



**2018 SPSP**  
Annual Convention

*Atlanta*

**SPSP 2018**

SOCIETY FOR PERSONALITY  
AND SOCIAL PSYCHOLOGY 

# Uncovering Hidden Moderators with Machine Learning

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# Hidden Moderators

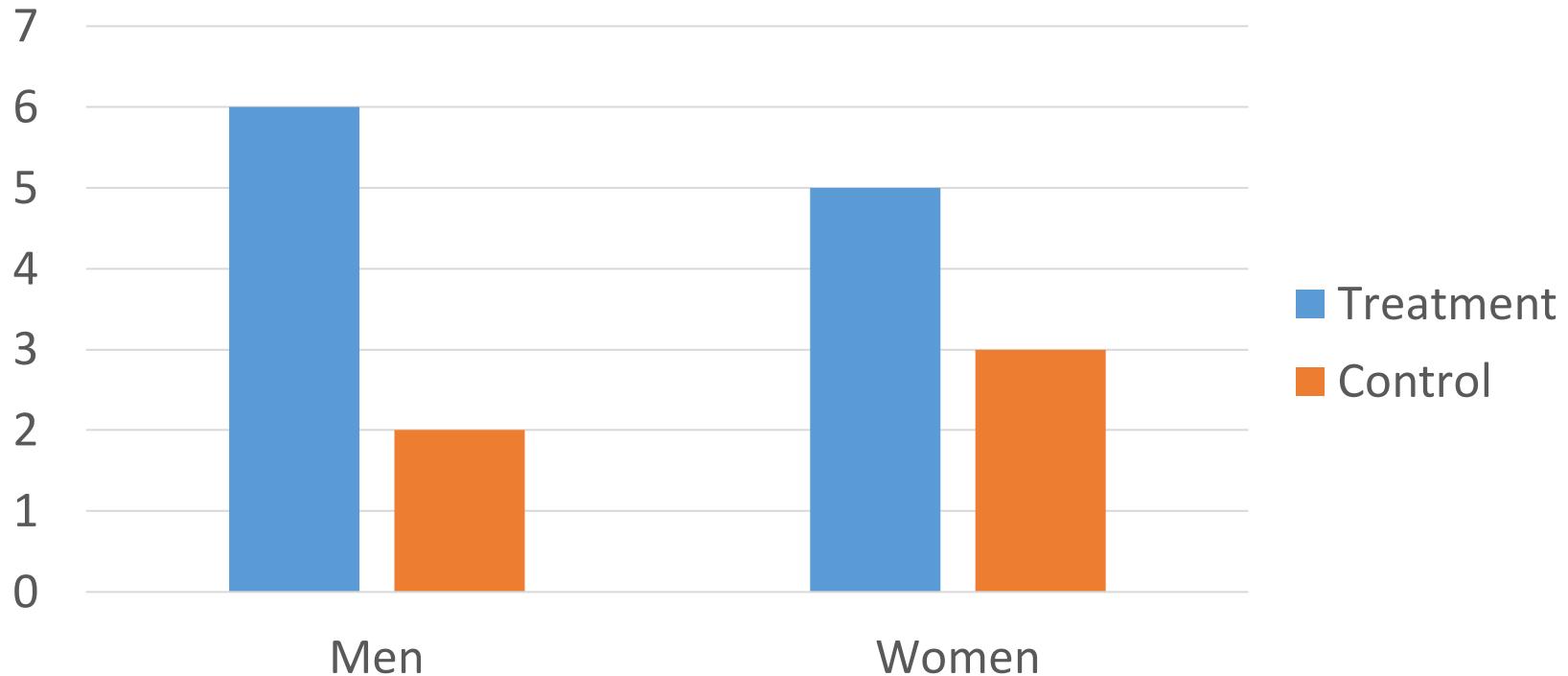
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- Moderators change an effect size, but we may not know all moderators ahead of time
- Failures to replicate effects may be the result of not accounting for crucial (but unknown) moderators
- Identifying hidden moderators can also help us determine if interventions work better for some people (see Imai & Strauss, 2011; Imai & Ratkovic, 2013)
- We want a ***test*** to determine if there are hidden (not predicted) moderators

