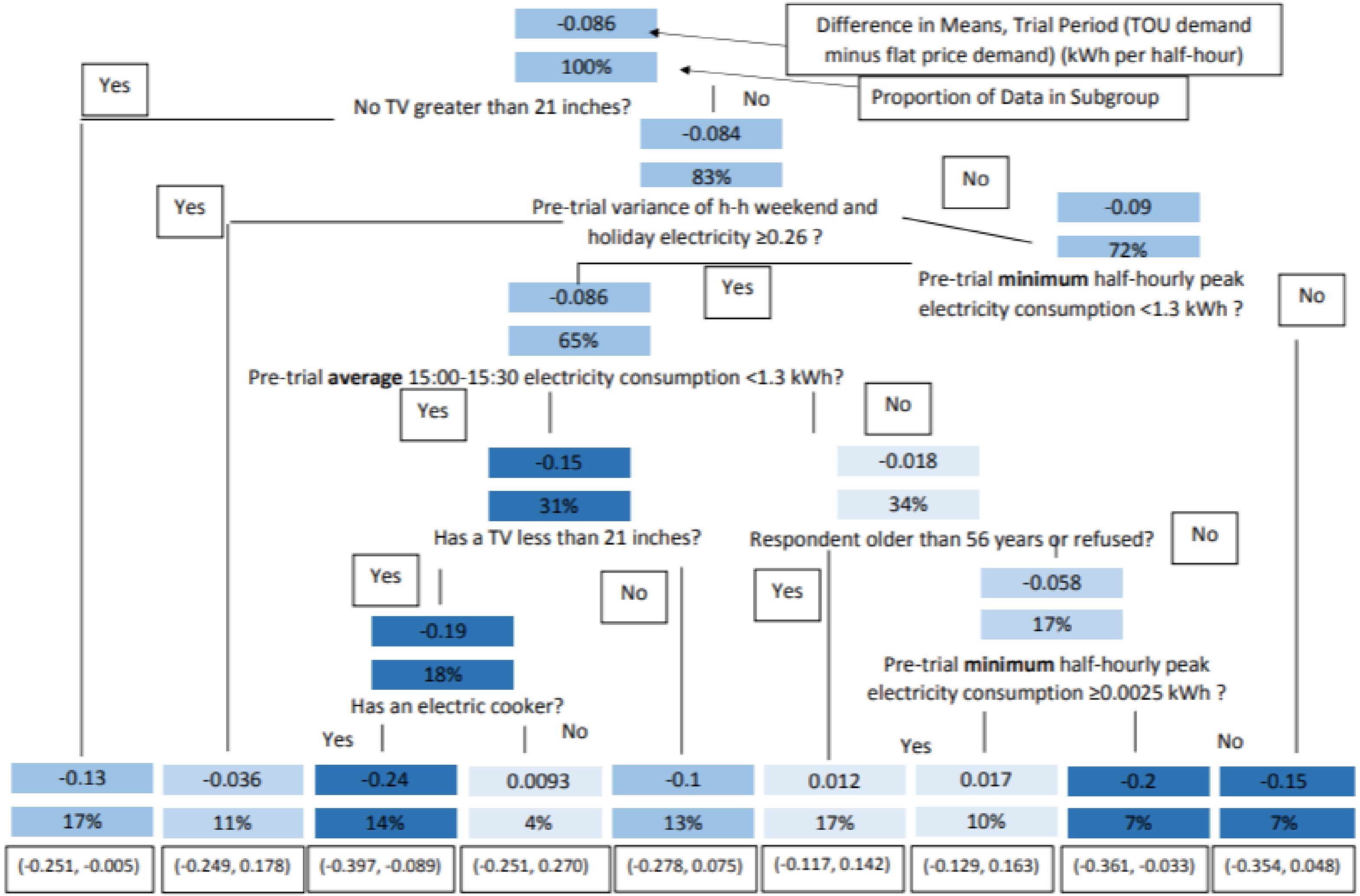
Panel D: Political Preferences

Example

Causal Tree Estimation of Heterogeneous Household Response to Time-Of-Use Electricity Pricing Schemes

