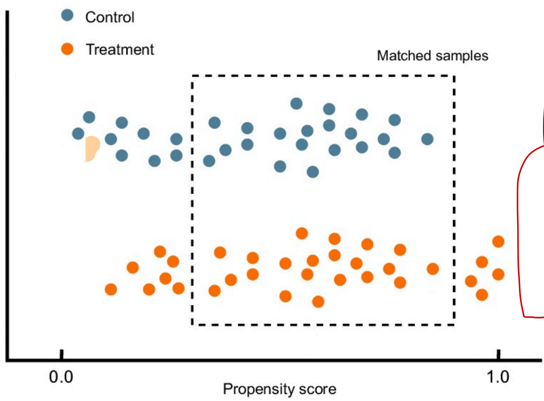
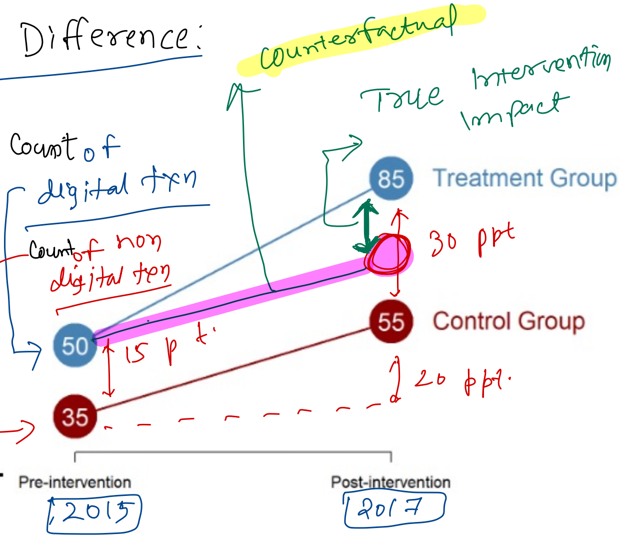
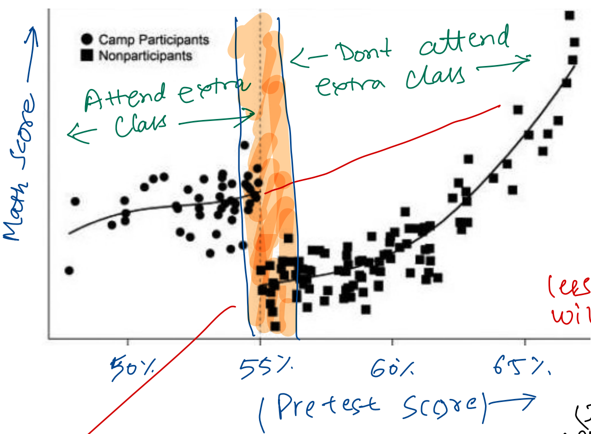
Estimating Causal Effects

Doing RCT is not always possible (due to budget, ethical)
We employ Retrospective data study to evaluate causal Effects.

- Propensity Matching
  Samples → Algorithm → (Propensity score)
  (Statistical Equivalence of some property)
- Regression Discontinuity:
- Difference-in-Difference:







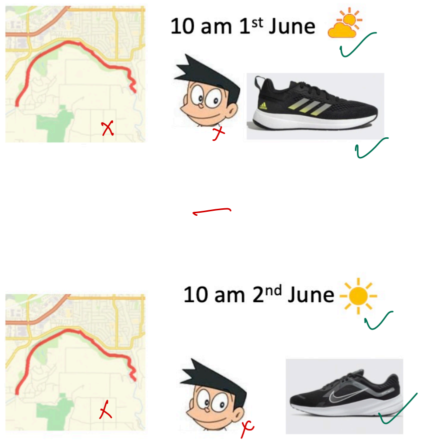
1. Extrapolation doesnt work if underlying trend itself is not linear
2. ppl who got 54% & ppl who got 56% are same.

