

随机化实验: 前后-✓

Chapter 7 MPE

Matched-pairs Experiment

原因: ① SRE 特例
 有独生子

② 观察性研究: 匹配

$$MPE = \frac{SRE}{\text{每-层两个样本}} = \frac{\text{SRE}}{\text{对数}}$$

独生子女特例

$$\text{SRE} = \sqrt{\sum_{k=1}^K \frac{n_{[k]}^{-2}}{\left(\frac{\hat{S}_{[k]1}^2}{n_{[k]1}} + \frac{\hat{S}_{[k]0}^2}{n_{[k]0}}\right)}}$$

公式不适用

$$n_{[k]1} \geq 2$$

$$n_{[k]0} \geq 2$$

新记录 (i, j) $\rightarrow ij$
 对 $i=1 \dots n$ $j=1, 2$

$Y_{ij}(1), Y_{ij}(0) \rightarrow$ 对从何而来,

$$Z_i = \begin{cases} 1 & (i,1) \text{ 处理} \\ 0 & (i,2) \text{ 处理} \end{cases}$$

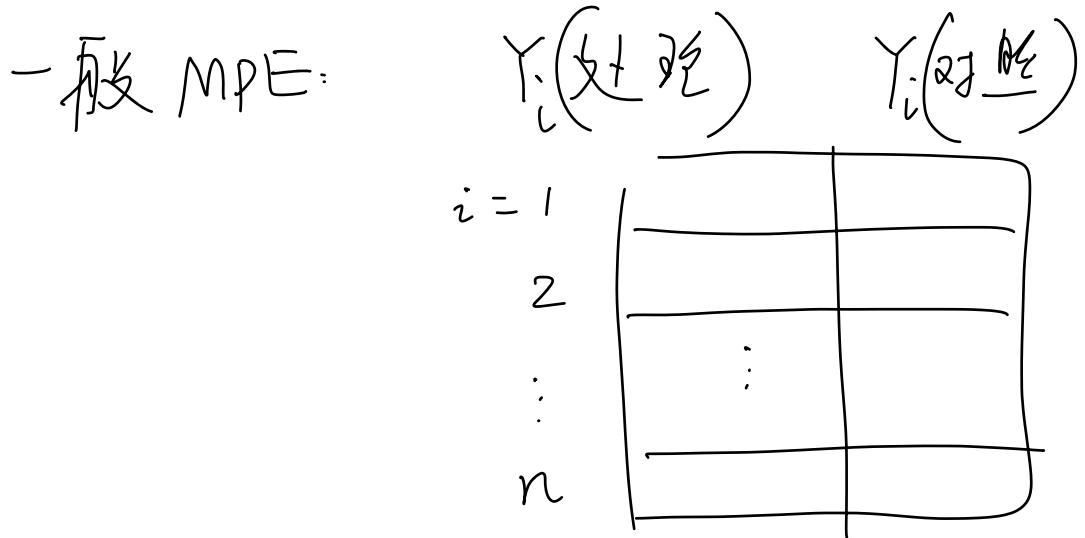
试验设计
优化问题

$$\text{MPE} = Z_i \text{ 's } \underbrace{\text{iid}}_{\text{独立同分布}} \text{ Bern}\left(\frac{1}{2}\right)$$

观察到

$$\begin{cases} Y_{i1} = Z_i Y_{i1}(1) + (-Z_i) Y_{i1}(0) \\ Y_{i2} = Z_i Y_{i2}(0) + (1-Z_i) Y_{i2}(1) \end{cases}$$

数据: $(Z_i, Y_{i1}, Y_{i2})_{i=1}^n$



```
> library("HistData")
> ZeaMays
  pair  pot  cross   self  diff
1     1    1 23.500 17.375 6.125
2     2    1 12.000 20.375 -8.375
3     3    1 21.000 20.000 1.000
4     4    2 22.000 20.000 2.000
5     5    2 19.125 18.375 0.750
6     6    2 21.500 18.625 2.875
7     7    3 22.125 18.625 3.500
8     8    3 20.375 15.250 5.125
9     9    3 18.250 16.500 1.750
10   10    3 21.625 18.000 3.625
11   11    3 23.250 16.250 7.000
12   12    4 21.000 18.000 3.000
13   13    4 22.125 12.750 9.375
14   14    4 23.000 15.500 7.500
15   15    4 12.000 18.000 -6.000
```

