

# A comparison between propensity score matching, and weighting, in multiple treatment groups: A simulation study

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# Plan for today

What is the **problem**?

- Issues in the application of propensity score techniques with multiple groups

How to **address** the problem?

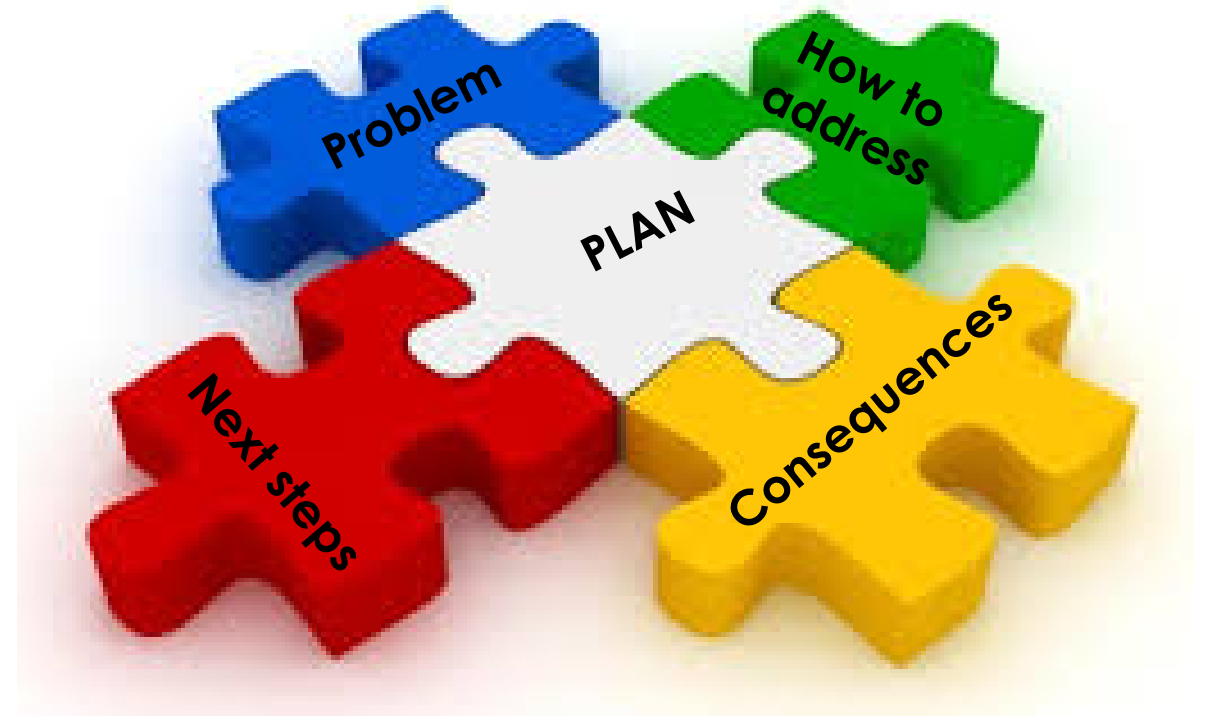
- Pose some questions addressing some application issues that can be common
- Suggest solutions to the questions
- Implementations of the solutions

What are the **consequences** of the solutions?

- Findings & Interpretations

Next steps?

- Directions for future research



# Before we start:

## Propensity score analysis approaches

### 1. Matching

- find matches between treated and non-treated cases

### 2. Stratification

- assign treated and non-treated observations into strata with the same propensity score range

### 3. Weighting

-weight to account for non-constant variability on the observed covariate between treated and non-treated groups



# What is the problem?

Given the differences in the implementation of propensity scores,  
how do we select an appropriate propensity score technique?

**In multiple treatment-groups settings**



# How to address the problem?

Compare the performance of propensity score analysis using **matching**, and **weighting** techniques in multiple treatment group settings under various data conditions:

a. Variable conditions:

1. Distributional characteristics of the treatment & outcome related variables (5 conditions)
2. Correlation between the treatment and outcome variable (3 conditions)

b. Sample size (3 conditions)