EPRG Working Paper 1906
Cambridge Working Paper in Economics 1865

Eoghan O'Neill and Melvyn Weeks



(1) causalForest variable importance	(2)	(3) grf variable importance	(4)	(5) p-value
attic insulated	0.04	*water instantly heated*	0	0.9
mean 01:00-01:30 usage	0.08	*number of washing machines*	0.17	0.95
mean 00:30-01:00 usage	0.1	*unheated, lack of money*	0.22	0.78
prop. elec. saving lightbulbs	0.14	*electric plugin heating*	0.25	0.27
mean 07:30-08:00 usage	0.16	*electric central heating*	0.34	0.95
mean usage - weekdays	0.86	*prop. double glazed windows*	0.42	1
mean 00:00-00:30 usage	1.3	*number of electric cookers*	0.52	1
variance daytime usage	1.37	*number of tumble dryers*	0.59	1
external walls insulated	1.51	*number of dishwashers*	0.73	1
mean 08:00-08:30 usage	1.8	*number of immersion heaters*	0.81	1
mean 05:00-05:30 usage	1.89	*sex of respondent*	1.08	1
variance nonpeak usage	2.03	*type of cooker*	1.08	1
mean h-h coef. of variation	2.12	*attic insulated*	1.12	1
lagging jacking	2.31	*own or rent home*	1.21	1
mean 04:00-04:30 usage	2.33	*no. of elec. convector heaters*	1.22	1
mean 05:30-06:00 usage	2.53	*regular internet user*	1.24	1
mean daytime usage	2.56	*water pumped from elec. well*	1.4	1
mean 02:00-02:30 usage	2.81	*water immersion*	1.41	0.99
no. of elec. convector heaters	3.19	*number of instant elec. showers*	1.47	1
water pumped from elec. well	3.31	*other internet users*	1.48	0.61
mean 06:00-06:30 usage	3.4	*external walls insulated*	1.49	1
number of desktop PCs	3.42	*number of hot tank elec. showers*	1.63	1
mean 03:30-04:00 usage	3.75	*water centrally heated*	2.12	0.98
min. half-hourly usage	3.86	*lagging jacking*	2.16	0.74
number of freezers	4.02	*age of home*	2.39	1
number of instant elec. showers	4.39	*has an energy rating*	2.85	0.6
variance of usage	4.91	*number of small TVs*	3.01	1
number of big TVs	4.96	*number of games consoles*	3.29	0.85
number of games consoles	5.1	*lives alone*	3.39	0.82
prop. double glazed windows	5.64	mean 02:30-03:00 usage	4.03	1
max. half-hourly usage	5.73	*type of home*	4.06	1