(+2)
less than 55% (agg.) will attend extra class of math

Neighborhood acts as proxy for RCT and we can evaluate Avg. Treatment Effect (ATE).

(Just-do-it)
(Phil Knight)

Threat: The admin can lower the scores artificially to increase the exposure.
Hide: Assignment Rule from Admin.

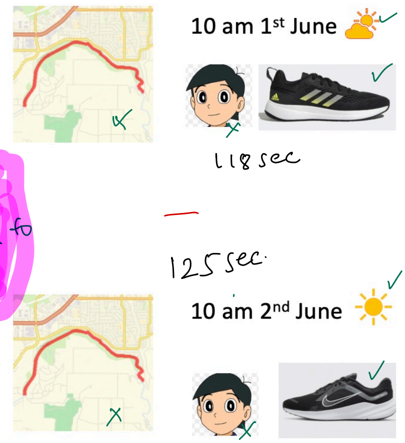


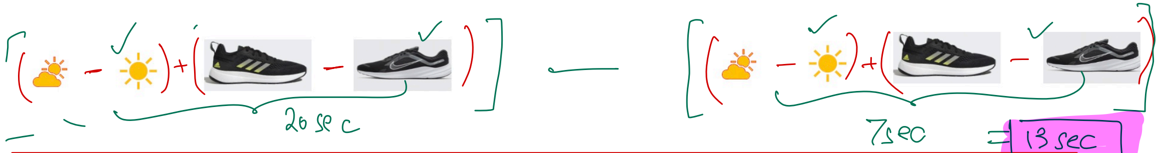
125sec

(20sec)