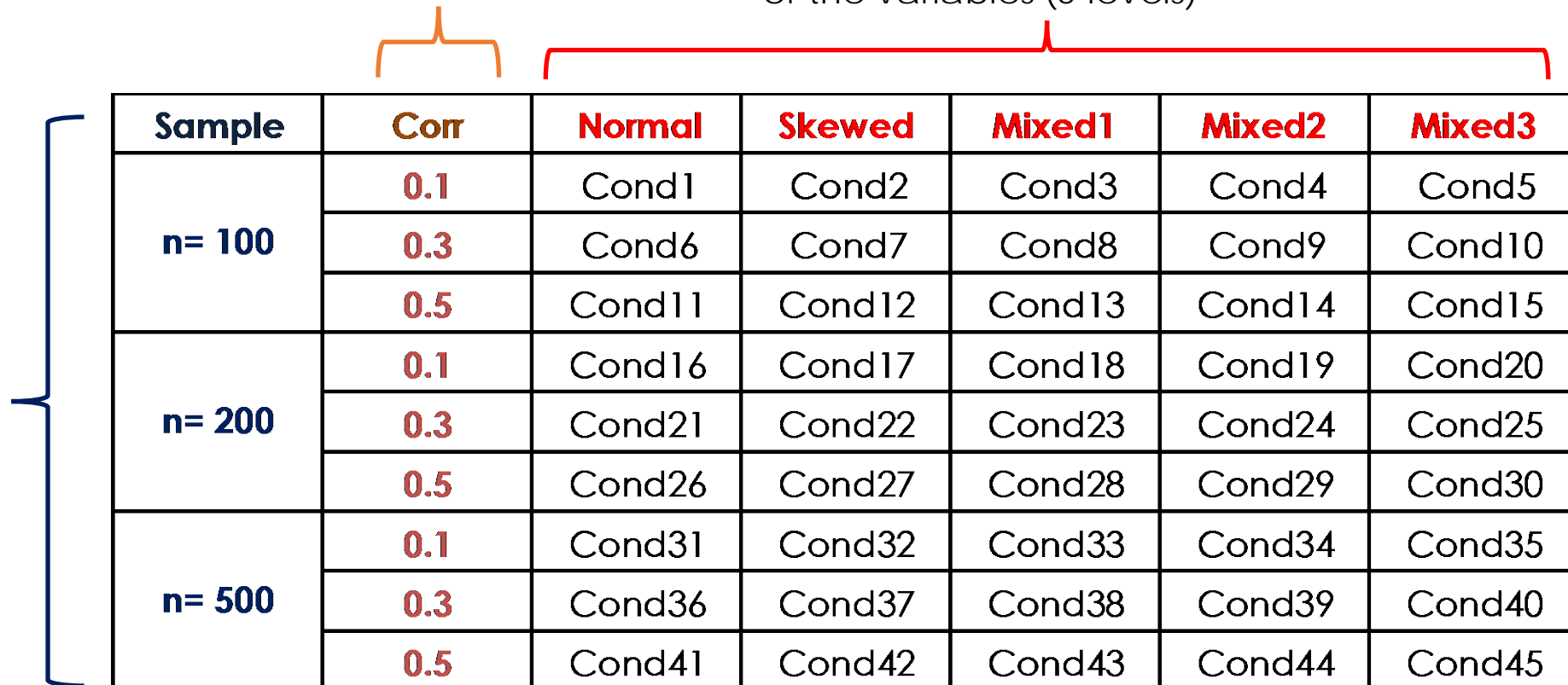


# Data conditions

**Condition 2:** Correlation between the variables (3 levels)

**Condition 3:** Distributional characteristics of the variables (5 levels)

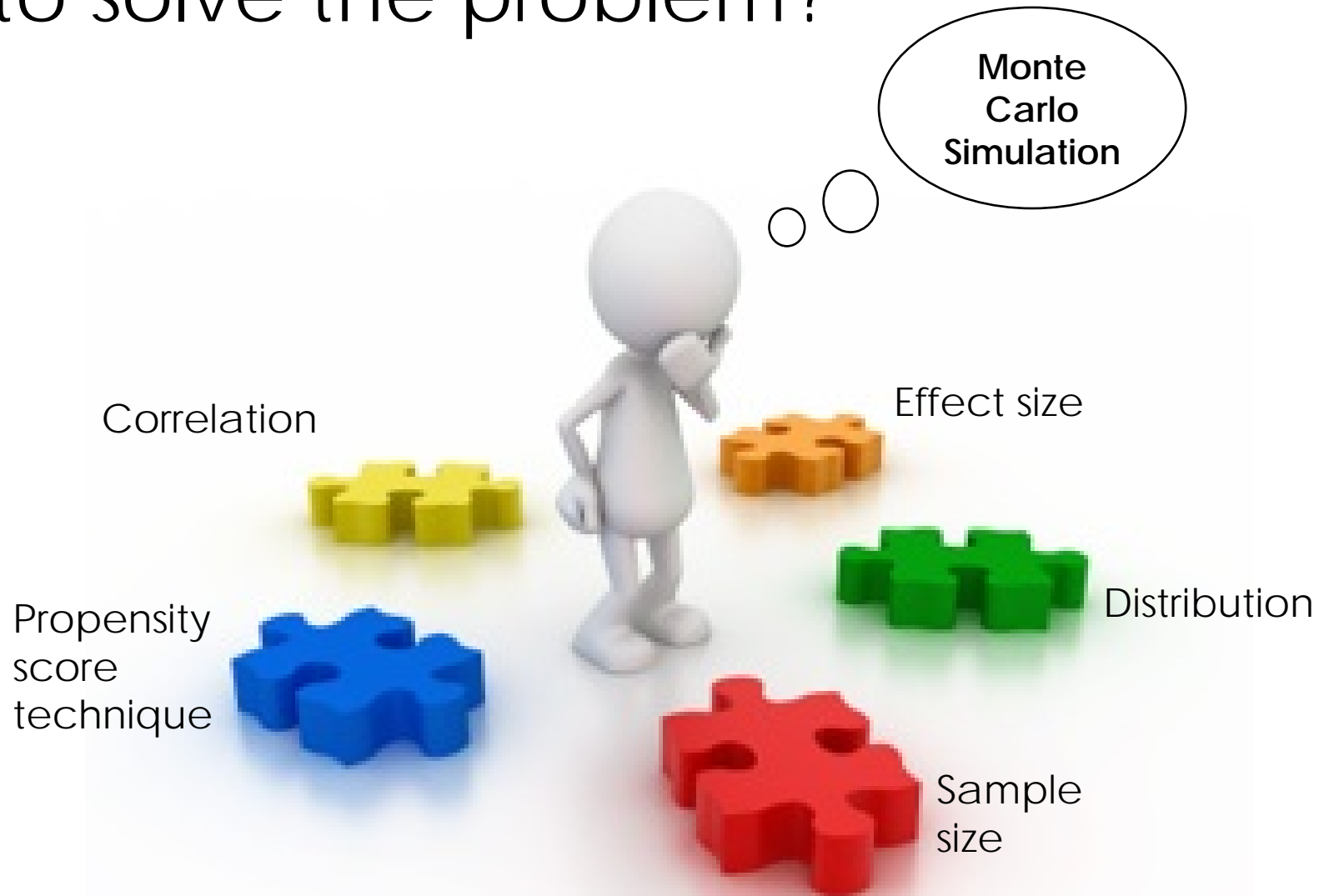
**Condition 1:** sample size (3 levels)