mean 08:30-09:00 usage	6.29	*age of respondent*	4.25	1
var. usage - weekdays	6.52	*education*	4.26	1
mean 03:00-03:30 usage	7.72	mean 12:00-12:30 usage	4.28	1
has an energy rating	8.97	*number of bedrooms*	4.52	0.96
mean 01:30-02:00 usage	9.69	*prop. elec. saving lightbulbs*	4.56	1
mean nonpeak usage	9.69	*internet access*	4.94	0.1
mean of usage	10.08	mean 03:30-04:00 usage	4.96	1
number of laptop PCs	10.44	mean 06:00-06:30 usage	5.3	1
mean 09:00-09:30 usage	12.29	mean 03:00-03:30 usage	5.4	1
mean 02:30-03:00 usage	15.9	mean 00:30-01:00 usage	5.7	1
var. night usage - weekends	23.13	mean 05:30-06:00 usage	6.01	1
mean 04:30-05:00 usage	25.78	mean 04:30-05:00 usage	6.03	1
mean 16:00-16:30 usage	26.07	mean 01:30-02:00 usage	6.29	1
mean 17:00-17:30 usage	27.02	mean 11:00-11:30 usage	6.46	1
mean daily min. usage	28.03	mean 04:00-04:30 usage	6.54	1
mean 17:30-18:00 usage	28.56	mean 05:00-05:30 usage	6.73	1
mean 18:30-19:00 usage	28.87	*number of desktop PCs*	7.16	0.12
mean 18:00-18:30 usage	29.28	mean night usage - weekends	7.24	0.97
variance night usage	29.51	*social class*	7.51	0.7
mean July peak usage	29.74	*number of big TVs*	7.76	0.53
mean 06:30-07:00 usage	30.99	mean 01:00-01:30 usage	7.91	1
mean 15:30-16:00 usage	31.99	*employment*	7.93	0.57
mean September peak usage	32.25	mean 11:30-12:00 usage	8.1	0.99
mean 19:00-19:30 usage	32.69	mean 02:00-02:30 usage	8.1	0.98
mean November peak usage	32.81	mean 12:30-13:00 usage	8.15	1
var. August peak usage	33.2	mean night usage	8.2	0.88
number of washing machines	33.87	mean night usage - weekdays	8.88	0.91
mean 20:00-20:30 usage	34.29	mean of usage	8.99	0.18
mean 13:30-14:00 usage	35.56	mean night / mean day usage	9.09	1
mean 19:30-20:00 usage	35.69	mean nonpeak usage - weekdays	9.14	0.29
var. November peak usage	35.92	mean nonpeak usage	9.38	0.22
mean 09:30-10:00 usage	36.4	mean 13:30-14:00 usage	9.41	0.95
mean 20:30-21:00 usage	36.68	mean 14:00-14:30 usage	9.41	0.92
mean 14:00-14:30 usage	36.97	mean usage - weekdays	9.57	0.19
mean August peak usage	39.59	mean 07:00-07:30 usage	9.91	1
age of home	40.15	mean usage - weekends	10.02	0.23

