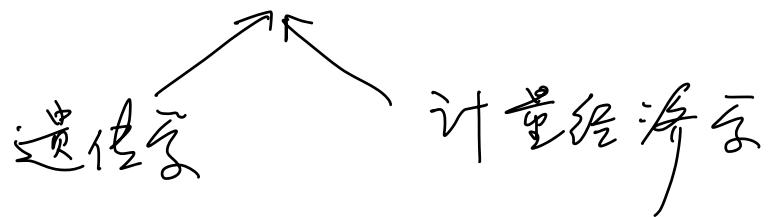


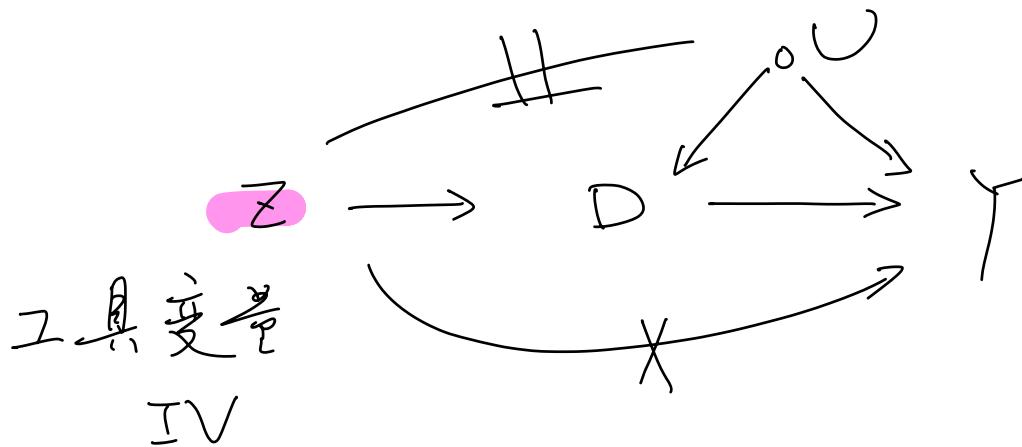
Chapter 23

IV : Econometric perspective



S. Wright

路径分析
path analysis



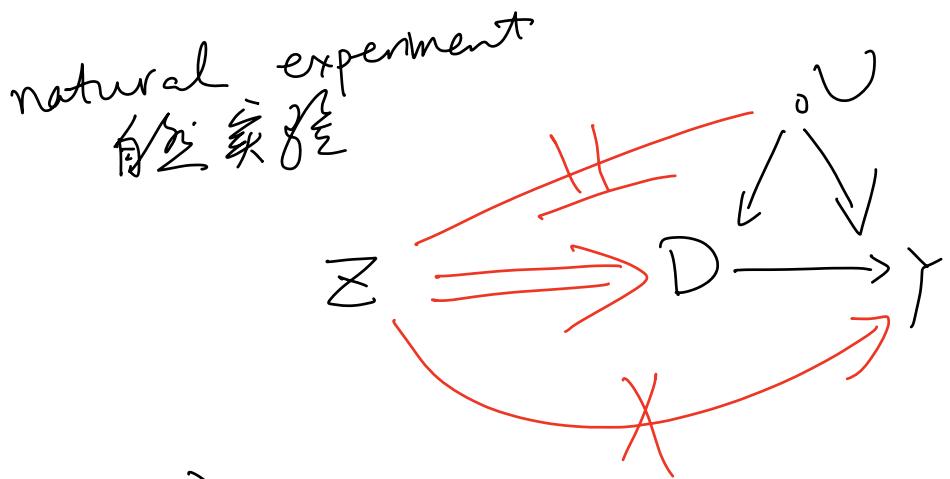
经济生物学

— 大部分都是观察性研究

— $D \rightarrow Y$ 同果水用

— D 没有随机性

—— 给这个变量，也无法完全
消除混淆



问题：何处找 Z？

例 23.1 鼓励性实验

例 23.2 Angrist (1990) TSLS
服兵役 收入

```
graph LR; Service --> Income;
```

Hearst et al (1986 NEJM)

越战

彩票數 \implies 服役

彩票數 \rightarrow 死亡率

彩票數 \rightarrow 服役 \rightarrow 死亡率

例 23.3 Angrist & Krueger (1991)