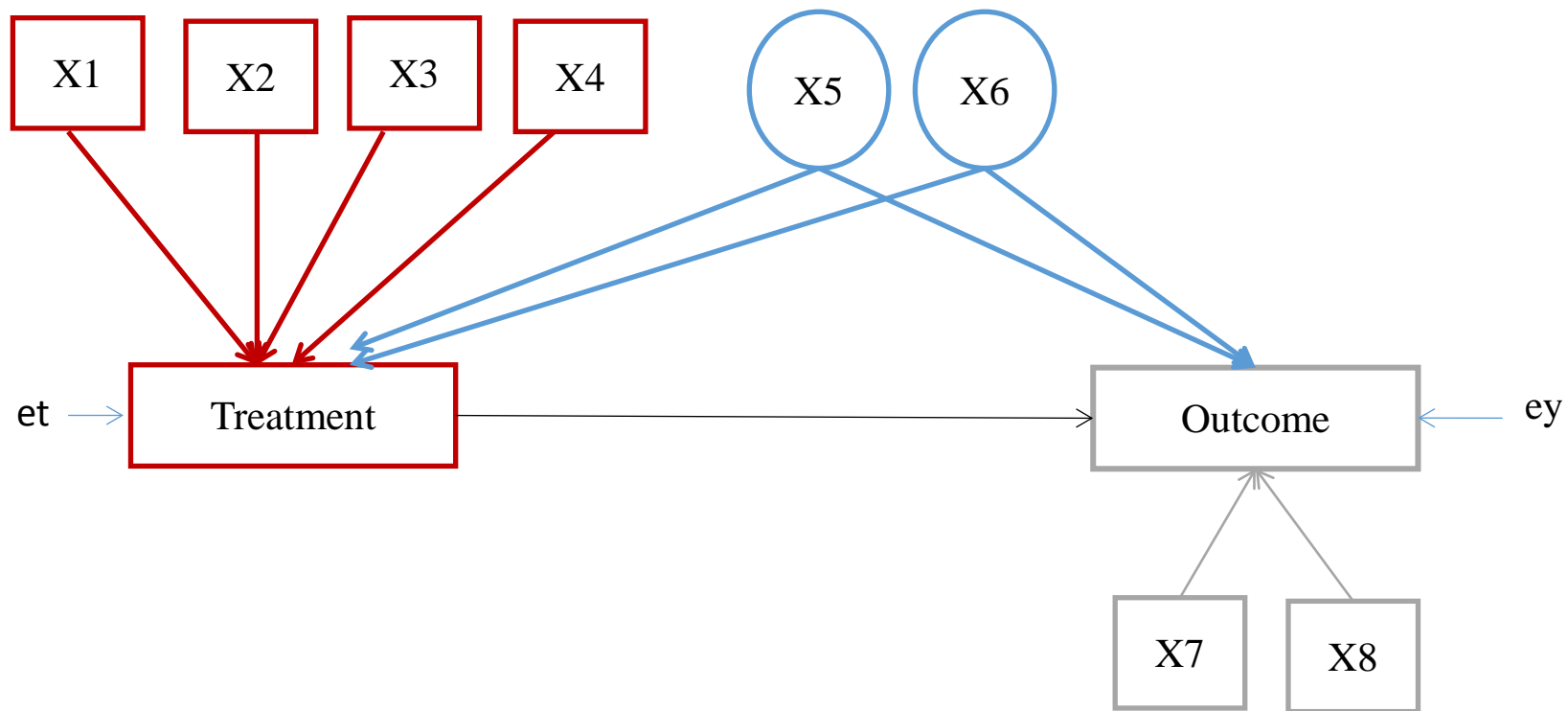
Sample	Corr	Normal	Skewed	Mixed1	Mixed2	Mixed3
n= 100	0.1	Cond1	Cond2	Cond3	Cond4	Cond5
	0.3	Cond6	Cond7	Cond8	Cond9	Cond10
	0.5	Cond11	Cond12	Cond13	Cond14	Cond15
n= 200	0.1	Cond16	Cond17	Cond18	Cond19	Cond20
	0.3	Cond21	Cond22	Cond23	Cond24	Cond25
	0.5	Cond26	Cond27	Cond28	Cond29	Cond30
n= 500	0.1	Cond31	Cond32	Cond33	Cond34	Cond35
	0.3	Cond36	Cond37	Cond38	Cond39	Cond40
	0.5	Cond41	Cond42	Cond43	Cond44	Cond45

Notes: skewed = positively skewed, Mixed 1= Treatment variables are normal & outcome assigned variables are positively skewed, Mixed 2= Treatment variables are positively skewed & outcome variables are normal, Mixed 3 = one treatment and one outcome variable is positively skewed and the rest are all normal