# What is a Moderator?

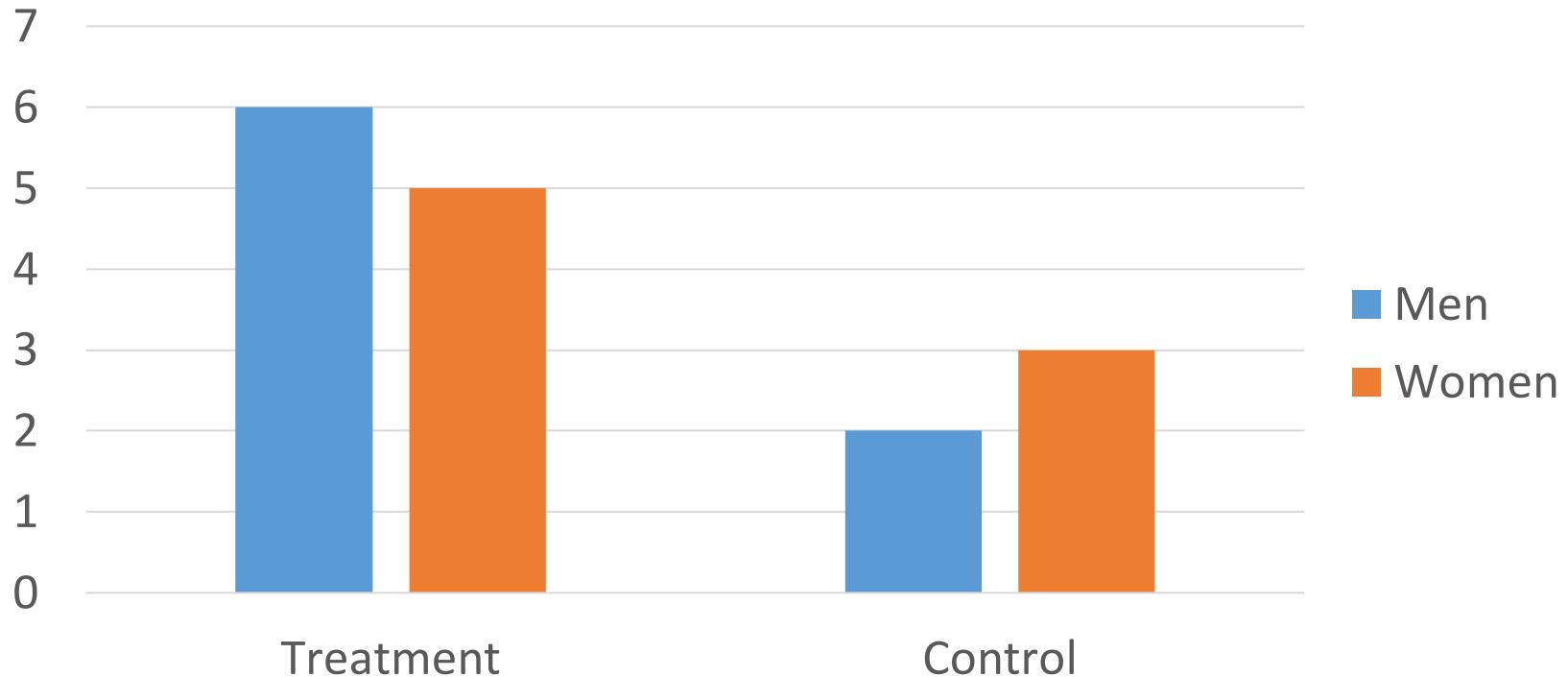
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A variable that *changes* an effect size