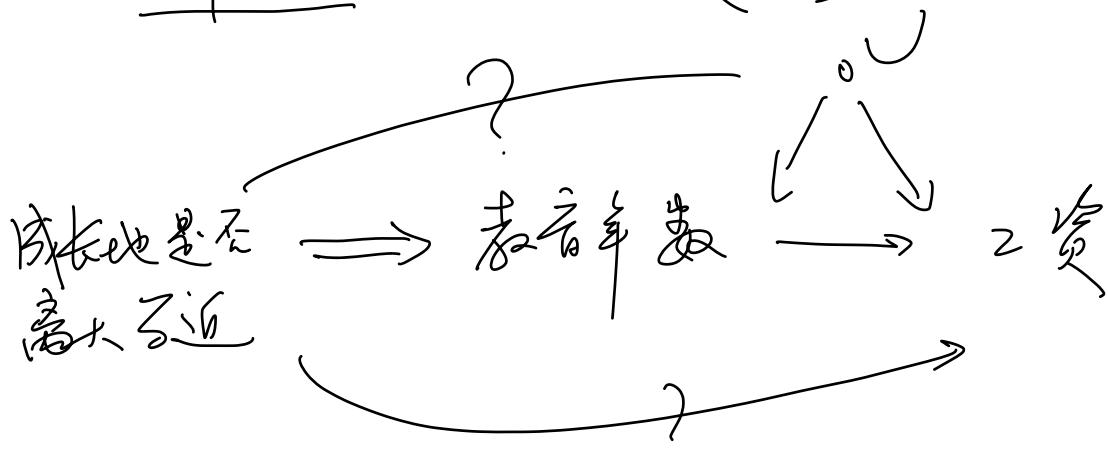
生年序位 \implies 教育年数 \rightarrow 收入

例 23.4 Angrist & Evans (1998)

前两个孩子 \implies 孩子数目 \rightarrow 家庭收入

12/23.5

Card (1993)