# How to solve the problem?

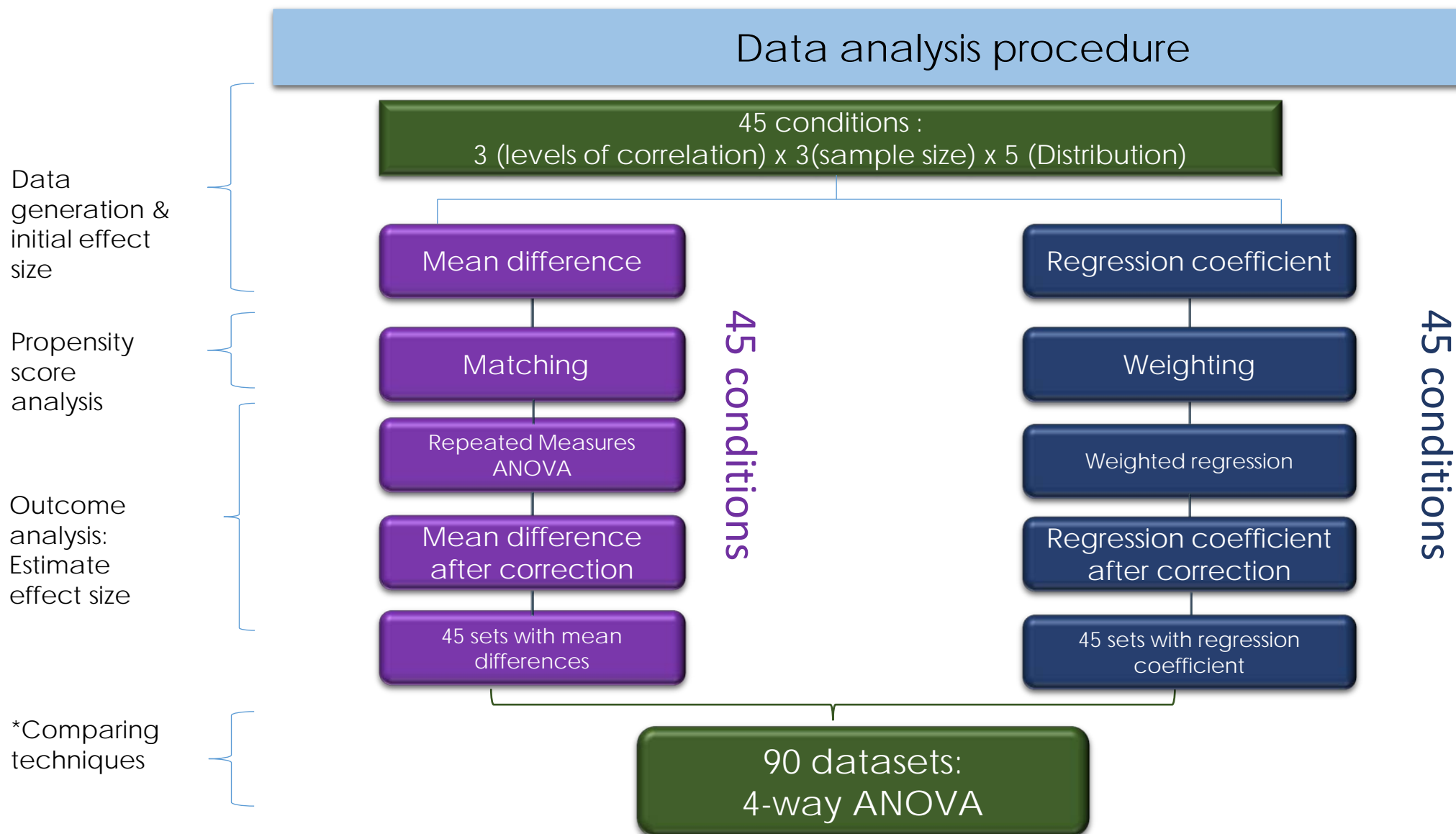


# Model depiction





# Procedure



# How it was analyzed?

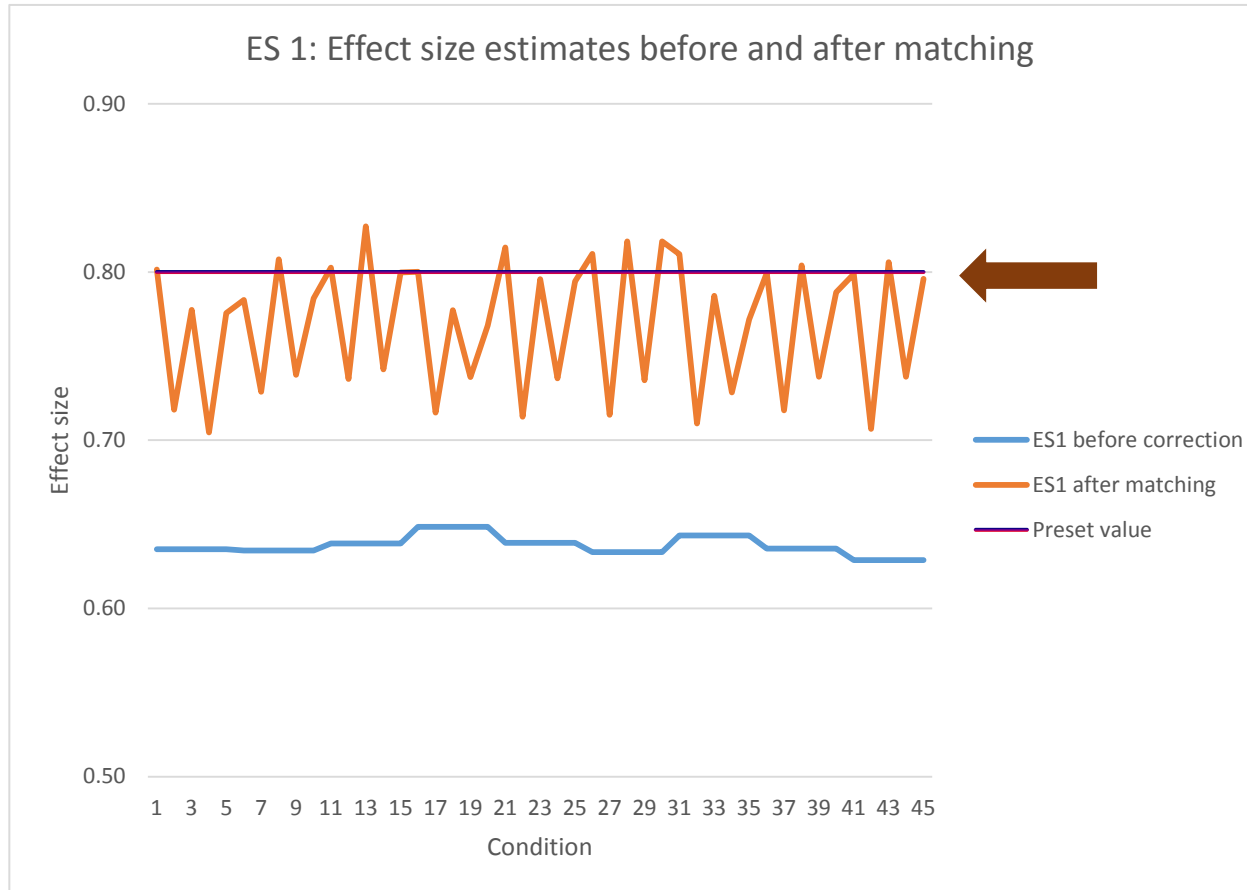


- **Two 2x3x3x5** Analysis of Variance
  - **X1 vs Control, X2 vs Control**
- Used to evaluate the effects of
  1. **Propensity score technique**  
(2 levels: technique)
  2. **Sample size** (3 levels: Sample size)
  3. **Level of correlation** (3 levels : Level (degree of correlation))
  4. Distributional characteristics of the variables  