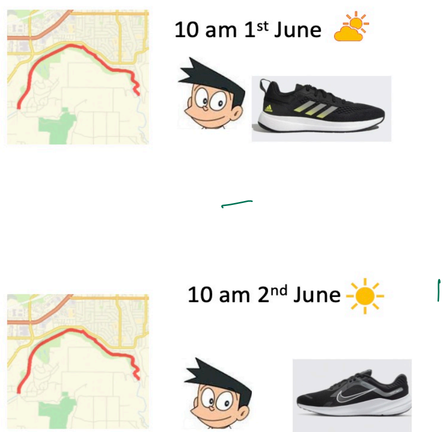
145sec

13 sec diff is attributed to weather + shoes



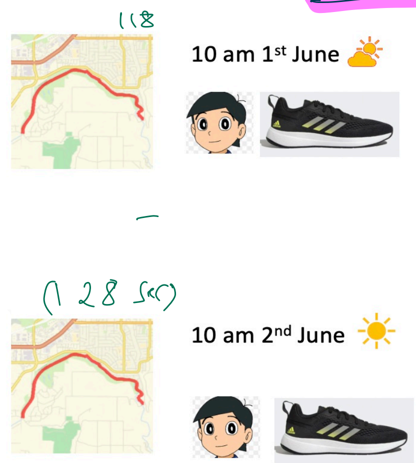


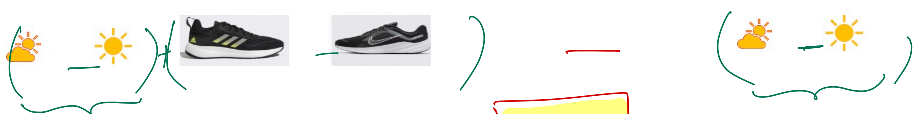
= 13 sec



125

145



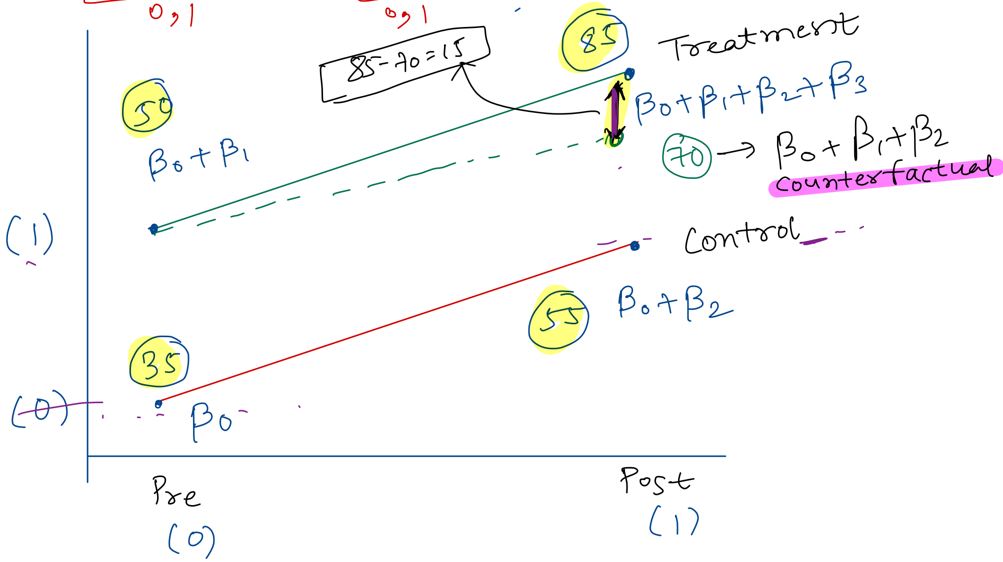


= 10sec

= 20 − 10 = 10sec is attributed solely to the change in shoes.

https://ds4ps.org/PROG-EVAL-III/DiffInDiff.html
https://evalf20.classes.andrewheiss.com/example/diff-in-diff/

$y = \beta_0 + \beta_1 \underbrace{\text{Treatment}}_{0,1} + \beta_2 \underbrace{\text{post}}_{0,1} + \beta_3 \underbrace{\text{Treatment} \times \text{Post}}$



$y = \beta_0 + \beta_1 \underbrace{\text{Treatment}} + \beta_2 \underbrace{\text{post}} + \beta_3 \underbrace{\text{Treatment} \times \text{Post}}$

Post = 0, Treatment = 0 ; $y = \beta_0 \longrightarrow 35$

Post = 0, Treatment = 1 ; $y = \beta_0 + \beta_1 \longrightarrow 50$

Post = 1, Treatment = 0 ; $y = \beta_0 + \beta_2 \longrightarrow 55$

Post = 1, Treatment = 1 ; $y = \beta_0 + \beta_1 + \beta_2 + \beta_3 \longrightarrow 85$

β_0: 35

(T) B_1: 15

(P) β_2: 20

(T×P) β_3: 15

Estimating True Impact had there been no intervent

$(\text{Treatment}_{post} - \text{Treatment}_{pre}) = (\text{Control}_{Post} - \text{control}_{pre})$

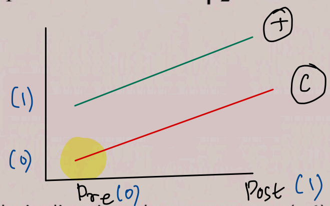
$(X - 50) = (55 - 35)$

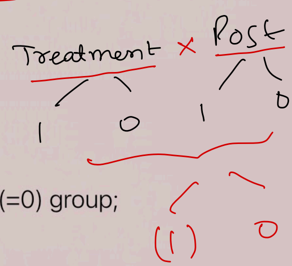
$\boxed{X = 70}$

In mathematical terms, we are interested in estimating 3 coefficients, as in the following equation:

$$Y = \beta_0 + \beta_1 * \text{Treatment} + \beta_2 * \text{Post} + \beta_3 * \text{Treatment} * \text{Post} + e$$

Where:





Y is our outcome variable;

