Wage Decomposition in Economics(I)

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Zhaopeng Qu

Nanjing University

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Section 1

Introduction

Review Previous Lectures

- A framework of Causal Inference
- “Furious Seven”
    - Observables:RCTs,OLS,Matching
    - Unobservables:IV,RD,Panel
    - “hybrid”: Decomposition

Wage Decomposition: Introduction

- Wage Decomposition methods are used to analyze **distributional differences** in an outcome variable **between groups or time points**.
- In particular, the methods decompose the **observed difference** between two groups(or across two time points) into a components that is due to **compositional differences** between the groups, and a component that is due to **differential mechanisms**.

Wage Decomposition Methods: Introduction

- A Classical Case: **Gender Wage Gap**
  - How can the difference in average wages between men and women be explained?
  - Is the gap due to

1. group differences in wage determinants (i.e. in characteristics that are relevant for wages, such as education)? (**compositional differences**)
2. differential compensation for these determinants (e.g. different returns to education for men an women, or wage discrimination against women)? (**differential mechanisms**)

- The typical question is needed to answer is "what the pay(or other outcomes) would be *if women had* the same characteristics as men?"
- It will help us construct a **counterfactual** state by using decomposition method to recovery the causal effect(sort of causal) of a certain factor or a groups of determinants.

Decomposition Methods: Introduction

- The method can be tracked back from the seminal work by Solow(1957) for **"growth accounting"**.
- Seminal Work: Oaxaca (1973) and Blinder (1973), who analyzed mean wage differences between groups (males vs. females, whites vs. blacks).
- Once widely used in the area of labor economics, especially in the topics of **earnings inequality** since 1990s. Now it is popular used in many topics in many fields of economics.
- These more recent developments focus on topics such as
  - distributional measures other than the mean
  - non-linear models for categorical variables
  - taking into selection bias and other type endogenous.
  - combine with other quasi-experimental methods
  - extending into spatial econometric model

Decomposition Methods to Gaps: Two Categories

1. In Mean
   - Oaxaca-Blinder(1974):**OB**
   - Brown(1980): **Brown**
   - Fairlie(1999): **Fairlie**
2. In Distribution(Skipped)
   - Juhn, Murphy and Pierce(1993): **JMP**
   - Machado and Mata(2005): **MM**
   - DiNardo, Fortin and Lemieux(1996): **DFL**
   - Firpo, Fortin and Lemieux(2007,2010): **FFL**

Decomposition Methods: Pros and Cons

- Pros
  - It is a naturally way to distengle cause and effect based on OLS or other Linear regressions.
- Cons
  - In particular, decomposition methods inherently follow a partial equilibrium.
  - The results cannot be fully explained as causal inference.

Decomposition Methods to Gaps

- Although some of methods listed above is quite sophisicated and frontier in the filed, the OB is so fundemental that all other methods can explained by it.
- Therefore,in our lecture, we will **only** cover **OB** and its extension versions.

Section 2

Basic Oaxaca-Blinder Decomposition

A naive way to identification gender gap

- Use a dummy variable in a regression function

$$Y = \beta_0 + \beta_1 D + \Gamma X' + u$$

- $D = 1$ denotes that the gender of the sample is male, and $D = 0$ denotes female.
- X' denotes a series control variables, thus personal characteristics such as education,working experience,etc.
- So if $\hat{\beta}_1$ is large enough and significant statistically,
- then the result can only answer to that question: "*is there a wage gap between men and women in the labor market when other things equal(X)?*"

Oaxaca-Blinder Decomposition

- Assume that a multiple OLS regression equation is

$$Y_i = \beta_0 + \beta_1 X_{1i} + ... + \beta_k X_{ki} + u_i$$

where Y_i is dependent variable,$X_i s$ are a series independent(controlling) variables which affect Y_i.And u_i are error terms which satisfied by $E(u_i|X_1, ..., X_k) = 0$