(5 levels: normality/skewness)on the **effect size** (treatment effect)
- **Effect size**  
= Mean outcome of treatment group– Mean outcome of control group
- **Interactions** and **main effects** of the four factors on the amount of bias were examined

# How was the performance?

## Propensity score matching

ES1



After matching, the estimates were closer to the true estimate

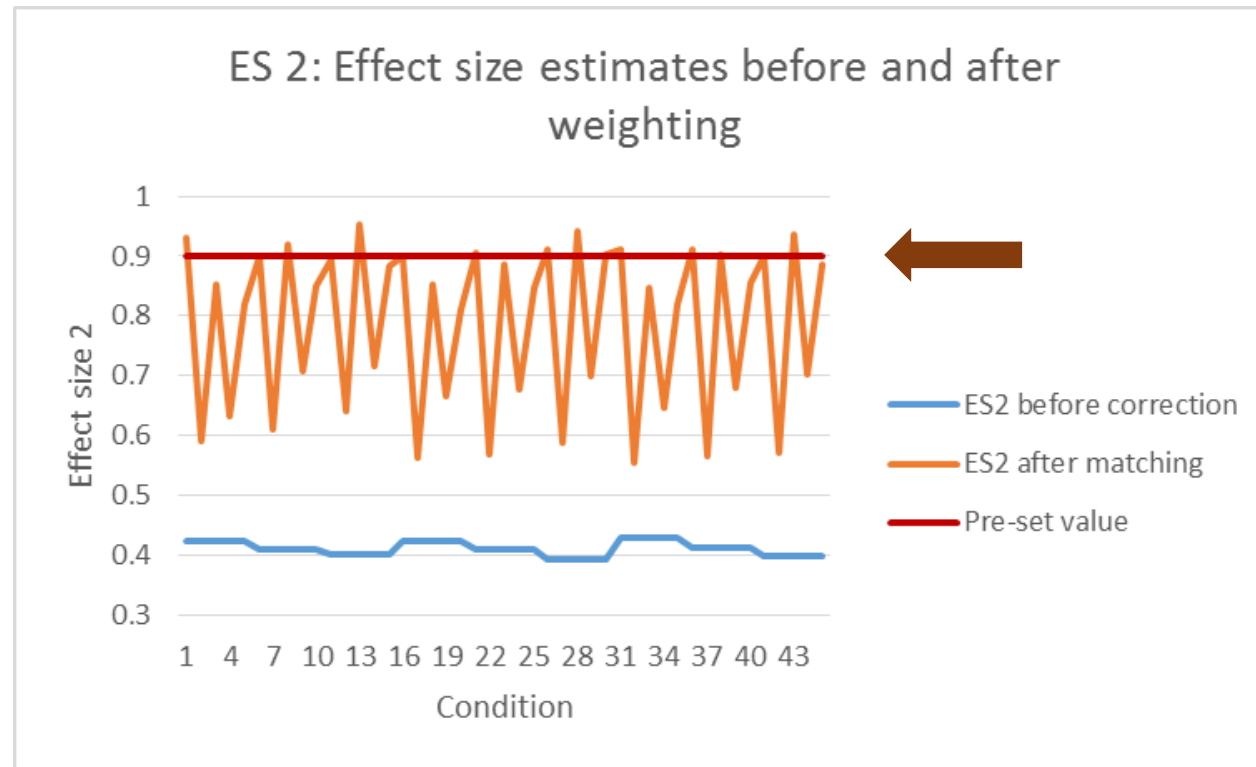
The estimates are initially biased (The estimated were below the true estimate)