Fisher(1935)

DoE

FRT 因子

Darwin 父母

$$\hat{\Sigma}_i = Y_i(\text{处理}) - Y_i(\text{对照})$$

MPE → FRT : H₀F: $\bar{Y}_{ij}(1) = \bar{Y}_{ij}(0)$
 $\forall i \forall j$

$$\bar{T} = \bar{T}(\hat{\tau}_i; s)$$

permutation test

= permute $\hat{\tau}_i$'s ↗
 2^n freq

Neymanian:

$$E\left(\hat{\bar{\tau}}_i\right) = \bar{\tau}_i$$

SRE (誤差)

$$\hat{\bar{\tau}} = \frac{1}{n} \sum_{i=1}^n \hat{\tau}_i , E(\hat{\bar{\tau}}) = \bar{\tau}$$

$$\text{Var}(\hat{\bar{\tau}}) = HW$$

fitting 方案?

SRE 公式
 不可用

$$\text{def: } \bar{\tau}_i = \frac{1}{2} \sum_{j=1}^2 (Y_{ij}(1) - Y_{ij}(0))$$

$$\bar{\tau} = \frac{1}{n} \sum_{i=1}^n \bar{\tau}_i$$

$$\hat{\bar{\tau}}_i = (2Z_{i-1}) (Y_{i1} - Y_{i2})$$

$$\hat{\bar{\tau}} = \frac{1}{n} \sum_{i=1}^n \hat{\bar{\tau}}_i \xrightarrow{\text{无偏性}} \bar{\tau}$$

$$\text{Var}\left(\frac{\hat{\bar{\tau}}}{\bar{\tau}}\right) = \frac{1}{n^2} \sum_{i=1}^n \text{Var}\left(\frac{\hat{\bar{\tau}}_i}{\bar{\tau}_i}\right)$$

$$\text{Var}\left(\frac{\hat{\bar{\tau}}}{\bar{\tau}}\right) = \frac{1}{n(n-1)} \sum_{i=1}^n \left(\frac{\hat{\bar{\tau}}_i}{\bar{\tau}_i} - \frac{\hat{\bar{\tau}}}{\bar{\tau}} \right)^2$$

道理 MPE 下 $\hat{\bar{\tau}}$ 保偏估计
 $\text{Var}\left(\frac{\hat{\bar{\tau}}}{\bar{\tau}}\right)$:

$$E(\hat{\bar{\tau}}) - \text{Var}\left(\frac{\hat{\bar{\tau}}}{\bar{\tau}}\right) = \frac{1}{n(n-1)} \sum_{i=1}^n \left(\frac{\hat{\bar{\tau}}_i}{\bar{\tau}_i} - \frac{\hat{\bar{\tau}}}{\bar{\tau}} \right)^2 \geq 0$$

$$\begin{aligned}
 \text{Var}(\hat{\tau}) &:= E\left(n(n-1) \hat{\tau}^2\right) \\
 &= E\left(\sum_{i=1}^n (\hat{\tau}_i - \bar{\tau})^2\right) \\
 &= E\left(\sum_{i=1}^n \hat{\tau}_i^2 - n \bar{\tau}^2\right)
 \end{aligned}$$

$$E(\cdot) \stackrel{\text{定義}}{=} \sum_{i=1}^n E\left(\frac{\hat{\tau}_i^2}{\tau_i}\right) - n E(\bar{\tau}^2)$$

$$\text{方差} = \sum_{i=1}^n \left(\text{var}\left(\frac{\hat{\tau}_i}{\tau_i}\right) + \bar{\tau}_i^2 \right) - n \left(\text{var}(\bar{\tau}) + \bar{\tau}^2 \right)$$

$$\begin{aligned}
 \text{方差} &= \underbrace{\sum_{i=1}^n \text{var}\left(\frac{\hat{\tau}_i}{\tau_i}\right)}_{n^2 \text{ var}(\bar{\tau})} - n \text{var}(\bar{\tau}) + \left(\sum_{i=1}^n \bar{\tau}_i^2 - n \bar{\tau}^2 \right)
 \end{aligned}$$

$$\text{方差} = n(n-1) \text{var}(\bar{\tau}) + \sum_{i=1}^n (\bar{\tau}_i - \bar{\tau})^2$$