(1) causalForest variable importance	(2)	(3) grf variable importance	(4)	(5) p-value
mean 13:00-13:30 usage	40.68	*number of freezers*	10.02	0.09
mean 07:00-07:30 usage	40.77	mean h-h coef. of variation	10.51	1
var. September peak usage	40.78	mean daytime usage	10.83	0.19
number of bedrooms	40.9	variance night usage	11.03	0.98
mean 15:00-15:30 usage	41.1	mean 10:30-11:00 usage	11.33	0.94
own or rent home	41.21	mean 22:00-22:30 usage	11.4	0.76
mean 21:00-21:30 usage	41.43	mean 13:00-13:30 usage	11.82	0.86
variance peak usage	42.06	var. night usage - weekdays	11.86	0.99
mean 10:30-11:00 usage	42.13	mean 23:00-23:30 usage	12.09	0.93
number of small TVs	42.9	mean 14:30-15:00 usage	12.11	0.8
type of home	43.36	var. night usage - weekends	12.17	0.98
electric central heating	44.66	mean 21:30-22:00 usage	12.26	0.63
education	44.82	*number of laptop PCs*	12.56	0.19
mean peak usage	45	mean 22:30-23:00 usage	12.7	0.81
mean 14:30-15:00 usage	45.12	mean 06:30-07:00 usage	12.72	0.97
mean night usage	45.36	mean daytime usage - weekends	12.78	0.1
number of dishwashers	45.38	mean 00:00-00:30 usage	13.66	0.89
mean 12:30-13:00 usage	45.4	mean daytime usage - weekdays	14.16	0.12
other internet users	45.44	variance nonpeak usage	14.23	0.19
mean daily max. usage	45.54	var. nonpeak usage - weekdays	15	0.26
var. December peak usage	45.84	mean daily min. usage	15.84	0.9
mean 10:00-10:30 usage	46.8	mean 10:00-10:30 usage	15.89	0.64
electric plugin heating	46.85	mean 23:30-00:00 usage	15.9	0.78
mean 12:00-12:30 usage	47.19	mean 07:30-08:00 usage	16.37	0.98
mean 21:30-22:00 usage	47.5	min. half-hourly usage	16.51	0.88
mean 11:00-11:30 usage	48.6	variance daytime usage	16.58	0.14
lives alone	48.65	mean lunchtime / mean day usage	16.61	1
mean 11:30-12:00 usage	50.24	mean 18:00-18:30 usage	16.82	0.34
mean 22:00-22:30 usage	50.95	var. daytime usage - weekdays	17.6	0.18
unheated, lack of money	51.56	mean 21:00-21:30 usage	17.61	0.26
var. October peak usage	51.7	mean 09:00-09:30 usage	18	0.69
internet access	52.08	variance of usage	18.14	0.05
water centrally heated	52.25	var. usage - weekdays	18.29	0.06
mean 16:30-17:00 usage	52.6	max. half-hourly usage	18.53	0.87
mean 22:30-23:00 usage	52.7	mean 19:00-19:30 usage	18.67	0.21
type of cooker	53.21	mean 19:30-20:00 usage	19.41	0.15
water instantly heated	53.31	mean 16:00-16:30 usage	19.46	0.44
regular internet user	53.37	mean 20:00-20:30 usage	20.3	0.08
water immersion	54.64	mean 15:00-15:30 usage	21.12	0.28
mean 23:00-23:30 usage	54.82	var. usage - weekends	21.89	0.08
var. July peak usage	55.12	mean November peak usage	22.02	0.18
number of electric cookers	55.44	mean 18:30-19:00 usage	22.3	0.1
mean 23:30-00:00 usage	57.26	mean 08:00-08:30 usage	22.37	0.69
number of immersion heaters	57.53	mean 09:30-10:00 usage	23.8	0.37
mean night / mean day usage	59.33	var. daytime usage - weekends	23.94	0.06
mean December peak usage	59.96	mean 16:30-17:00 usage	24.27	0.36
social class	61.34	var. November peak usage	25.8	0.3
mean October peak usage	62.19	mean 15:30-16:00 usage	27.1	0.17
mean night usage - weekends	62.44	mean daily max. usage	27.36	0.04
var. daytime usage - weekdays	62.5	mean 08:30-09:00 usage	30.15	0.33
var. nonpeak usage - weekdays	64.71	mean peak usage - weekdays	33.35	0.03
number of tumble dryers	71	mean peak usage	34.52	0.01
age of respondent	71.25	mean 20:30-21:00 usage	36.62	0.01
mean lunchtime / mean day usage	71.33	variance peak usage	40.62	0.01
sex of respondent	71.68	var. peak usage - weekdays	40.73	0.05
mean nonpeak usage - weekdays	74.69	var. December peak usage	40.75	0.1
number of hot tank elec. showers	75.34	mean September peak usage	47.41	0.02
mean usage - weekends	78.1	mean 17:00-17:30 usage	52.63	0.01
employment	78.23	mean December peak usage	53.13	0
var. daytime usage - weekends	80.36	mean July peak usage	53.33	0.03
mean daytime usage - weekends	82.81	mean 17:30-18:00 usage	53.36	0
mean night usage - weekdays	85.08	mean August peak usage	54.18	0.01
var. peak usage - weekdays	87.83	var. July peak usage	55.36	0.1
var. usage - weekends	91.21	var. September peak usage	56.17	0.04
mean daytime usage - weekdays	94.64	mean October peak usage	64.96	0
var. night usage - weekdays	95.61	var. August peak usage	71.73	0
mean peak usage - weekdays	100	var. October peak usage	100	0