Note: ES = Effect size

# How was the performance?

## Propensity score matching

ES2



After matching, the estimates were closer to the true estimate

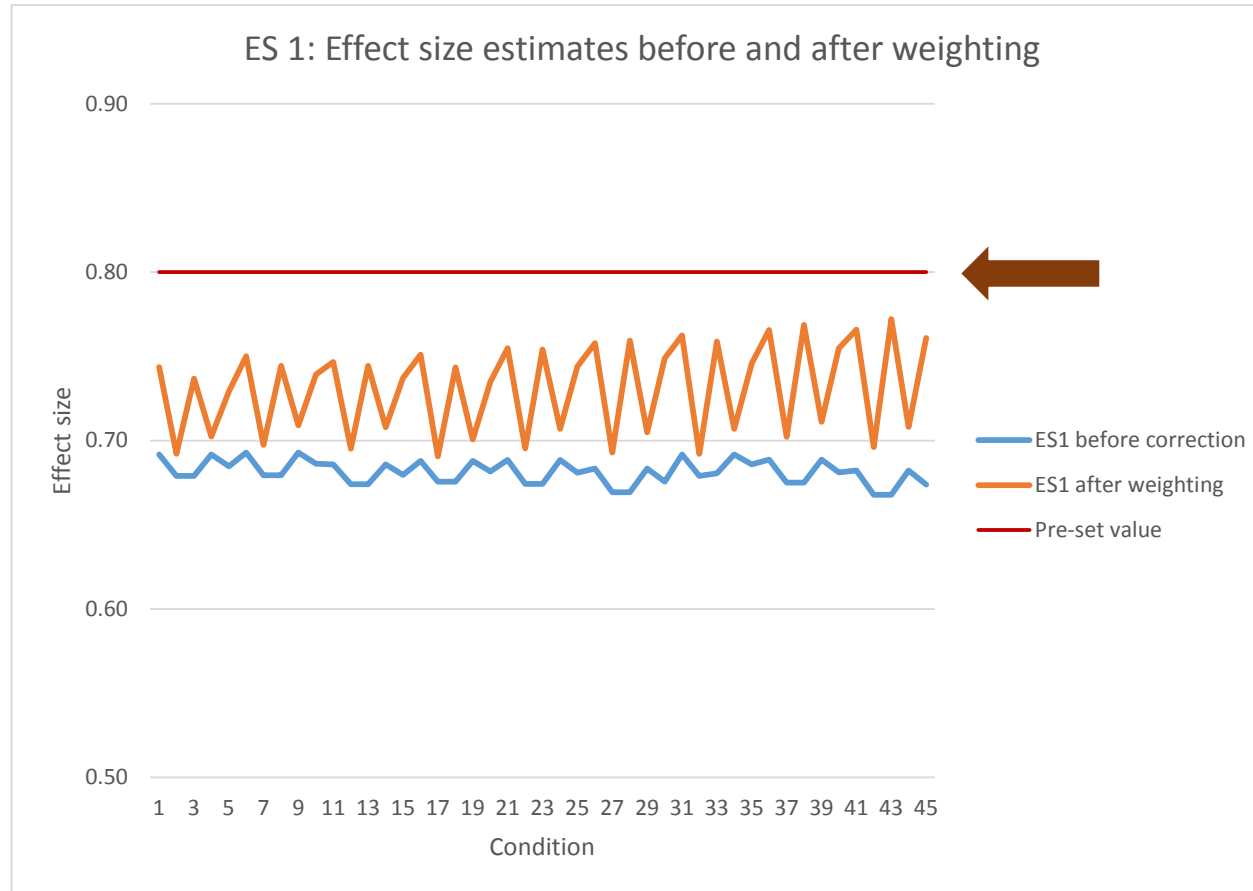
The estimates are initially biased (The estimates were below the true estimate)