# What is a Moderator?

A *covariate* with different effects across groups

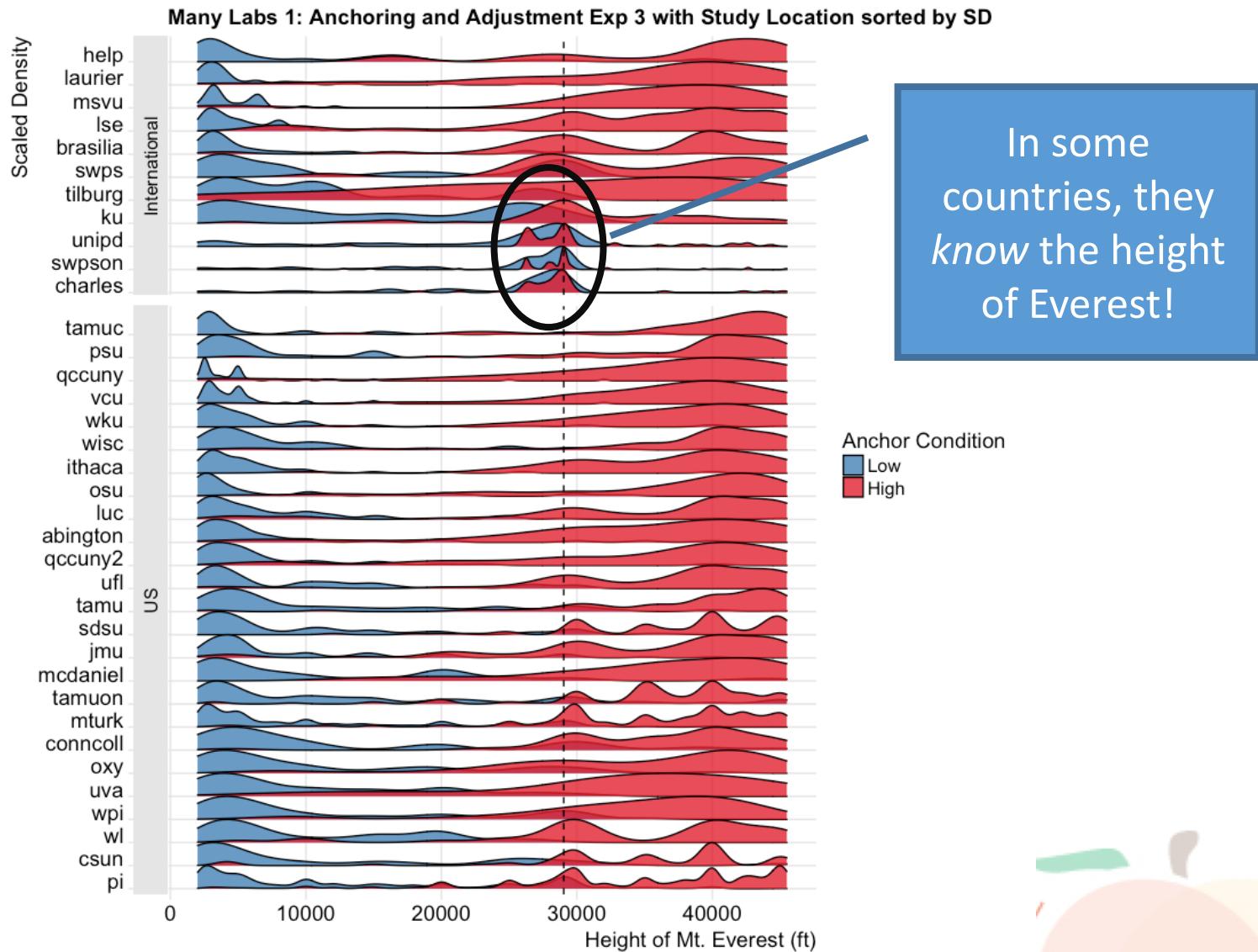


# The Many Labs 1 Data

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- 15 experiments, all involving two conditions
  - 10 of these were analyzed for the current project
  - Excluded studies with binary outcomes (for now)
- 36 data samples, with 6,344 participants
- Previous analysis used U.S./non-U.S. and Lab/Online as moderators, in a GLM framework
  - US/non-U.S. moderated 5 effects
  - Lab/online moderated 6 effects

# Finding Hidden Moderators the Old Fashioned Way



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# Finding Hidden Moderators the Regression Way

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- Regression analysis can be used to test whether a specific moderating effect is significant (Aiken & West, 1994)
- A special interaction term is created, and the significance of the regression coefficient is tested

$$\hat{Y} = b_0 + b_1X + b_2M + \textcircled{b}_3X * M$$

# Limitations to the Regression Approach

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- New terms need to be constructed for each potential moderator
- What if there are higher order interactions?
  - The effect is different not just for men and women, but according to ethnicity (intersectionality in moderators)