Survey variables are in italics.

Table 7: Variable Importance results

Causal Tree Estimation of Heterogeneous Household Response to Time-Of-Use Electricity Pricing Schemes

EPRG Working Paper 1906

Cambridge Working Paper in Economics 1865

Eoghan O'Neill and Melvyn Weeks

Heterogeneous treatment effects

- "Generic" approach (Chernozhukov et al, 2018)
  - A challenge with forests is that it is difficult to describe the output, since the estimated function may be quite complex.
  - In this approach, "the key will be to give up on estimating all the possible heterogeneity but focus on a limited number of core features (is there heterogeneity? what are the characteristics of those with the largest treatment effect?)"

Heterogeneous treatment effects

- "Generic" approach focuses on "key features" of the CATE, rather than the CATE itself
  - **Best Linear Predictor** (BLP) of the CATE (conditional avg. treatment effect) based on the ML proxy predictor
  - **Sorted Group Average Treatment Effects** (GATES): average treatment effect by heterogeneity groups induced by the ML proxy predictor
  - **Classification Analysis** (CLAN): average characteristics of the most and least affected units defined in terms of the ML proxy predictor.

Heterogeneous treatment effects

- **Best Linear Predictor:** where is the heterogeneity?

TABLE 3. BLP of Microfinance Availability

	Elastic Net		Random Forest	
	ATE (β_1)	HET (β_2)	ATE (β_1)	HET (β_2)
Amount of Loans	1,163	0.238	1,180	0.390
	(545,1737)	(0.021,0.448)	(546,1770)	(0.037,0.779)
	[0.000]	[0.060]	[0.001]	[0.062]
Output	5,096	0.262	4,854	0.190
	(230,10027)	(0.084,0.431)	(-167,9982)	(-0.099,0.498)
	[0.079]	[0.008]	[0.116]	[0.385]
Profit	1,554	0.243	1,625	0.275
	(-1344,4388)	(0.079,0.416)	(-1332,4576)	(0.036,0.510)
	[0.584]	[0.008]	[0.577]	[0.045]
Consumption	-59.2	0.154	-58.5	0.183
	(-161.4,43.9)	(-0.054,0.382)	(-167.0, 45.9)	(-0.177,0.565)
	[0.513]	[0.270]	[0.494]	[0.617]

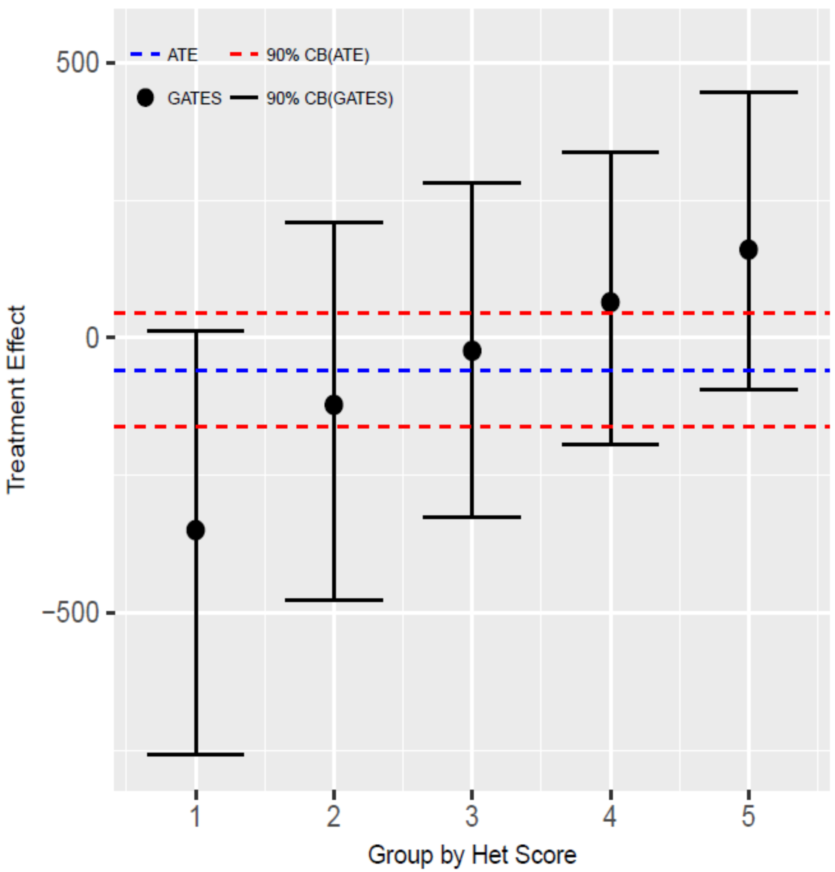
Notes: Medians over 100 splits. 90% confidence interval in parenthesis.
P-values for the hypothesis that the parameter is equal to zero in brackets.