Note: ES = Effect size

# How was the performance?

## Propensity score weighting

ES1



After weighting, the estimates were closer to the true estimate

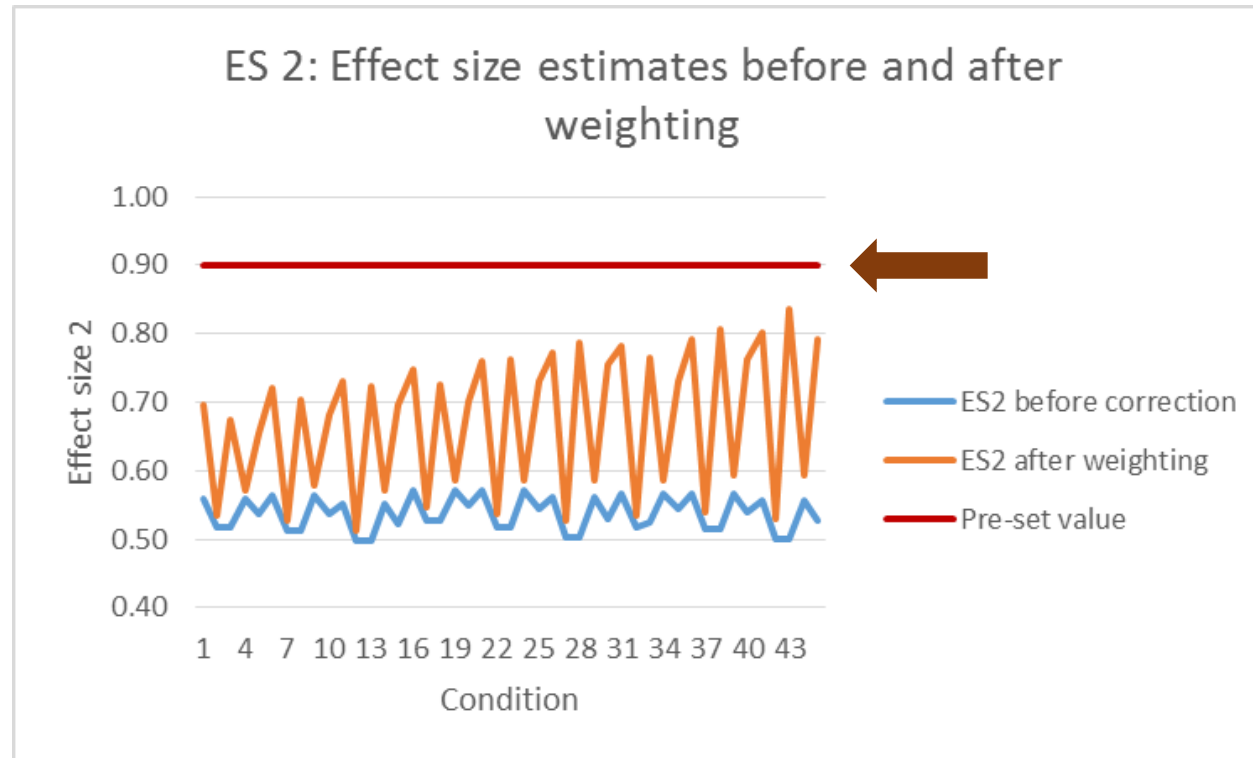
The estimates are initially biased (The estimates were below the true estimate)

Note: ES = Effect size

# How was the performance?

Propensity score weighting

ES2



After matching, the estimates were closer to the true estimate

The estimates are initially biased (The estimates were below the true estimate)