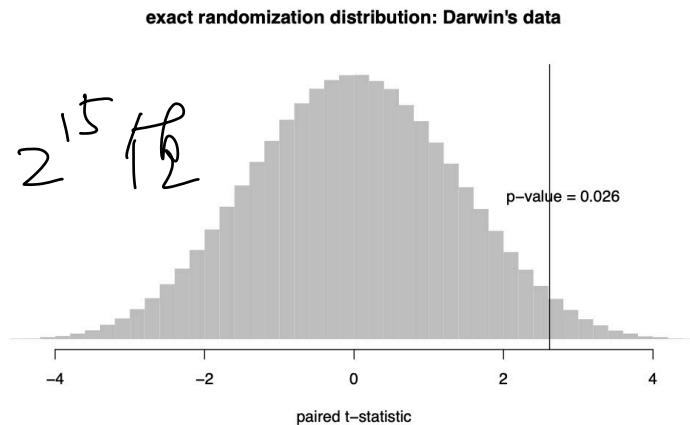
□

MPE :

$$\left\{ \begin{array}{l} \hat{\tau} = \frac{1}{n} \sum_{i=1}^n \hat{\tau}_i \\ \hat{\sigma}^2 = \frac{1}{n(n-1)} \sum_{i=1}^n \left(\frac{\hat{\tau}_i}{\hat{\tau}_{ci}} - \bar{\hat{\tau}} \right)^2 \end{array} \right.$$

CLT : $\frac{\hat{\tau}}{\hat{\sigma}} \pm 1.96 \sqrt{\hat{\sigma}^2}$

```
> library("HistData")
> ZeaMays
  pair pot cross self diff
1     1   1 23.500 17.375 6.125
2     2   1 12.000 20.375 -8.375
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15   15   4 12.000 18.000 -6.000
```



Darwin

达尔文

FIGURE 7.1: Randomization distribution of $\hat{\tau}$ using Darwin's data

FRT $\frac{\hat{\tau}}{\hat{\sigma}}$

HW 7.6 $(\hat{\tau}, \hat{\sigma}^2)$

Chapter 8

Fisherian > 線—
Neymanian

$$H_0F : Y_i(1) = Y_{i(0)} \quad \forall i$$

if $H_0N : \bar{Y} = 0$

Fisher: H_0F , 任何統計量
都可

P_{FRT} 精確

不需要漸近理論

Neyman: H_0N

只計 \bar{Y}

渐近理论 $n \rightarrow \infty$

CLT

P_{FRT} 基本依赖 $H_0 F$

但是 在 $H_0 F$ 有精确 P 值

也是最低要求

\Rightarrow ∵ 考虑 FRT

但是 $H_0 F$ 从手稿无解

万一还想检验 $H_0 N : \tau = 0$?

推荐:

用 FRT + t 统计量

$$\Rightarrow \begin{cases} H_0 F : & P_{FRT} \text{ 精确} \\ H_0 N : & P_{FRT} \text{ 渐近 } \checkmark \end{cases}$$

FRT + t

$$CRE : t = \frac{\hat{c}}{\sqrt{\hat{v}}}$$

$$= \frac{\frac{\hat{c}}{\hat{v}}}{\sqrt{\text{Var}(\hat{c})}} \quad \begin{matrix} \text{Var}(\hat{c}) \\ \downarrow \sqrt{\hat{v}} \end{matrix}$$

$$H_0 N : \begin{matrix} CLT \downarrow d \\ \tau = 0 \quad N(0,1) \end{matrix} \quad \begin{matrix} \downarrow P \\ C \leq 1 \end{matrix}$$