***What if we could test all of the possible moderating relationships in one step?***

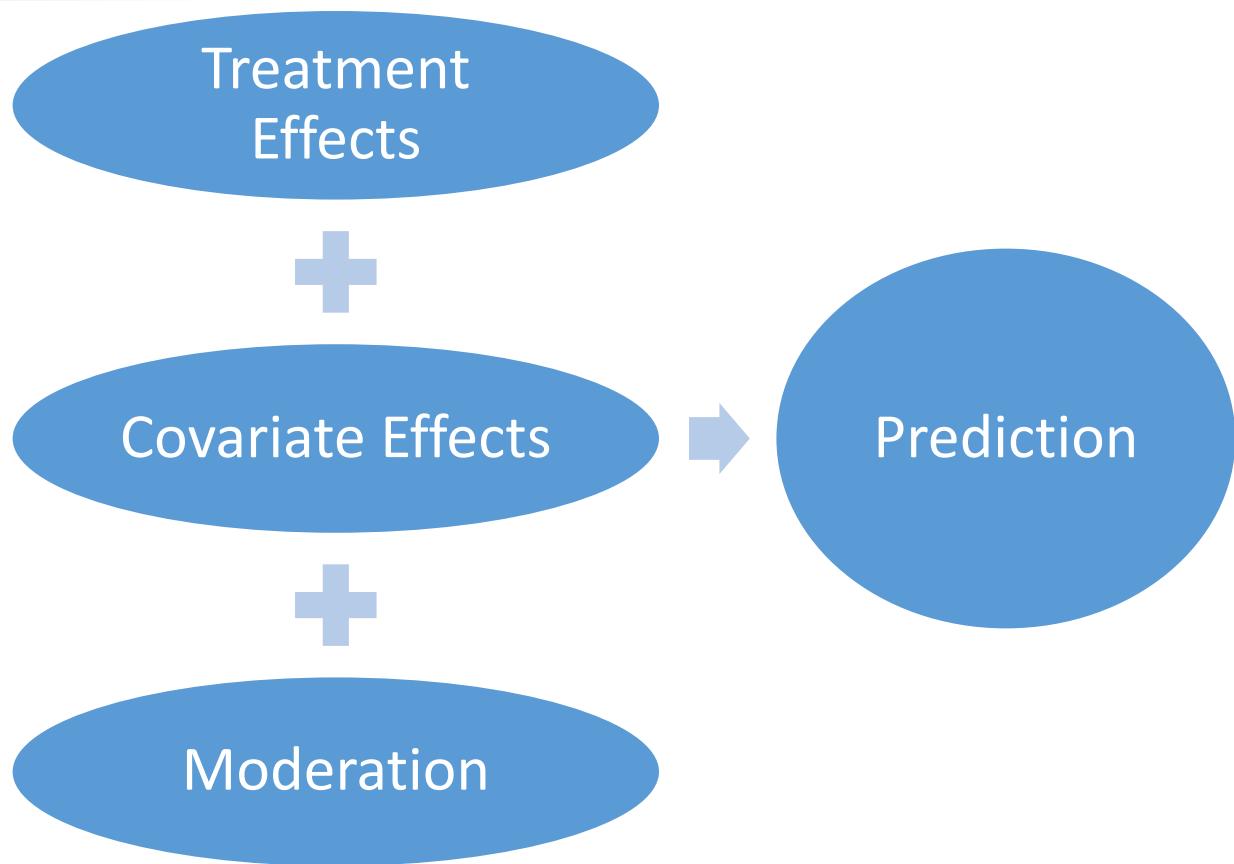
# Machine Learning

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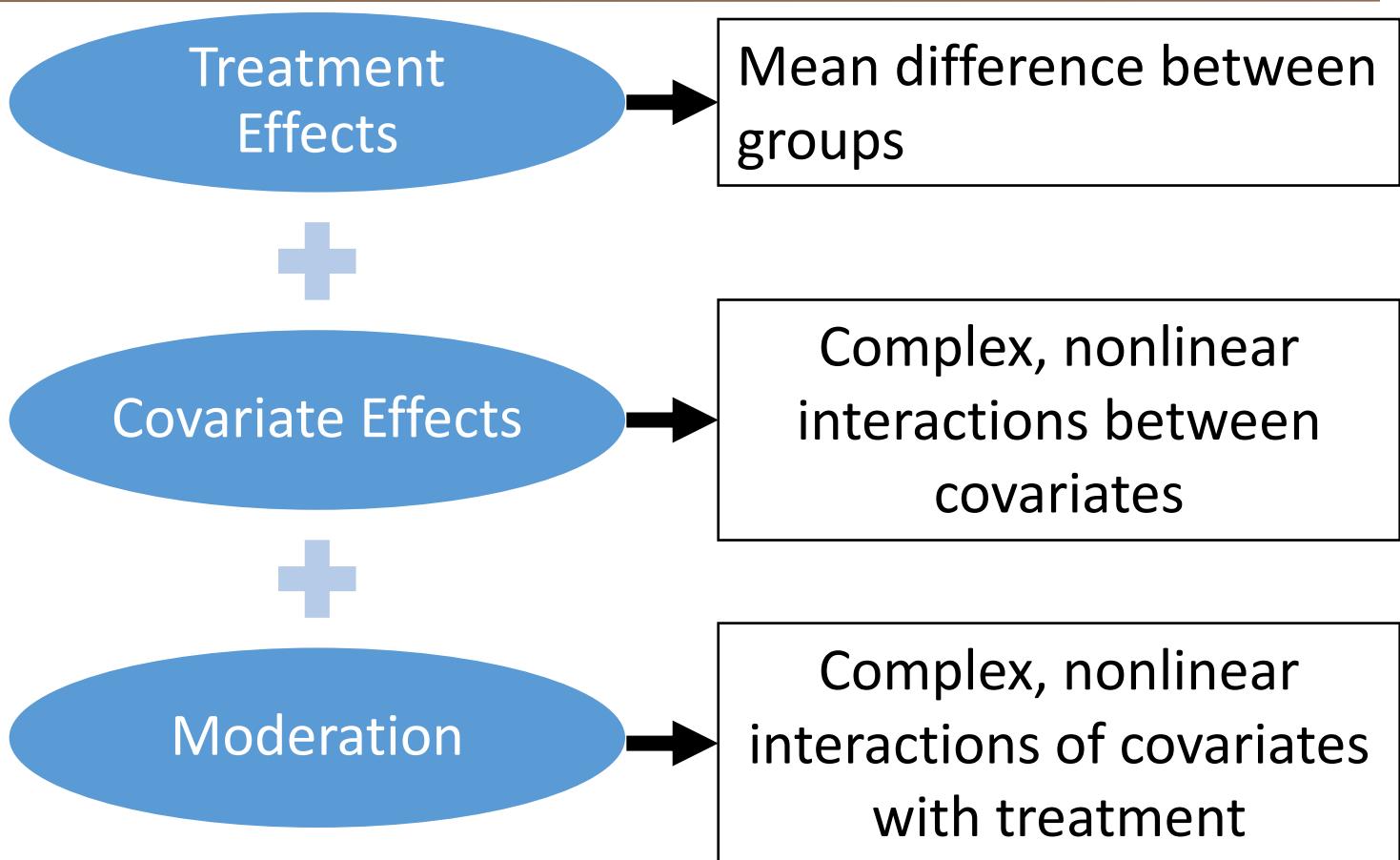
- Emphasize accurate prediction of the overall model, without testing specific predictors
  - “Success” is based on accurate prediction of *new data*
  - Not based on a significance test or p-value
- Flexible algorithms allow for nonlinearity and interactions between variables to be discovered bottom-up
- Typically require larger data sets to reliably identify complex patterns