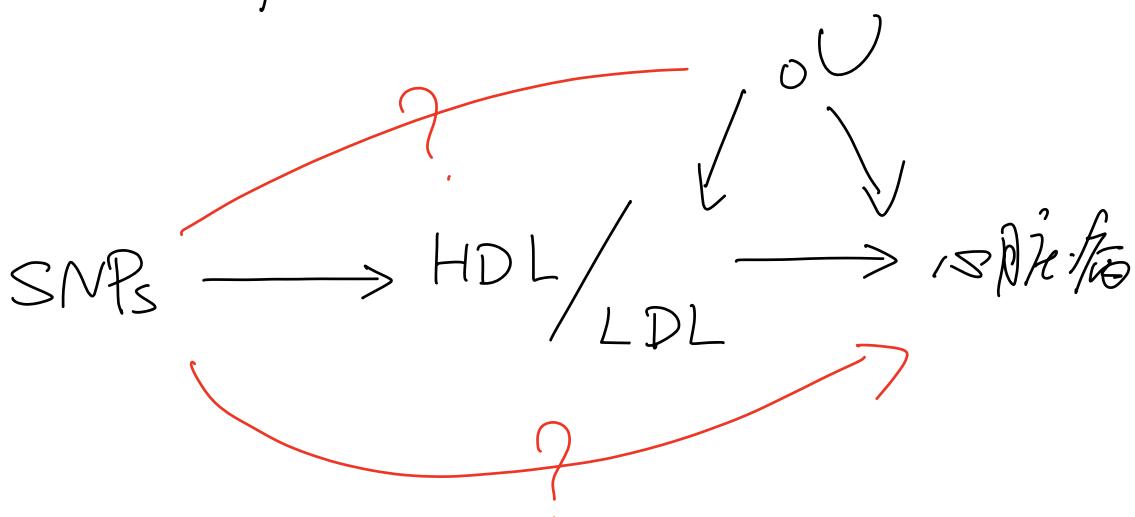


反例: 父母三过

12/23.6

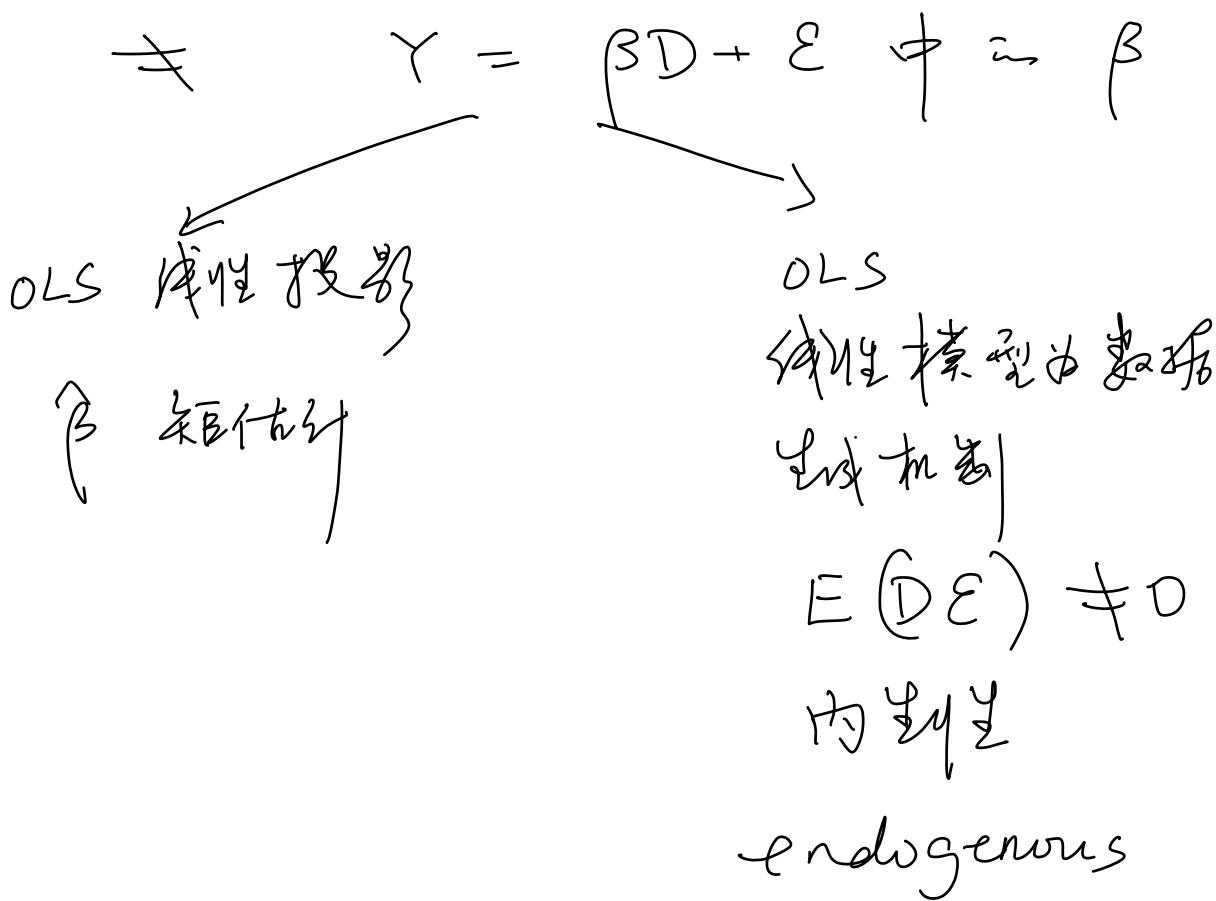
Chapter 25

Mendelian Randomization



回顾 OLS: $\ln(Y \sim D)$

$$\hat{\beta} \xrightarrow{P} E(DD^T)^{-1} E(DY)$$



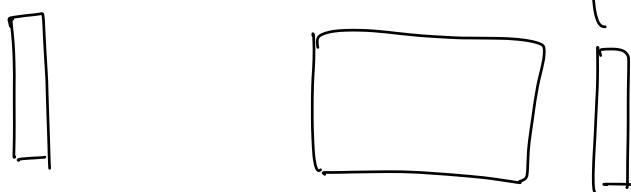
解决内生性: IV

$$\left\{ \begin{array}{l} Y = D^T \beta + \varepsilon \\ E(\varepsilon Z) = 0 \end{array} \right. \quad Z \rightarrow D \rightarrow Y$$