- The means of Y_i

$$E(Y) = \beta_0 + \beta_1 E(X_1) + ... + \beta_k E(X_k) + E(u_i)$$

- Using the sample estimator to replace the population parameters and considering the definition of error term, thus $\sum u_i = 0$, then

$$\bar{Y} = \hat{\beta}_0 + \hat{\beta}_1 \bar{X}_1 + ... + \hat{\beta}_k \bar{X}_k$$

Oaxaca-Blinder Decomposition: Two groups

- If we assume that whole sample can be divided into 2 groups: A and B,then we could regress the similar regression using A and B subsamples, repectively. Thus,

$$Y_{Ai} = \beta_{A0} + \beta_{A1}X_{1i} + ... + \beta_{Ak}X_{ki} + u_{Ai}$$
$$Y_{Bi} = \beta_{B0} + \beta_{B1}X_{1i} + ... + \beta_{Bk}X_{ki} + u_{Bi}$$

- Accordingly, we can obtain the means of outcome Y for group A and group B are

$$\bar{Y}_A = \hat{\beta}_0^A + \hat{\beta}_1^A \bar{X}_{A1} + ... + \hat{\beta}_k^A \bar{X}_{Ak}$$
$$\bar{Y}_B = \hat{\beta}_0^B + \hat{\beta}_1^B \bar{X}_{B1} + ... + \hat{\beta}_k^B \bar{X}_{Bk}$$

Oaxaca-Blinder Decomposition: Two groups

- Denote

$$\bar{X}_A = (1, \bar{X}_{A1}, \bar{X}_{A2}, ..., \bar{X}_{Ak})$$

- And

$$\hat{\beta}_A = (\hat{\beta}_0^A, \hat{\beta}_1^A, \hat{\beta}_2^A, ..., \hat{\beta}_k^A)$$

- Then

$$\bar{Y}^A = \hat{\beta}_A \bar{X}'_A$$

- Denote as the same way

$$\bar{Y}^B = \hat{\beta}_B \bar{X}'_B$$

Oaxaca-Blinder Decomposition: difference in mean

- The difference in mean of Y_i of group A and B is

$$\bar{Y}_A - \bar{Y}_B = \hat{\beta}_A \bar{X}'_A - \hat{\beta}_B \bar{X}'_B$$

- A small trick: plus and minus a term $\hat{\beta}_B \bar{X}'_A$,then

$$\begin{aligned} \bar{Y}_A - \bar{Y}_B &= \hat{\beta}_A \bar{X}'_A - \hat{\beta}_B \bar{X}'_B \\ &= \hat{\beta}_A \bar{X}'_A - \hat{\beta}_B \bar{X}'_A + \hat{\beta}_B \bar{X}'_A - \hat{\beta}_B \bar{X}'_B \\ &= (\hat{\beta}_A - \hat{\beta}_B)\bar{X}'_A + \hat{\beta}_B(\bar{X}'_A - \bar{X}'_B) \end{aligned}$$

- Then the second term is **characteristics effect** which describes how much the difference of outcome, Y, in mean is due to differences in the levels of explanatory variables(characteristics).
- the first term is **coefficients effect** which describes how much the difference of outcome, Y, in mean is due to differences in the magnitude of regression coefficients.

A Classical Case: Gender Wage Gap

- Male-female average wage gap can be attributed into two parts:
  1. Explained Part: due to differences in the levels of explanatory variables: such as schooling years,experience,tenure,industry,occupation,etc
     - **characteristics effect**
     - **endownment effect**
     - **composition effect**
- In the literature of labor economics, we think that the wage gap due to this part is reasonable...

A Classical Case: Gender Wage Gap

- Male-female average wage gap can be attributed into two parts:
  2. Unexplained Part:due to differences in the coefficients to explanatory variables: such as **returns** to schooling years, experience and tenure and **premium** in industry and occupation,etc
     - **coefficients effect**
     - **returns effect**
     - **structure effect**
- In the literature of labor economics, we think that the wage gap due to this part is unreasonable,often it is called **discrimination** part...