# Types of Effects

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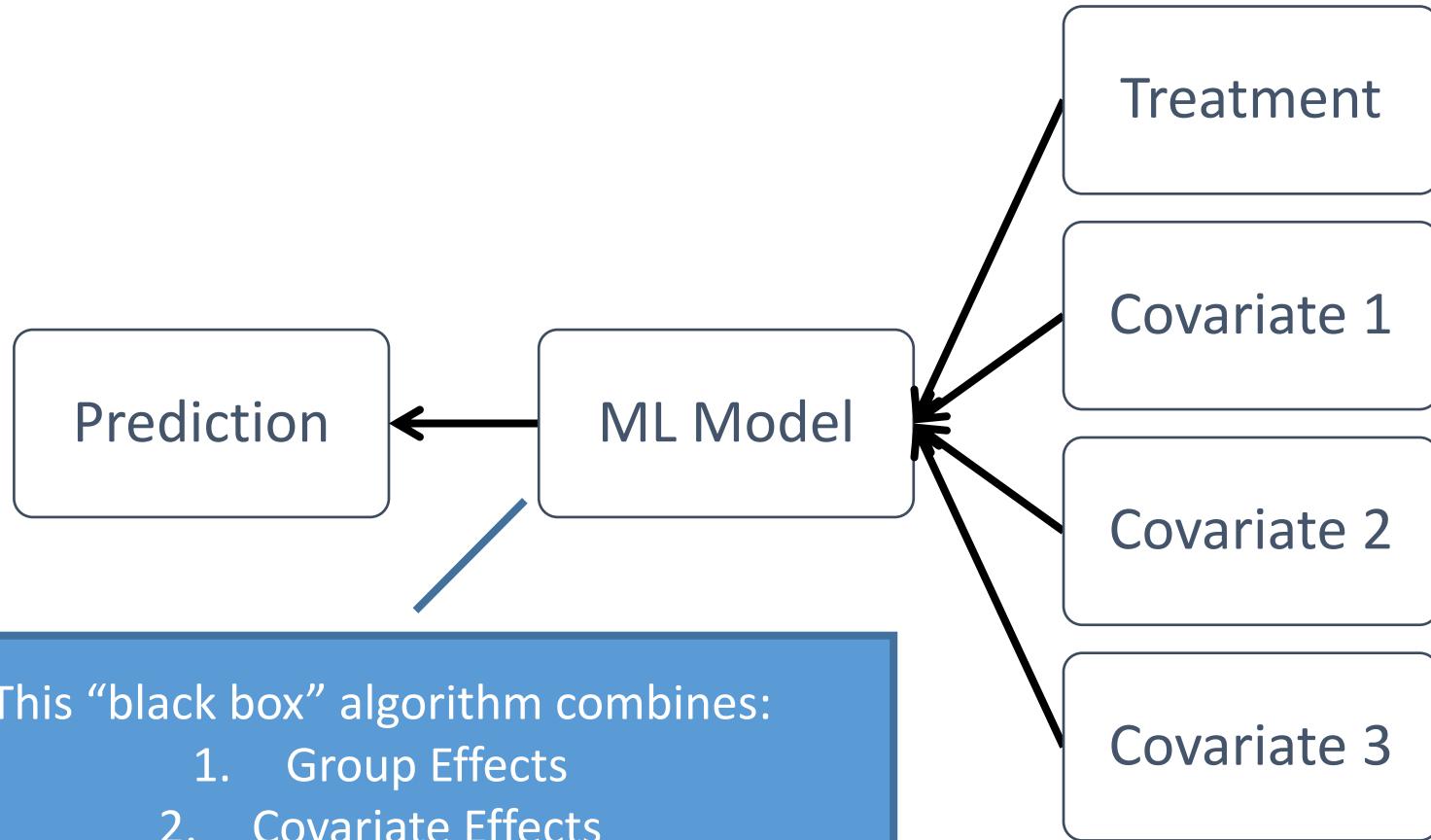