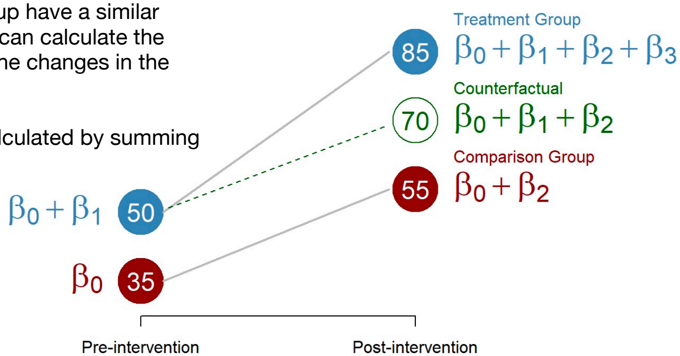
Treatment is a dummy variable indicating the treatment (=1) and control (=0) group;

Post is a dummy variable indicating pre (=0) and post (=1) treatment;

Treatment * Post is a dummy variable indicating whether the outcome was observed in the treatment AND it was observed after the intervention (=1), or any other case (=0).

The difference-in-difference model assumes that - in the absence of treatment - the treatment and control group have a similar trend over time, so as we can calculate the counterfactual based on the changes in the control group

Why: Counterfactual is calculated by summing



β	HYPOTHESES
b_0	Is the average outcome of the control group before the treatment ≠ 0?
b_1	Is the difference between the control and treatment group before the treatment ≠ 0?
b_2	Is the difference between the average outcome of the control group before and after the treatment ≠ 0?
b_3	Difference in difference estimator. Does the treatment have an impact?

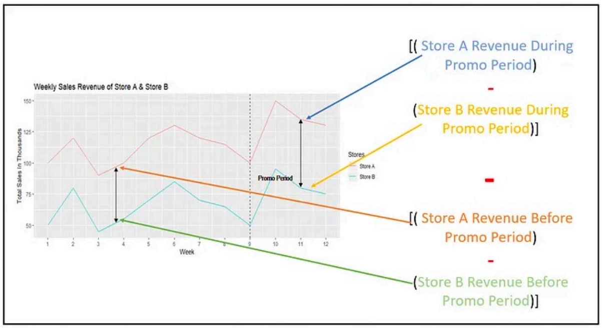

```
Call:
lm(formula = Sales ~ Post_Promotion, data = storeA)

Residuals:
     Min       1Q   Median       3Q      Max
-20.5556 -10.5556   0.5556   9.4444  19.4444

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)     110.556      4.267  25.908 1.69e-10 ***
Post_Promotion   27.778      8.535   3.255  0.00865 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 12.8 on 10 degrees of freedom
Multiple R-squared:  0.5144,    Adjusted R-squared:  0.4658
F-statistic: 10.59 on 1 and 10 DF,  p-value: 0.008651
```

Difference of Weekly Average Revenue Between Pre and Post Promotion Period




```
Call:
lm(formula = Sales ~ Post_Promotion + Test_Group + Post_Promotion *
    Test_Group, data = storeAB)

Residuals:
     Min       1Q   Median       3Q      Max
-20.5556 -10.5556  -0.8333   9.4444  21.6667

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)                 63.333      4.381  14.455 4.75e-12 ***
Post_Promotion              20.000      8.763   2.282   0.0336 *
Test_Group                  47.222      6.196   7.621 2.45e-07 ***
Post_Promotion:Test_Group    7.778     12.393   0.628   0.5374
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 13.14 on 20 degrees of freedom
Multiple R-squared:  0.8322,    Adjusted R-squared:  0.8071
F-statistic: 33.07 on 3 and 20 DF,  p-value: 6.021e-08
```

Weekly Average Revenue Due to Free Sample Promotion alone

<u>Assumptions for Difference in Difference</u>

1. Parallel Trend Assumptions: The counterfactual is considered to have parallel trends with the treatment group. Statistically, counterfactuals can be obtained by performing Dynamic Diff-in-Diff as well

2. Stable Unit Treatment Value Assumption (SUTVA)

a). The composition of the treatment and control group is stable for repeated cross-sectional design

b). No interference effect: The outcome of treatment should not be impacted by the interaction between the members of the treatment and control group

3. There should not be any Anticipation Effect: The analysis results will be biased if the customers will know about the promotions from before.