Gustafusson and Li(2000): Gender gaps in China

Table 7. Results of decomposition of gender difference of earnings in urban China

	$\beta m X_m - \beta m X_f$	Percent of total	$\beta m X_f - \beta f X_f$	Percent of total
1988				
Intercept	0	0	0.3628	203.12
Age group	0.0340	19.02	0.0110	6.14
Minority status	0.00005	0.03	0.0011	0.59
Party membership	0.0124	6.92	−0.0057	−3.19
Education	0.0056	3.14	0.0059	3.33
Ownership	0.0184	10.32	−0.0354	−19.83
Occupation	0.0122	6.85	−0.1476	−82.64
Economic sector	−0.0003	−0.16	−0.1240	−69.41
Type of job	0.0039	2.17	0.0067	3.76
Province	−0.0014	−0.78	0.0190	10.62
Total	0.0849	47.51	0.0937	52.49
1995				
Intercept	0	0	0.0462	19.87
Age group	0.0169	7.28	0.0645	27.74
Minority status	0.0001	0.02	0.0014	0.59
Party membership	0.0142	6.12	−0.0037	−1.60
Education	0.0172	7.40	0.0001	0.02
Ownership	0.0208	8.96	−0.0163	−7.03
Occupation	0.0114	4.92	−0.0199	−8.58
Economic sector	0.0003	0.14	0.0087	3.76
Type of job	0.0026	1.12	0.0060	2.59
Province	0.0020	0.84	0.0601	25.86
Total	0.0855	36.80	0.1469	63.20

Source: Urban household income surveys 1989 and 1996.

Decomposition Methods to Gaps

- **OB Decomposition** is a tool for separating the influences of *quantities* and *prices* on an observed **mean difference**.
- The aim of the OB decomposition is to explain
- *how much of the difference in mean outcomes* across two groups is
    - due to *group differences in the levels of explanatory variables*,and
    - how much is due to *differences in the magnitude of regression coefficients*(**Oaxaca 1973; Blinder 1973**).
- Although most applications of the technique can be found in the labor market and discrimination literature, it can also be useful in other fields.
- In general, the technique can be employed to study group differences in any (continuous or categorical) outcome variable.

Section 3

Reference group problem

A different reference group

- what if we use a *different reference group*: plus and minus a term $\hat{\beta}_A \bar{X}'_B$,then

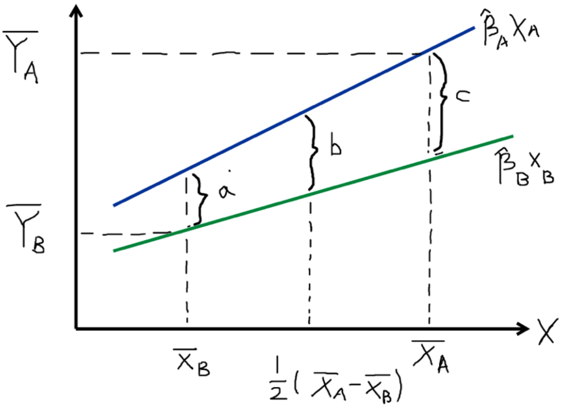
$$\begin{aligned}\bar{Y}_A - \bar{Y}_B &= \hat{\beta}_A \bar{X}'_A - \hat{\beta}_B \bar{X}'_B \\ &= \hat{\beta}_A \bar{X}'_A - \hat{\beta}_A \bar{X}'_B + \hat{\beta}_A \bar{X}'_B - \hat{\beta}_B \bar{X}'_B \\ &= (\hat{\beta}_A - \hat{\beta}_B)\bar{X}'_A + \hat{\beta}_B(\bar{X}'_A - \bar{X}'_B)\end{aligned}$$

- Then again the first term is **characteristics effect** or **endownment effect** as the amount of X_j can be seen as an endownment for group A or B.
- The second term is **coefficients effect** or **price(returns) effect** as the estimate coefficents $\hat{\beta}_j$ can be seen as the market price of or the returns to a certain X_j.
- **Question**: *is the result as same as the first decomposition?*

Reference group problem

- What is the **ture** coefficient or characteristics effect ?