# Types of Effects



# Simple Predictive Model

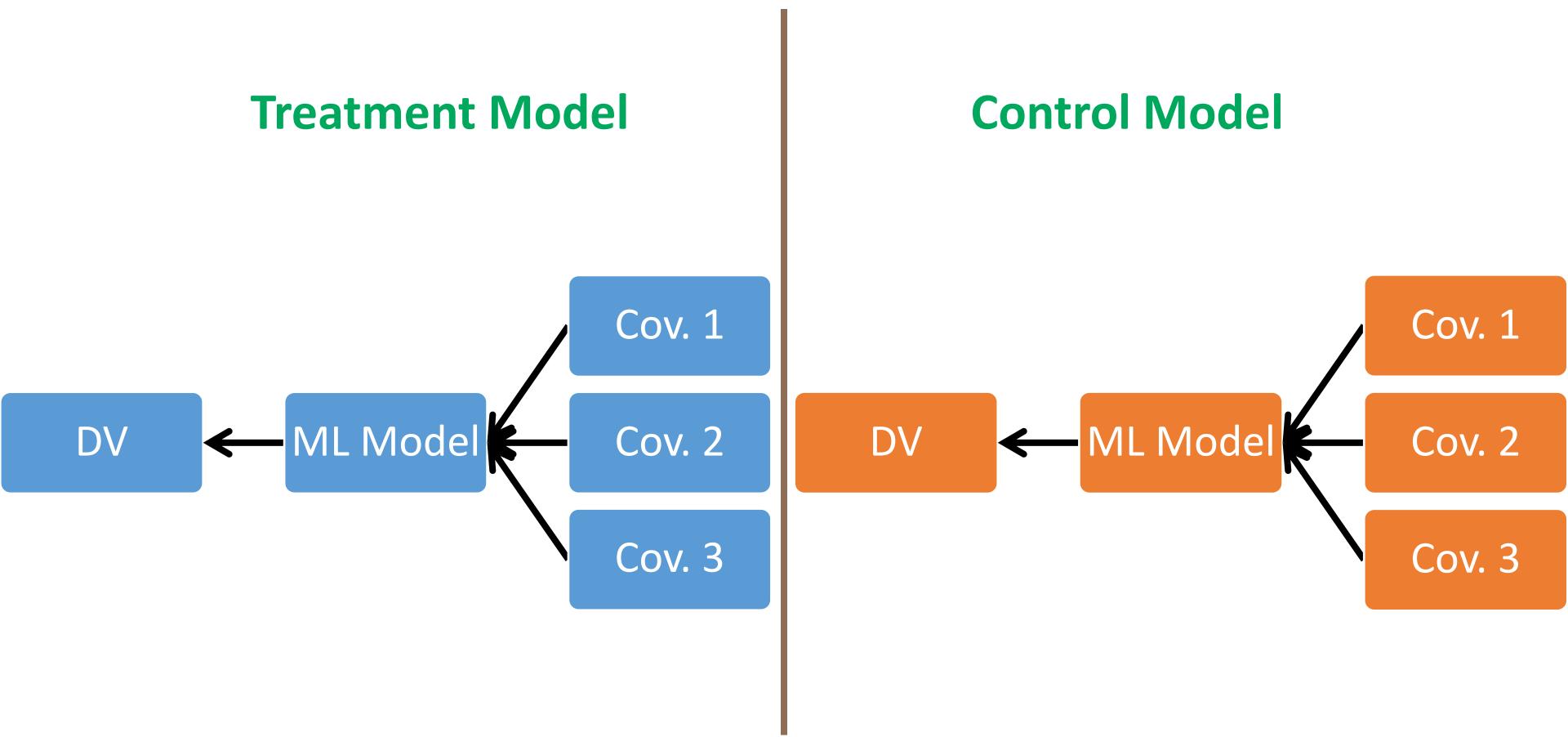
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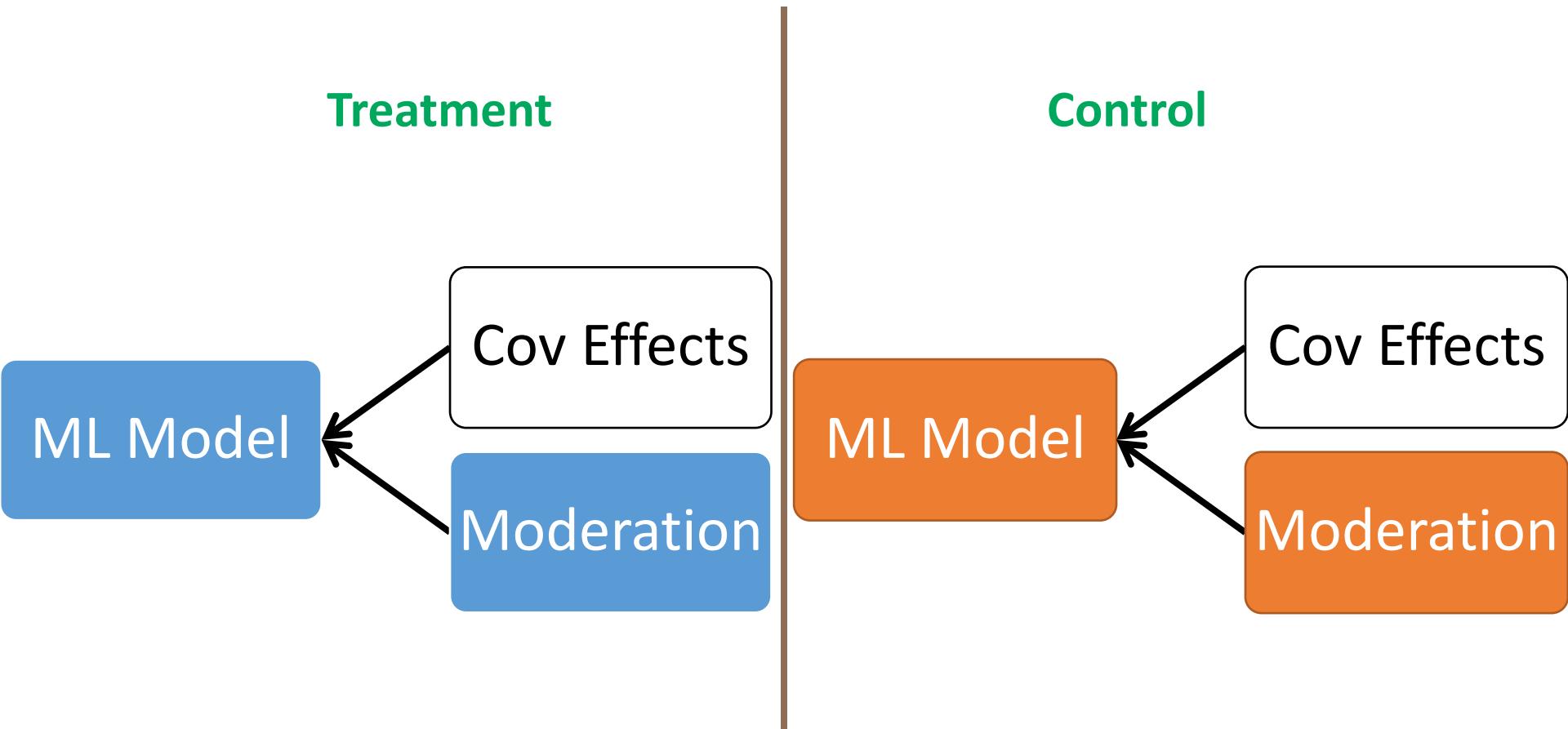
This “black box” algorithm combines:

1. Group Effects
2. Covariate Effects
3. Moderation Effects

# Separate Models for Conditions

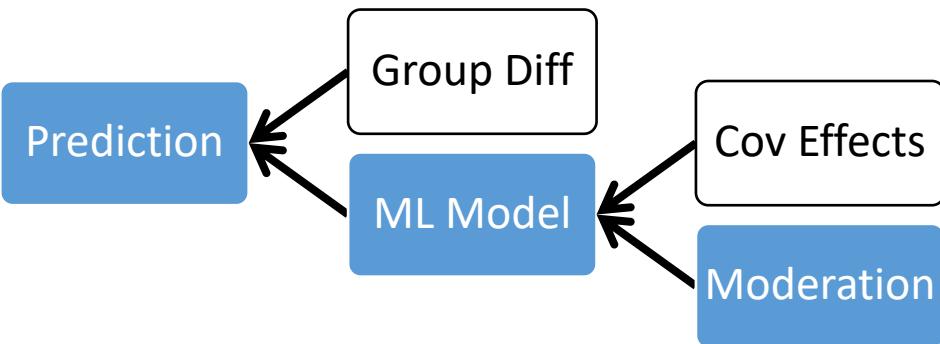


# Differences Between the Algorithms

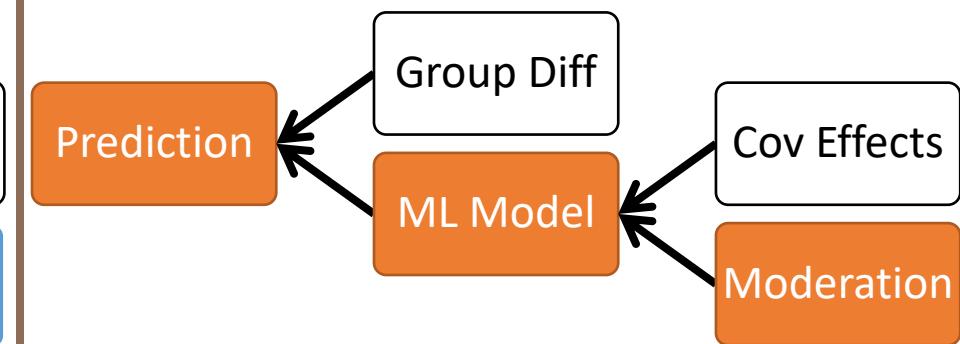


# Counterfactual Thinking

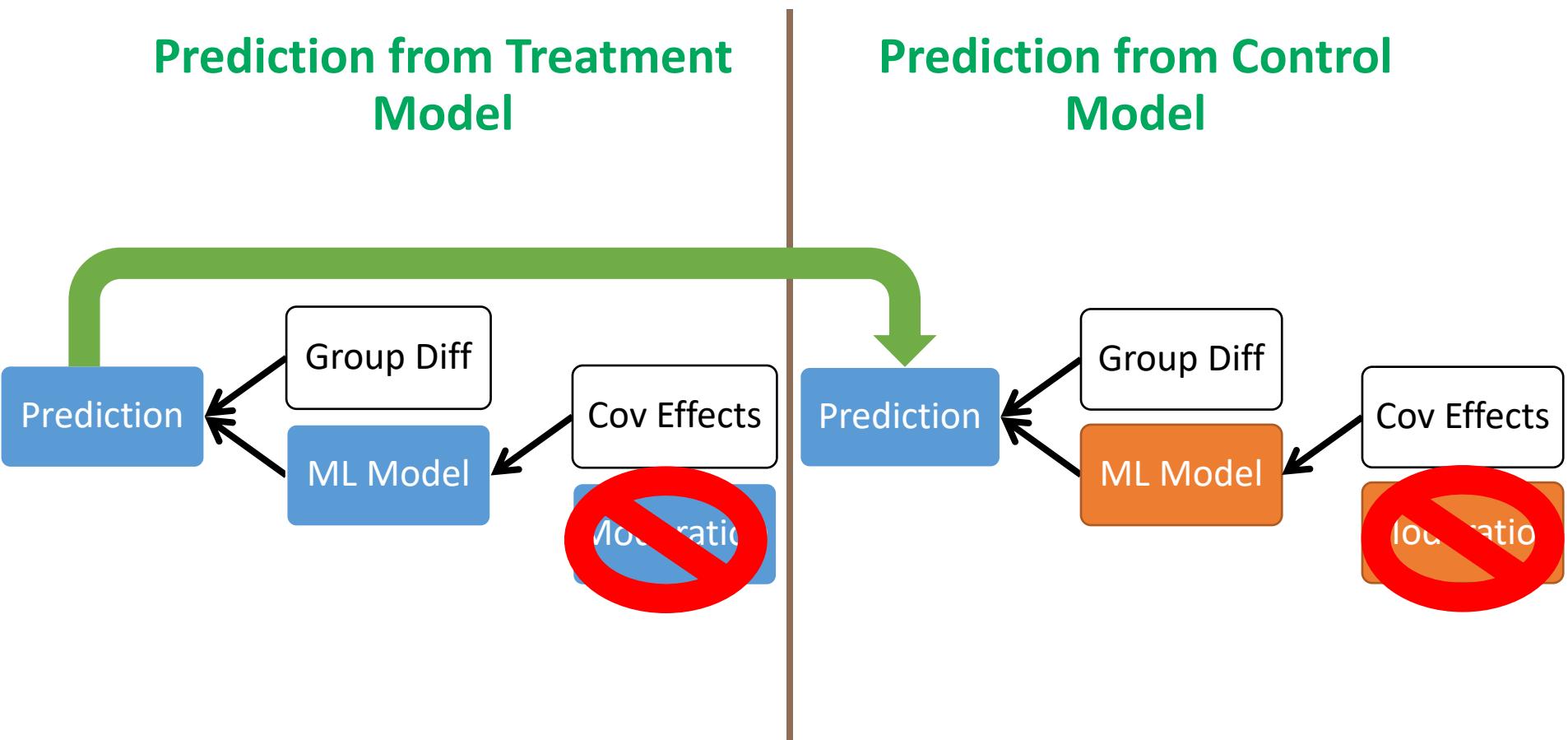
## Prediction from Treatment Model



## Prediction from Control Model



# No Moderation



# Our Approach

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1. Divide the data into two groups, according to who was in the *treatment* and who was in the *control* group
2. Train *random forest models* on each group separately, including all potential moderators.
3. Examine the *difference in predictive accuracy* for each model