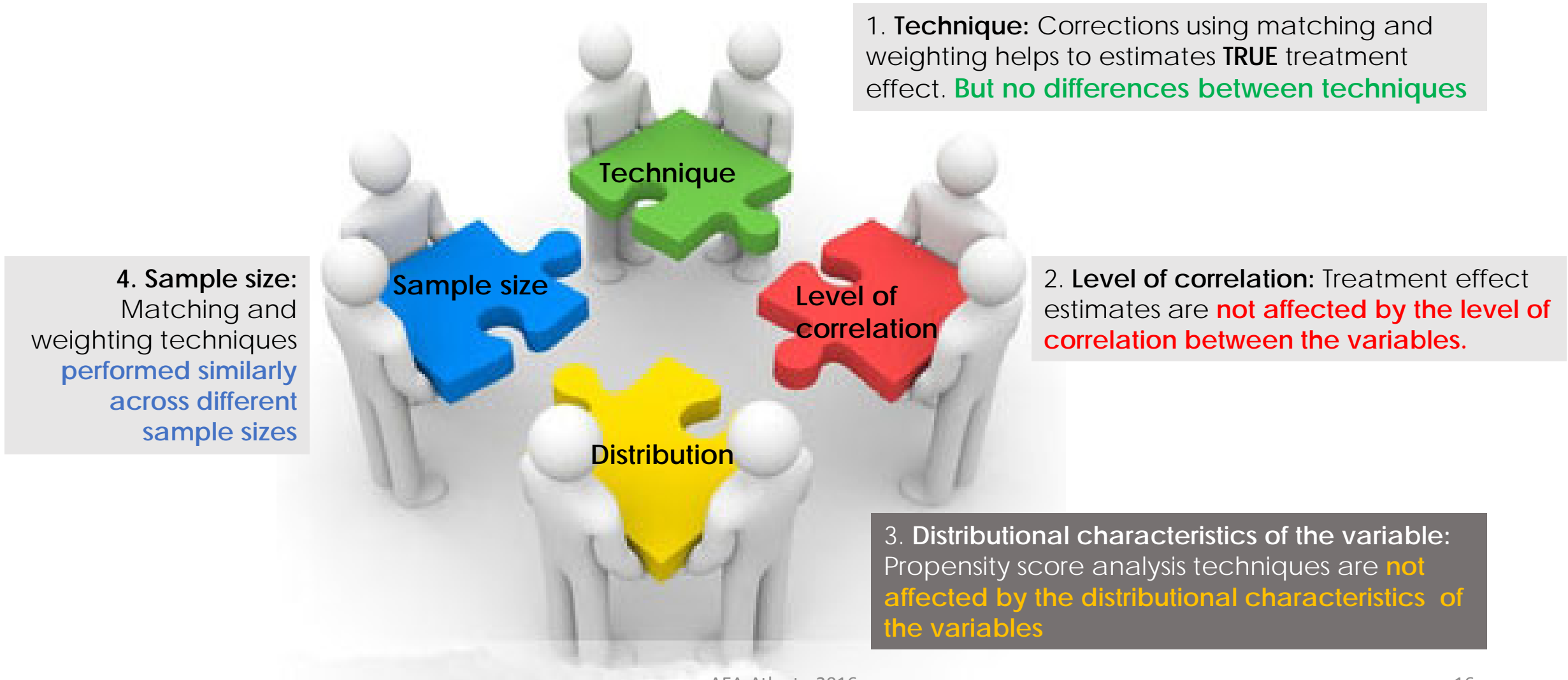
Note: ES = Effect size

# Eta square results

Criteria:  $\eta^2 \geq 0.1$

	Eta square
Technique	0.0043
Sample	0.0001
Correlation	0.0003
Normality	0.0112
TechniqueXSample	0.0001
TechniqueXCorrelation	0.0001
SampleXCorrelation	0.0000
TechniqueXNormality	0.0003
SampleXNormality	0.0001
CorrelationXNormality	0.0002
TechniqueXSampleXCorrelation	0.0000
TechniqueXSampleXNormality	0.0001
TechniqueXCorrelationXNormality	0.0001
SampleXCorrelationXNormality	0.0001
TechniqueXSampleXCorrelationXNormality	0.0001

# What does the finding means?





# Next steps

## 3. Dependency:

Determine the consequences of estimating **treatment effect before & after** correcting for **dependency** in multiple treatment groups

## 2. Sensitivity analysis:

No clear direction is available for conducting and assessing **sensitivity analysis** for **hidden bias** in more than 2 groups

**1. Model:** Determine the sensitivity of matching, stratification & weighting with **poorly defined propensity score models**

3. Dependency

2. Sensitivity analysis

1. Model

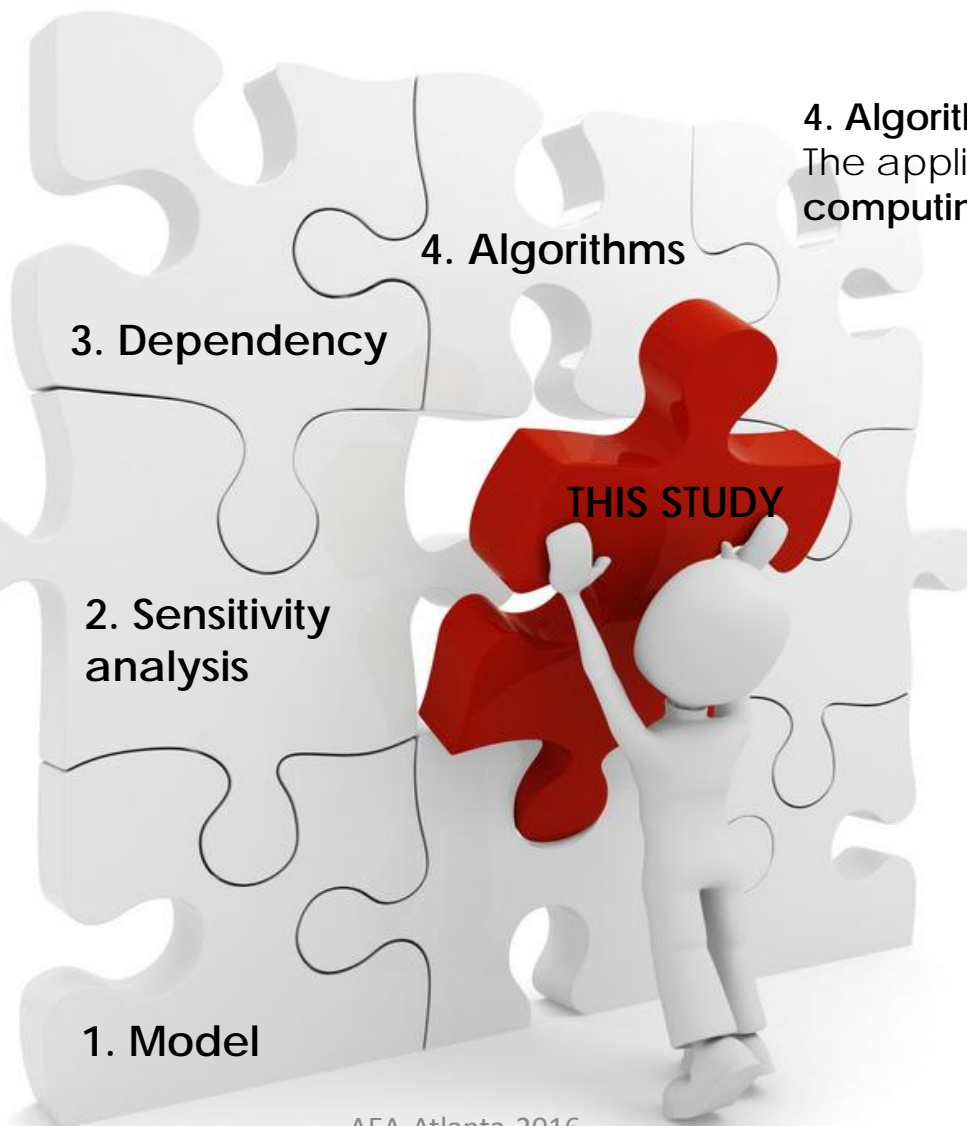
4. Algorithms

## 4. Algorithms:

The application of different **algorithms** in computing propensity scores

THIS STUDY

**THIS STUDY:** an initial step in increasing our understanding the application of propensity scores with more than 2 groups.



# Thank you

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