$$H_0 N \xrightarrow{d} C \cdot N(0,1)$$

理论分布

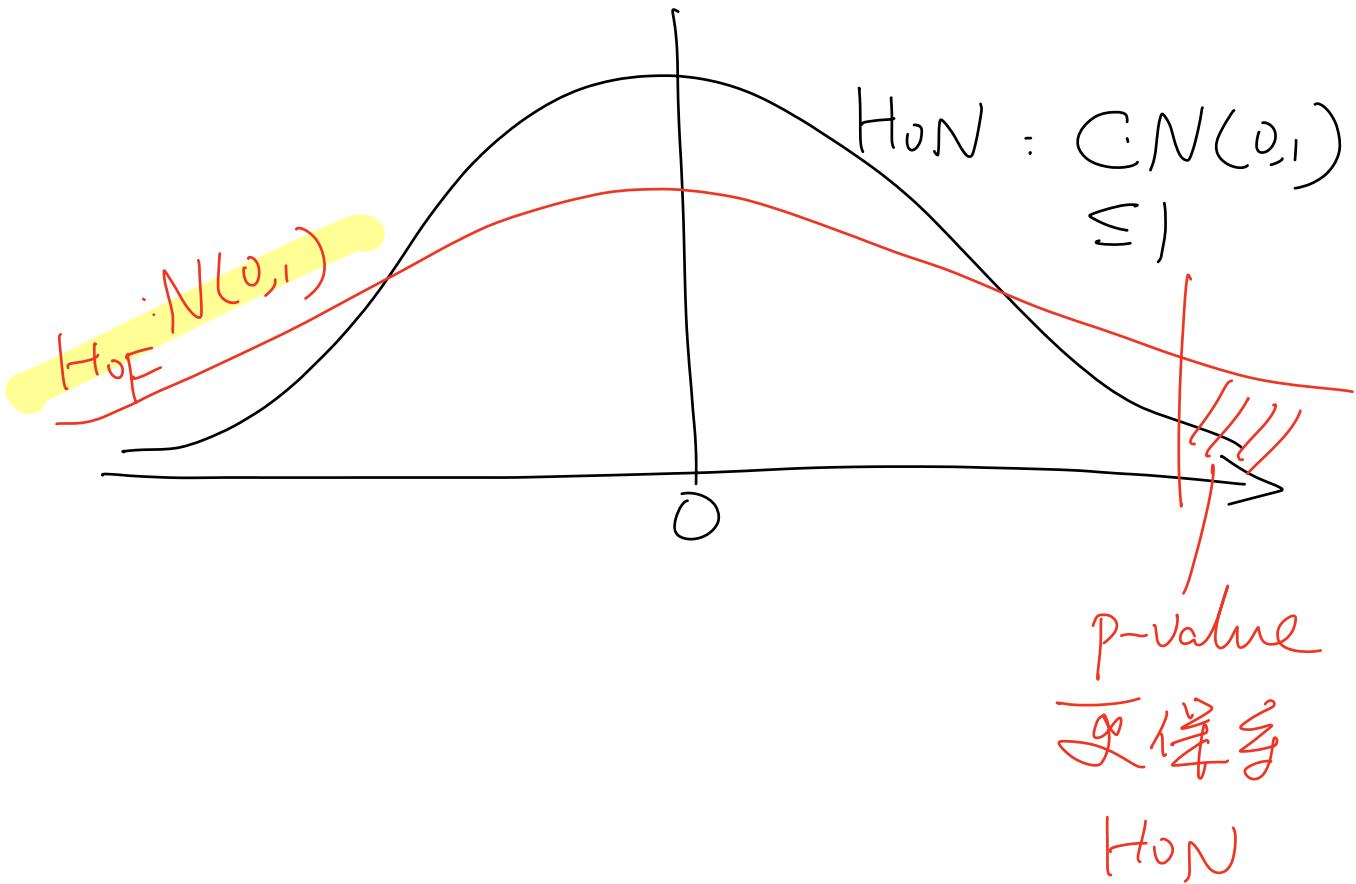
FRT 假想 $(Y_i, Y_i)_{i=1}^n$
 不相关且
 $(H_0 F)$

FRT 通过 -> 可计算分布

$$(t)^\pi = \left(\frac{\hat{t}}{\sqrt{C}} \right)^\pi$$

$$\xrightarrow{d} N(0, 1)$$

$C = 1$ 因为不相关



推論:

① 极变量

$$Lm: Y_i \sim l + Z_i + Z_i \cdot X_i$$

t-test

$$t_L = \frac{\bar{X}_L}{\sqrt{S_L}} \quad \text{EHWV}$$

②

SRE

$$t_S = \frac{\frac{1}{\bar{c}_S}}{\sqrt{\hat{V}_S}}$$

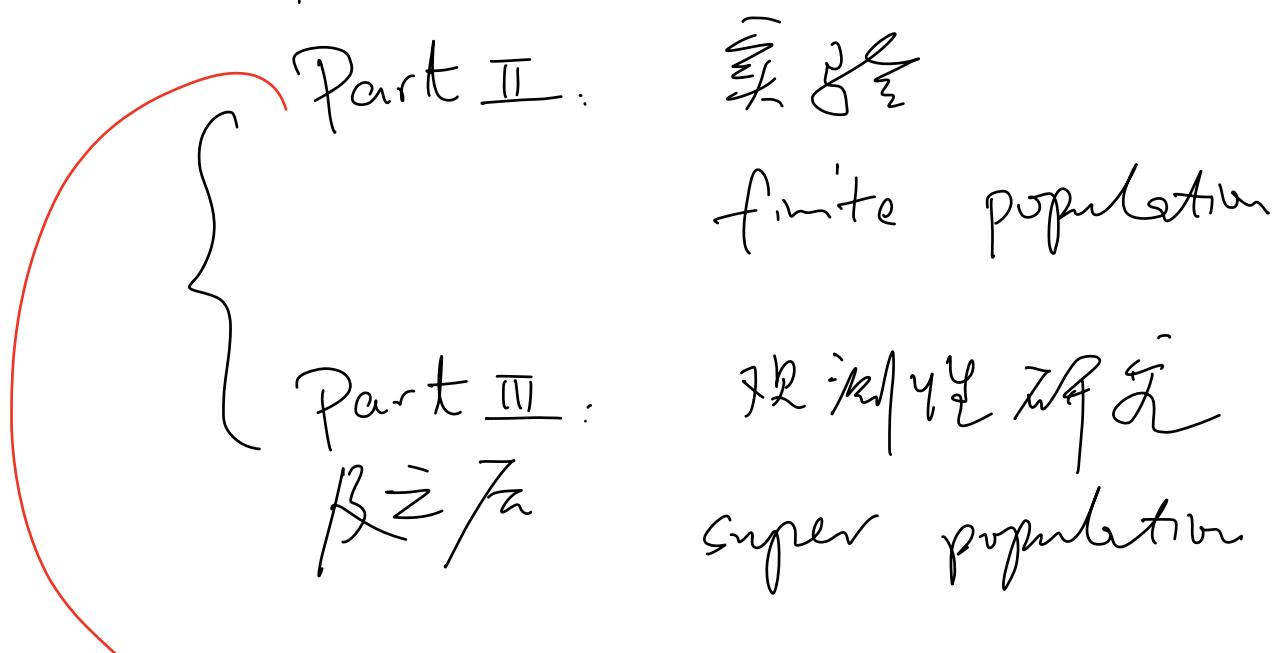
数理统计方法: Studentization

t-distribution
bootstrap 方法
高阶渐近 P. Hall

Chapter 9

Bridging finite and super population
causal inference

桥接理论



我们选择: Chapters 2 - 8

无法抛弃过去古典之美.

① 史文：想起來自 Neyman
Fisher

古典統計

抽樣調查 — 依設計 design-based

On the Two Different Aspects of the Representative Method: The Method of Stratified Sampling and the Method of Purposive Selection
Author(s): Jerzy Neyman
Reviewed work(s):
Source: *Journal of the Royal Statistical Society*, Vol. 97, No. 4 (1934), pp. 558-625
Published by: Wiley for the Royal Statistical Society
Stable URL: <http://www.jstor.org/stable/2342192>

Cochran

書

Fuller

實驗設計 — 沒有广泛應用

Statistical Problems in Agricultural Experimentation

Author(s): J. Neyman, K. Iwaszkiewicz and St. Kolodziejczyk

Source: *Supplement to the Journal of the Royal Statistical Society*, 1935, Vol. 2, No. 2 (1935), pp. 107-180

Published by: Wiley for the Royal Statistical Society

Stable URL: <http://www.jstor.com/stable/2983637>

② 今 : PhD info.

最著名的书

Imbens & Rubin book

D. B. Rubin — W. G. Cochran

Fisher, Yates

Rothamsted statistics

③ 什么设计?

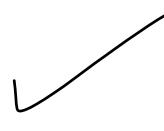
统计推断 → 基础设计?

随机化设计?