Oaxaca-Blinder Decomposition



Oaxaca-Blinder Decomposition: a general framework

- Let Y^* be a **nondiscriminatory potential** outcome, so β^* is such a **nondiscriminatory** coefficient **vector**, and X is still a vector of many x(characteristics). Then they satisfy as a following eqaution

$$Y^* = X\beta^* + \epsilon$$

where ϵ is the error term and satisfies $E(\epsilon|X) = 0$

Oaxaca-Blinder Decomposition: a general framework

- Then the difference of the potential outcomes between two groups can then be decomposed as follows

$$
\begin{aligned}
\bar{Y}_A - \bar{Y}_B &= \bar{X}'_A \hat{\beta}_A - \bar{X}'_B \hat{\beta}_B \\
&= \bar{X}'_A \hat{\beta}_A - \bar{X}'_A \hat{\beta}^* + \bar{X}'_A \hat{\beta}^* - \bar{X}'_B \hat{\beta}^* + \bar{X}'_B \hat{\beta}^* - \bar{X}'_B \hat{\beta}_B \\
&= (\bar{X}'_A - \bar{X}'_B)\hat{\beta}^* + [\bar{X}'_A(\hat{\beta}_A - \hat{\beta}^*) + \bar{X}'_B(\hat{\beta}^* - \hat{\beta}_B)]
\end{aligned}
$$

Oaxaca-Blinder Decomposition: a general framework

- The first term, $(\bar{X}'_A - \bar{X}'_B)\hat{\beta}^*$ is the **explained part** as usual
  - **characteristics effect**
  - **endownment effect**
  - **composition effect**

Oaxaca-Blinder Decomposition: a general framework

- The second term, the **unexplained part** can further be subdivided into
  1. "discrimination" *in favor* of group A(such as Men)

$$\bar{X}'_A(\hat{\beta}_A - \hat{\beta}^*)$$

  2. "discrimination" *against* group B(such as Women)

$$\bar{X}'_B(\hat{\beta}^* - \hat{\beta}_B)$$

- All variables are known but the nondiscriminatory coefficients β^*. So how to determine it?

Oaxaca-Blinder Decomposition: One reference group

- Assume that discrimination is directed toward only **one** group.
- Recall

$$\bar{Y}_A - \bar{Y}_B = (\bar{X}'_A - \bar{X}'_B)\hat{\beta}^* + [\bar{X}'_A(\hat{\beta}_A - \hat{\beta}^*) + \bar{X}'_B(\hat{\beta}^* - \hat{\beta}_B)]$$

- Assume that wage discrimination is directed **only** against women(denoted as group B) and there is **no** (positive) discrimination(favor) of men(denoted as group A).
- Then $\beta^* = \beta_A$ and the wage gap can be decomposed into as

$$\bar{Y}_A - \bar{Y}_B = (\bar{X}'_A - \bar{X}'_B)\hat{\beta}_A + \bar{X}'_B(\hat{\beta}_A - \hat{\beta}_B)$$

OB Decomposition: one reference group

- Similarly, if there is only (positive) discrimination(favor) of men but no discrimination of women, Then $\beta^* = \beta_B$, and the decomposition is

$$\bar{Y}_A - \bar{Y}_B = (\bar{X}'_A - \bar{X}'_B)\hat{\beta}_B + \bar{X}'_A(\hat{\beta}_A - \hat{\beta}_B)$$