$Z \not\perp D \sim IV$

$$\Rightarrow E(Z(Y - D^T \beta)) = 0$$

$$\Rightarrow E(ZY) = E(ZD^T)\beta$$



① $\dim(Z) < \dim(D)$

β 有 ∞ 個

under identified

② $\dim(Z) = \dim(D)$

$E(ZD^T)$ 滿足

just identified

$$\Rightarrow \beta = E(ZD^T)^{-1} E(ZY)$$

wf - wf

$$\hat{\beta}_{IV} = \left(\sum_{i=1}^n z_i D_i^\top \right)^{-1} \sum_{i=1}^n z_i y_i$$

~~by 3~~

$$\left\{ \begin{array}{l} Y = \alpha + \beta D + \varepsilon \\ E(\varepsilon) = 0, \text{ cov}(\varepsilon, Z) = 0 \end{array} \right.$$

$$\Rightarrow \text{cov}(Z, Y) = \beta \text{cov}(Z, D)$$

$$\Rightarrow \beta = \frac{\text{cov}(Z, Y)}{\text{cov}(Z, D)}$$

$$= \frac{\text{cov}(Z, Y) / \text{var}(Z)}{\text{cov}(Z, D) / \text{var}(Z)}$$

if $\text{cov}(Z, D) \neq 0$

$$= \frac{\ln(Y \sim Z) \text{ & wef}[2]}{\ln(D \sim Z) \text{ & wef}[2]}$$

$$Z = \hat{\beta} = \frac{E(Y|Z=1) - E(Y|Z=0)}{E(D|Z=1) - E(D|Z=0)}$$

$D = \mathbb{R}^k$ CACE is not

③ $\dim(Z) > \dim(D)$

over identified

$$E(ZY) = E(ZD^\top) \beta$$

估计可行 - if

$$\text{样本水平: } \left(\frac{1}{n} \sum_{i=1}^n Z_i Y_i \right) = \left(\frac{1}{n} \sum_{i=1}^n Z_i D_i^\top \right) \hat{\beta}$$

一般无序

GMM: generalized method of moment
(Hansen 1982)

古老之计量经济模型:

两步(阶段)最小二乘

Two-stage least squares (TSLS)

$$\textcircled{1} \quad \text{OLS}(D \sim Z)$$

$$\text{OLS}(D \stackrel{\text{OLS}}{\sim} \hat{D} \sim Z)$$

$$\Rightarrow \hat{D}_i \quad (i=1 \dots n)$$

$$\textcircled{2} \quad \text{OLS}(Y \sim \hat{D})$$

$$\Rightarrow \hat{\beta}_{\text{TSLS}} \xrightarrow{P} \beta$$

直觉:

$$\hat{\beta}_{\text{TSLS}} \stackrel{2}{=} \left(\sum_{i=1}^n \hat{D}_i \hat{D}_i^T \right)^{-1} \sum_{i=1}^n \hat{D}_i Y_i$$

$$\begin{aligned} \hat{D}_i &= \left(\sum_{i=1}^n \hat{D}_i \hat{D}_i^T \right)^{-1} \left(\sum_{i=1}^n \hat{D}_i D_i^T \right) \beta \\ &\quad + \left(\sum_{i=1}^n \hat{D}_i \hat{D}_i^T \right)^{-1} \left(\sum_{i=1}^n \hat{D}_i \varepsilon_i \right) \end{aligned}$$

$$\textcircled{1}: \hat{D}_i = \hat{D}_i + \check{D}_i$$

$$\sum_{i=1}^n \hat{D}_i \check{D}_i^\top = 0$$

$$\left. \right\} \Rightarrow \sum_{i=1}^n \hat{D}_i \hat{D}_i^\top = \sum_{i=1}^n \hat{D}_i \hat{D}_i^\top$$

$$\Rightarrow \hat{\beta}_{TSLS} = \beta + \left(\sum_{i=1}^n \hat{D}_i \hat{D}_i^\top \right)^{-1} \sum_{i=1}^n \hat{D}_i \varepsilon_i$$

方法论注解 $E(Z\varepsilon) = 0$

简单表示 $\hat{D}_i = \hat{T}^\top z_i$

代入: $\hat{\beta}_{TSLS} = \beta + \left(\hat{T}^\top \left(\frac{1}{n} \sum_{i=1}^n z_i z_i^\top \right) \hat{T} \right)^{-1} \hat{T}^\top \left(\frac{1}{n} \sum_{i=1}^n z_i \varepsilon_i \right)$