来自 Cochran's Design

对这套理论 is valid:

internal validity

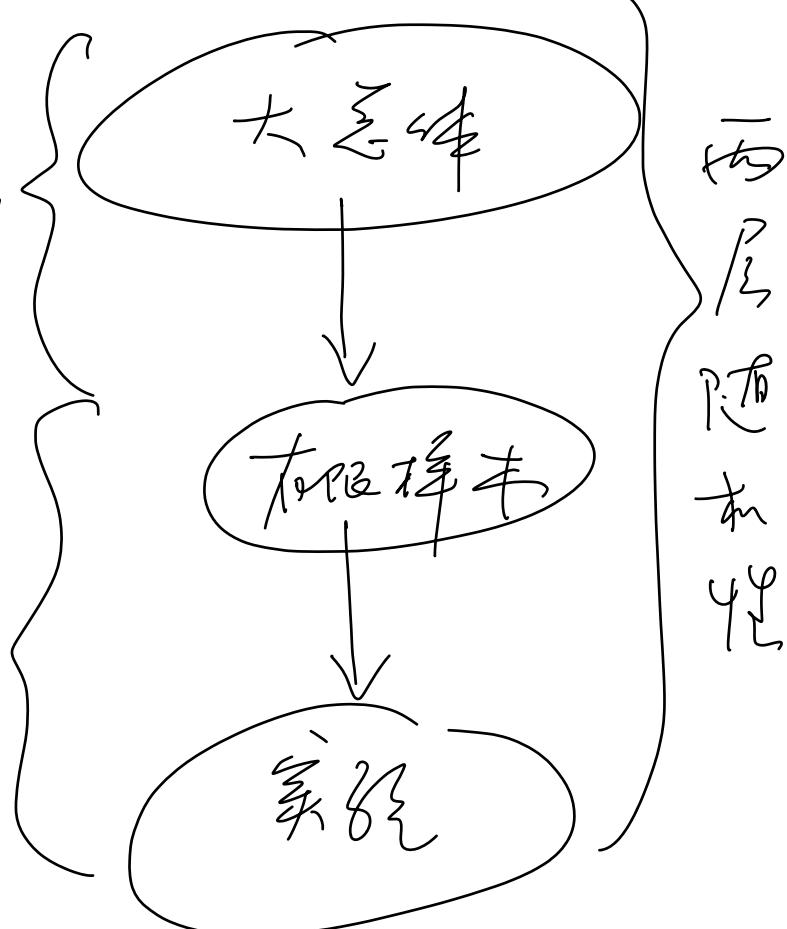


external validity

?

— 因素:
sampling process

Design-based
inference



Chapter 9 内容：设计 15 分钟

$$\text{CRE: } \left(z_i, Y_{i(1)}, Y_{i(0)} \right)_{i=1}^n \sim \text{i.i.d. } (z, Y_{(1)}, Y_{(0)})$$

潜在假设:

Rubin (1978)
(AIS)

$\bar{z} \perp\!\!\!\perp (Y_{(1)}, Y_{(0)})$ "strong ignorability"

$\Rightarrow \bar{\tau} = \mathbb{E}(Y_{(1)} - Y_{(0)})$

识别
方法
 $= \mathbb{E}(Y_{(1)}) - \mathbb{E}(Y_{(0)})$

证明
 $\Rightarrow = \mathbb{E}(Y_{(1)} | Z_{-1}) - \mathbb{E}(Y_{(0)} | Z_{-0})$

$= \mathbb{E}(Y | Z_{-1}) - \mathbb{E}(Y | Z_{-0})$

SRE: $X_i \stackrel{\text{ind}}{\sim} \{1 \dots k\}$

$$\left(X_i, Z_i, Y_{i(1)}, Y_{i(0)} \right)_{i=1}^n$$

$\underset{\text{ind}}{\sim} (X, Z, Y_{(1)}, Y_{(0)})$

$$Z \perp\!\!\!\perp \left(Y_{(1)}, Y_{(0)} \right) \mid \begin{array}{l} X=k \\ \forall k \end{array}$$

$$\Rightarrow \bar{T}_k = \mathbb{E}(Y_{(1)} - Y_{(0)} \mid X=k)$$

$$= \mathbb{E}(Y \mid Z=1, X=k) - \mathbb{E}(Y \mid Z=0, X=k)$$

$$\Rightarrow \bar{T} = \mathbb{E}(Y_{(1)} - Y_{(0)})$$

$$= \sum_{k=1}^K \Pr(X=k) \bar{T}_k$$

分子
分母
已經
證明！

$$= \sum_{k=1}^K P(X=k) \cdot \left[E(Y|Z=1, X=k) - E(Y|Z=0, X=k) \right]$$