# Simulation Results

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- 300 Ps randomly assigned to treatment or control
- 3 potential moderators
- Conditions:
  - 0, 1, 2, or all 3 are actually moderators
  - There are 1, 2, or 3 two-way multiplicative interactions between moderators and the effect
- Qs:
  - Can we identify whether hidden moderators are present?

# Are Moderators Present?

- A  $t$ -test of differences in prediction error for treatment vs control

Condition	Proportion of Sig $t$ -tests	
	$p < .05$	$p < .01$
No mods	8.5%	2.5%
1 mod	94.6%	85.4%
2 mod	99.8%	99.2%
3 mod	100.0%	100.0%
1 2way	100.0%	100.0%
2 2way	100.0%	100.0%
3 2way	100.0%	100.0%



# Many Labs 1: Moderators

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- U.S. or International Sample
- Whether participants were together or separate
- Order of presentation for the study
- Participant gender
- Participant age
- Participant race
- What day the study was conducted
- What time of day the study was conducted
- How long the participant took completing the survey

# Many Labs 1: Results

Study	Group Diff	Error Diff	t	p-value
Anchoring: Baby	1.476	0.041	11.777	<.001
Anchoring: Chicago	1.331	0.046	8.682	<.001
Anchoring: Mt. Everest	1.510	0.098	15.488	<.001
Anchoring: NYC	1.006	0.046	8.096	<.001
Currency Priming	-0.019	-0.006	-1.371	.170
Flag Priming	0.029	-0.009	-2.237	.025
Imagined Contact	0.130	0.004	0.761	.446
Quote Attribution	0.317	0.006	1.249	.212
Rev. Gambler's Fal	0.597	0.066	12.892	<.001
Sunk Cost	-0.272	-0.004	-0.970	.332

# Can we identify specific moderators?

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Short answer: No

Long answer: Maybe

- Random Forest Models include measures of “variable importance” based on how much a particular variable improved prediction.
- We can compare the *ratio* of variable importance in the treatment model to that of the control model

# Simulation: Which Moderators Are Important?

	No mods	1 mod	2 mod	3 mod	1 2 way	2 2 way	3 2 way
M1 LM	0.00	<b>0.87</b>	<b>0.87</b>	<b>0.86</b>	<b>4.34</b>	<b>7.82</b>	<b>7.79</b>
M1 RF*	0.03	<b>2.58</b>	<b>2.57</b>	<b>2.53</b>	<b>66.20</b>	<b>207.60</b>	<b>207.35</b>
M2 LM	0.00	0.00	<b>0.87</b>	<b>0.86</b>	<b>4.33</b>	<b>4.35</b>	<b>7.82</b>
M2 RF*	0.03	0.06	<b>2.55</b>	<b>2.54</b>	<b>66.09</b>	<b>69.53</b>	<b>210.11</b>
M3 LM	0.00	0.00	0.00	<b>0.87</b>	<b>0.87</b>	<b>4.35</b>	<b>7.81</b>
M3 RF*	0.02	0.04	0.01	<b>2.56</b>	<b>5.52</b>	<b>69.81</b>	<b>207.45</b>

\*Ratios of variable importance measures

# Many Labs 1: Which Moderators are Important?

Study	Order	Sex	Age	Race	US/In	Sep?	Day	T.O.D	Time
Anchoring: Baby	6.22	4.89	5.75	7.14	6.35	6.50	5.98	5.50	5.13
Anchoring: Chicago	1.93	0.51	1.32	1.87	1.40	1.64	1.70	1.93	1.94
Anchoring: Mt. Everest	0.87	0.62	0.83	0.66	0.55	0.58	0.79	0.82	0.90
Anchoring: NYC	1.81	1.79	1.81	1.63	1.14	1.51	1.67	1.69	1.72
Currency Priming	0.97	0.94	1.04	1.08	1.06	1.01	0.98	0.95	0.97
Flag Priming	1.04	1.07	1.01	0.96	0.98	1.07	1.02	1.06	1.04
Imagined Contact	0.91	0.81	0.91	0.89	0.94	0.95	0.92	0.92	0.94
Quote Attribution	1.19	1.48	1.22	1.01	1.21	1.31	1.17	1.17	1.19
Rev. Gambler's Fal	2.12	2.57	2.40	2.37	3.06	1.96	2.03	1.98	1.96
Sunk Cost	1.47	1.38	1.11	1.57	1.50	1.47	1.37	1.43	1.42

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# Limitations

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- Favors prediction over interpretability.
  - Allows for systems of interacting variables
- Promising simulation results so far, but more tests needed.
  - Wider range of effect sizes, categorical moderators, exponential and higher order polynomials as moderators
- Results suggest new hypotheses to test. They do not definitively prove the presence of moderators.



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*Institute for the Study of Human Flourishing*

# Thank You!

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JOHN TEMPLETON  
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