$\xrightarrow{P} \beta \quad \downarrow P \quad E(Zz^\top) \quad \downarrow P \quad E(Z\varepsilon) = 0$

SPECIFICATION AND ESTIMATION OF SIMULTANEOUS EQUATION MODELS

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方程 IV is
方程

Contents

1. Introduction	392
2. Model specification	396
3. Identification	402
4. Estimation	408
4.1. Single equation estimation	408
4.2. System estimation	413
4.3. Reduced-form estimation	417
4.4. Maximum likelihood estimation	418
4.5. Estimation with covariance restrictions	426
4.6. Other considerations	428
5. Specification tests	430
6. Non-linear specifications	436
References	445

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Instrumental Variables: An Econometrician's Perspective¹

Guido W. Imbens

讲稿

Abstract. I review recent work in the statistics literature on instrumental variables methods from an econometrics perspective. I discuss some of the older, economic, applications including supply and demand models and relate them to the recent applications in settings of randomized experiments with noncompliance. I discuss the assumptions underlying instrumental variables methods and in what settings these may be plausible. By providing context to the current applications, a better understanding of the applicability of these methods may arise.

Key words and phrases: Simultaneous equations models, randomized experiments, potential outcomes, noncompliance, selection models.

HW 23.3

TSLS 線形形式

控制函數
control function

① OLS($D \sim Z$) $\Rightarrow \check{D}_i$
補充

② OLS($Y \sim D + \check{D}$)
 $\Rightarrow \text{cwf}(D) = \hat{\beta}_{CF}$

結論: $\hat{\beta}_{CF} = \hat{\beta}_{TSLS}$

重叠模型

Structural form

$$\left\{ \begin{array}{l} Y_i = \beta_0 + \beta_1 D_i + \beta_2^T X_i + \varepsilon_i \\ D_i = \gamma_0 + \gamma_1 Z_i + \gamma_2^T X_i + \varepsilon_{2i} \end{array} \right.$$

- 级
- 加变量

即 $"D"$ = $\begin{pmatrix} 1 \\ D \\ X \end{pmatrix}$, $"Z"$ = $\begin{pmatrix} 1 \\ Z \\ X \end{pmatrix}$

reduced form

$$\left\{ \begin{array}{l} Y_i = \Gamma_0 + \Gamma_1 Z_i + \Gamma_2^T X_i + \varepsilon_{1i} \\ D_i = \gamma_0 + \gamma_1 Z_i + \gamma_2^T X_i + \varepsilon_{2i} \end{array} \right.$$

$= \beta_1 \gamma_1$

内生
变量

外生变量

间接法. > Indirect Least Squares (ILS)

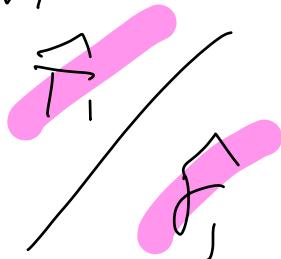
① OLS ($Y \sim Z + x$)

$$\Rightarrow \text{wef}(Z) = \hat{\beta}_1$$

② OLS ($D \sim Z + x$)