"Reject null hypothesis of no heterogeneity in TE of Micro-finance on output"

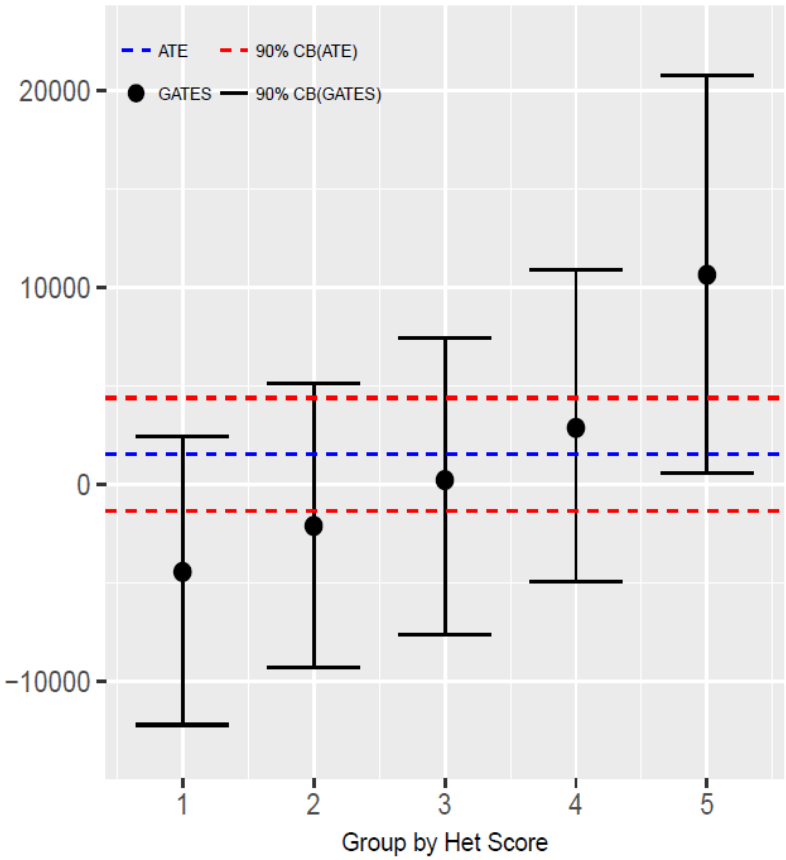
Heterogeneous treatment effects

- **Sorted Group Average Treatment Effects** (GATES):

Consumption



Total profit



Class

	Elastic Net		
	10% Most (δ_{10})	10% Least (δ_1)	Difference ($\delta_{10} - \delta_1$)
Amount of Loans			
Head Age	29.3	35.2	-6.6
	(26.3,32.4)	(32.2,38.2)	(-10.9,-2.4)
	-	-	[0.004]
Non-agricultural self-emp.	0.199	0.068	0.123
	(0.159,0.238)	(0.030,0.108)	(0.069,0.178)
	-	-	[0.000]
Borrowed from Any Source	0.144	0.169	-0.038
	(0.099,0.189)	(0.124,0.212)	(-0.101,0.025)
	-	-	[0.448]
Output			
Head Age	36.280	36.708	-0.896
	(33.4,39.1)	(33.6,39.6)	(-5.242,3.432)
	-	-	[1.000]
Non-agricultural self-emp.	0.275	0.050	0.226
	(0.233,0.315)	(0.007,0.093)	(0.169,0.285)
	-	-	[0.000]
Borrowed from Any Source	0.193	0.215	-0.033
	(0.142,0.241)	(0.167,0.262)	(-0.102,0.034)
	-	-	[0.687]
Profit			
Head Age	34.1	40.4	-6.5
	(31.2,37.0)	(37.5,43.4)	(-10.7,-2.5)
	-	-	[0.003]
Non-agricultural self-emp.	0.181	0.108	0.082
	(0.140,0.222)	(0.068,0.149)	(0.022,0.138)
	-	-	[0.014]
Borrowed from Any Source	0.180	0.257	-0.091
	(0.130,0.230)	(0.207,0.307)	(-0.160,-0.022)
	-	-	[0.020]

Notes: Medians over 100 splits. 90% confidence interval in parenthesis.
P-values for the hypothesis that the parameter is equal to zero in brackets.