$$\Rightarrow \text{wef}(Z) = \hat{\gamma}_1$$

③ $\hat{\beta}_1, \text{ILS} =$



这题 23.1
习题

$$\hat{\beta}_1, \text{ILS} = \hat{\beta}_1, \text{TLS}$$

Chapter 25

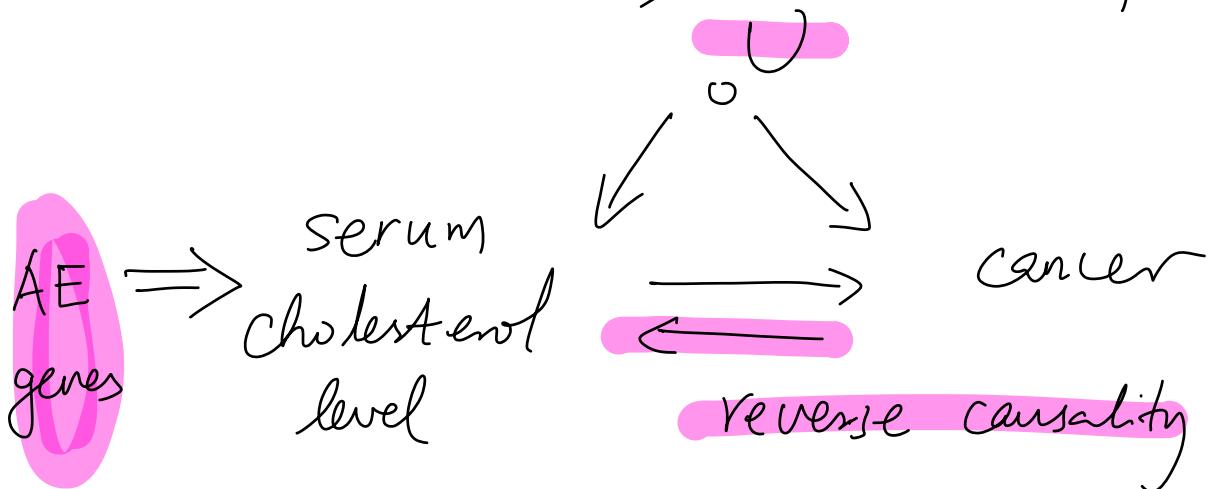
IV 痘因：MR

Mendelian Randomization

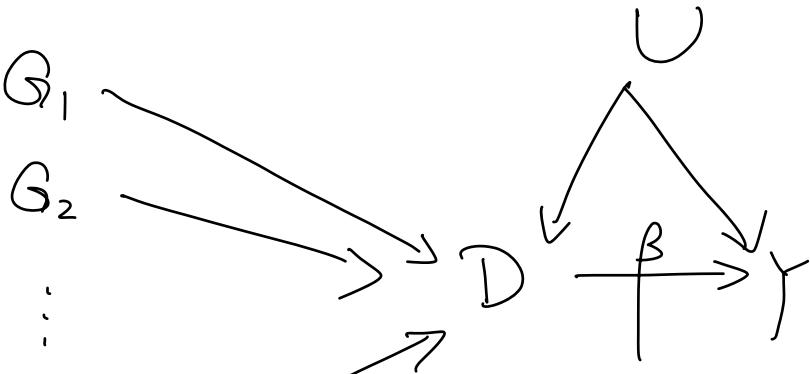
25.4 : ~~随机~~ MR

先假设这组随机不存在

Katan (1986) 双盲对照研究



- 个体差异之关系：AE → cancer
genes



$$\begin{aligned}
 & \left. \begin{array}{l} Y = \beta_0 + \beta D + \beta_u U + \epsilon_Y \\ D = r_0 + r_1 G_1 + \dots + r_p G_p + r_u U + \epsilon_D \end{array} \right\} \\
 \Rightarrow & \left\{ \begin{array}{l} Y = (\beta_0 + \beta \hat{r}_0) + \hat{\beta} r_1 G_1 + \dots + \hat{\beta} r_p G_p + (\beta_u + \beta_0 r_u) U + \epsilon_Y \\ D = r_0 + r_1 G_1 + \dots + r_p G_p + r_u U + \epsilon_D \end{array} \right.
 \end{aligned}$$

若有个体数据： TSLS

若没有个体数据：

$$\left(\begin{array}{c} \hat{r}_1 \\ \vdots \\ \hat{r}_p \end{array} \right) \dots \left(\begin{array}{c} \hat{r}_1 \\ \vdots \\ \hat{r}_p \end{array} \right) : \text{若 } Y \sim \text{GWAS}$$

$$\begin{pmatrix} \hat{\beta}_1 \\ se_{D_1} \end{pmatrix} \dots \begin{pmatrix} \hat{\beta}_P \\ se_{D_P} \end{pmatrix} : \text{关于 } D_i \text{ 的 GWAS}$$

模型设计: $T_j = \beta_j \hat{\gamma}_j \quad (j=1 \dots P)$

β_j 到 $\hat{\beta}_j$ 的推导: $\hat{T}_j = \hat{\beta}_j \hat{\gamma}_j$

$$\hat{\beta}_j = \frac{\hat{T}_j}{\hat{\gamma}_j}$$

如何组合? ————— meta-analysis

荟萃分析

$$\left(\hat{\beta}_j, se_j^2 \right) = \left(se_{T_j}^2 + \hat{\beta}_j^2 se_{D_j}^2 \right) / \hat{\gamma}_j^2$$

$$j=1 \dots P$$

Fisher 组合:

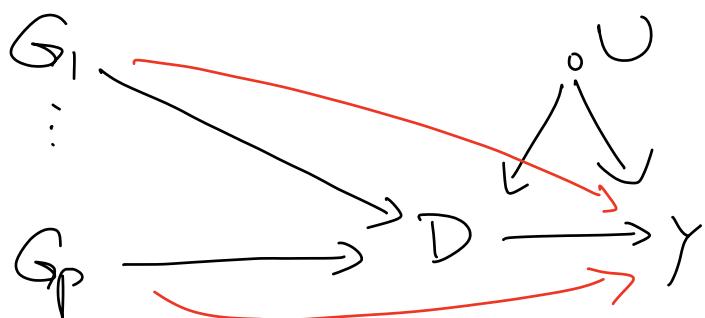
$$\hat{\beta}_{\text{fisher}0} = \frac{\sum_{j=1}^p \hat{\beta}_j / se_j^2}{\sum_{j=1}^p 1 / se_j^2}$$

$$\hat{\beta}_{\text{fisher}1} = \frac{\sum_{j=1}^p \hat{\beta}_j / \text{错误之方差}}{\sum_{j=1}^p 1 / \text{错误之方差}}$$

$$= \frac{\sum_{j=1}^p \hat{T}_j \hat{r}_j / se_{rj}^2}{\left(\sum_{j=1}^p \hat{r}_j^2 / se_{rj}^2 \right)}$$

文商大叶序足

讲义：比上面模型稍微更广



→ : 偏差
w.r.t. true 偏差,

工具变量识别

① OLS → nonparametric

$$\left\{ \begin{array}{l} y = g(x) + \varepsilon \quad \text{加法} \\ \qquad \qquad \qquad \text{誤差} \\ \qquad \qquad \qquad \text{誤差} \\ E(\varepsilon | z) = 0 \end{array} \right.$$

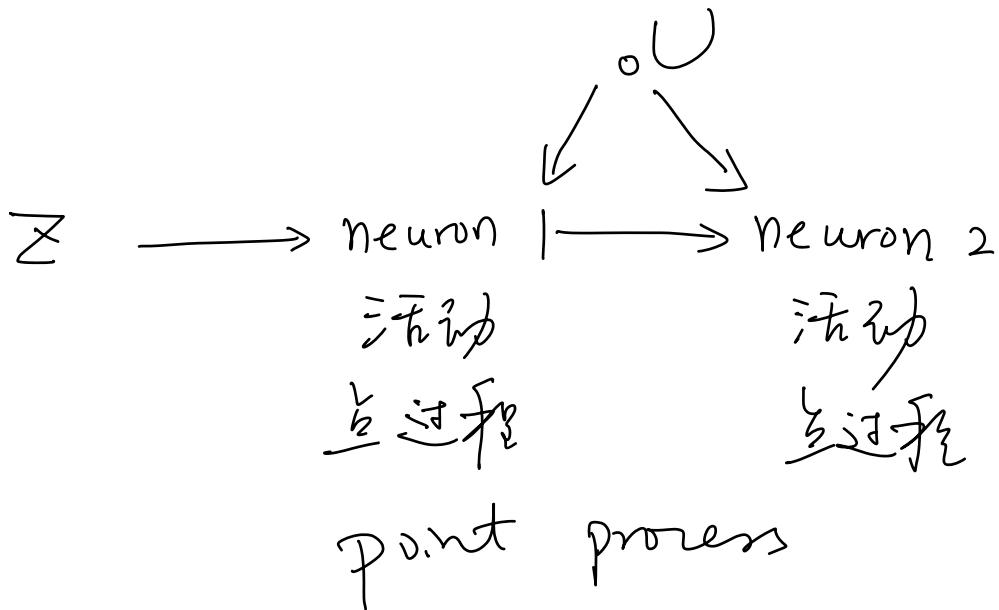
$$\Rightarrow E(y|z) = E(g(x)|z) + 0$$

$$\Rightarrow E(y|z) = \underbrace{\int g(x)}_{?} f(x|z) dx$$

和方程 $y(x)$

矩估计 \rightarrow 常数估计

② 估计 α_2 的
Tiang, Chen, Ding (Biometrika 2023)



JOURNAL ARTICLE CORRECTED PROOF

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