"Treatment effect on profits is larger for younger heads of household"

Other closely-related methods

- Causal Forests
  - Stefan Wager and Susan Athey. 2017. Estimation and inference of heterogeneous treatment effects using random forests. *JASA*
- SVM-based approach
  - Kosuke Imai, Marc Ratkovic, et al. 2013. Estimating treatment effect heterogeneity in randomized program evaluation. *Annals of Applied Statistics*
- Targeted Maximum Likelihood
  - Mark J van der Laan and Daniel Rubin. 2006. Targeted maximum likelihood learning. *The International Journal of Biostatistics*
- Meta-Learners
  - Künzel, S.R., Sekhon, J.S., Bickel, P.J., Yu, B., 2019. Metalearners for estimating heterogeneous treatment effects using machine learning. *Proceedings of the National Academy of Sciences*

Key Citations (Heterogeneous TE's)

- Athey, Susan and Guido W. Imbens (2016). "Recursive Partitioning for Heterogeneous Causal Effects". *Proceedings of the National Academy of Sciences*
- Chernozhukov, V., Demirer, M., Duflo, E., Fernández-Val, I., 2018. "Generic Machine Learning Inference on Heterogenous Treatment Effects in Randomized Experiments". NBER Working Paper No. 24678
- Wager, Stefan and Susan Athey (2018). "Estimation and Inference of Heterogeneous Treatment Effects Using Random Forests". *Journal of the American Statistical Association*

Outline

- Motivation
- ML for measurement
- Inference after selection
- Selecting among many controls
- Selecting among many instruments
- Heterogeneous treatment effects
- **Other topics**

Other topics

- Also worth knowing about
  - ML to determine which outcomes are affected
    - Ludwig, J., Mullainathan, S., Spiess, J., 2019. "Machine-Learning Tests for Effects on Multiple Outcomes."
    - Ludwig, J., Mullainathan, S., Spiess, J., 2019. "Augmenting pre-analysis plans with machine learning"
  - Adaptive experimentation, ML to guide data collection and experimentation
    - If new units arrive over time, and we can adapt treatment choices, we can learn optimal treatment quickly
    - Bubeck, S. and Cesa-Bianchi, N. (2012). Regret Analysis of Stochastic and Nonstochastic Multi-armed Bandit Problems. *Foundations and Trends in Machine Learning*

Other topics

- Also worth knowing about
  - Causal inference and casual/do-calculus
    - Pearl, J., 2009. Causality. Cambridge university press.
    - Pearl, J., Mackenzie, D., 2018. The Book of Why: The New Science of Cause and Effect. Basic Books
    - Pearl, J., 2019. The seven tools of causal inference, with reflections on machine learning. *Communications of the ACM*

Summary

- Contributions from causal inference
  - Identification and estimation of causal effects
  - Classical theory to yield asymptotically normal and centered confidence intervals
- Contributions from ML
  - Practical, high performance algorithms for personalized prediction and policy estimation
- Putting them together
  - Practical, high performance algorithms
  - Causal effects with valid confidence intervals

Good resources/repositories

- Key readings on bCourses
- Main innovators
  - Susan Athey, Alex Belloni, Victor Chernozhukov, Christian Hansen, Guido Imbens, Sendhil Mullainathan, Hal Varian
- Dario Sansone's list of resources
  - https://sites.google.com/view/dariosansone/resources/machine-learning
- Colin Cameron's list of resources
  - http://cameron.econ.ucdavis.edu/e240f/machinelearning.htm