OB Decomposition: weighted reference group

- However, there is no specific reason to assume that the coefficients of one or the other group are nondiscriminating.
- So the value of β^* should be a math combination of $\hat{\beta}_A$ and $\hat{\beta}_B$,
  - Reimers(1983)therefore proposes using the **average** coefficients over both groups as an estimate for the nondiscriminatory parameter vector; that is,
$$\hat{\beta}^* = 0.5\hat{\beta}_A + 0.5\hat{\beta}_B$$
  - Cotton (1988) suggests to **weight** the coefficients by the **group sizes**, n_A and n_B,
$$\hat{\beta}^* = \frac{n_A}{n_A + n_B}\hat{\beta}_A + \frac{n_B}{n_A + n_B}\hat{\beta}_B$$

OB Decomposition: Weighted Matrix

- More general,let W be a $k+1$ diagonal matrix of weights, such that

$$\beta^* = W\hat{\beta}_A + (1-W)\hat{\beta}_B$$

- Note here

$$\hat{\beta}_{A,B} = (\hat{\beta}_0^{A,B}, \hat{\beta}_1^{A,B}, \hat{\beta}_2^{A,B}, ..., \hat{\beta}_k^{A,B})$$

OB Decomposition: Weighted Matrix

- Then the difference between two groups can be expressed as

$$\bar{Y}_A - \bar{Y}_B = (\bar{X}'_A - \bar{X}'_B)[W\hat{\beta}_A + (I - W)\hat{\beta}_B]$$
$$[(I - W)'\bar{X}_A + W\bar{X}_B](\hat{\beta}_A - \hat{\beta}_B)]$$

- W is a matrix of relative weights given to the coefficients of group **A**, and I is the identity matrix.
  - e.g. If we choose $W = I$, then it is equivalent to setting

$$\beta^* = \beta_A$$

.

  - e.g. If we choose $W = 0.5I$, then it is equivalent to setting

$$\beta^* = 0.5\beta_A + 0.5\beta_B$$

.

Oaxaca-Blinder Decomposition: Weighted Matrix

- Oaxaca and Ransom (1994) show that $\hat{W}$ can be use following equation to estimate

$$\hat{W} = \Omega = (X'X)^{-1}(X'_A X_A)$$

- Neumark(1988) also use the coefficients from a *pooled model over both groups* as the reference coefficients,thus
- We pool all data and run a regression

$$Y = X\beta$$

Then β^* can be obtained by

$$\beta^* = (X'X)^{-1}(X'Y)$$

Oaxaca-Blinder Decomposition: OVB and Weighted

- However, Oaxaca and Ransom(1994) and Neumark(1998) can inappropriately transfer some of the unexplained parts of the differential into the explained component.
- Assume a simple OLS equation: Y_i on a single regressor X_i and a group specific intercepts α_A and α_B

$$Y_{Ai} = \alpha_A + \gamma_A X_{Ai} + u_{Ai}$$
$$Y_{Bi} = \alpha_B + \gamma_B X_{Ai} + u_{Bi}$$

- Let $\alpha_A = \alpha$ and $\alpha_B = \alpha + \delta$, where δ is the discrimination parameter. Then the model can also be expressed as

$$Y = \alpha + \gamma X + \delta D + u$$

where D as an indicator for group B, such as "female" in gender wage gap case

Oaxaca-Blinder Decomposition: OVB and Weighted

- Assume that $\gamma > 0$ (positive relation between X and Y) and $\delta < 0$ (discrimination against women).
- The true model is

$$Y = \alpha + \gamma X + \delta D + u$$

- But if as Oaxaca and Ransom (1994) suggested,we only estimate

$$Y = \alpha + \gamma X + e$$

- Then following the *Omitted Variable Bias* formula, we can obtain

$$\hat{\gamma} = \gamma + \delta \frac{Cov(X, D)}{Var(X)}$$

Oaxaca-Blinder Decomposition: OVB and Weighted

- Then the **explained part** of the differential is

$$(\bar{X}_A - \bar{X}_B)\hat{\gamma} = (\bar{X}_A - \bar{X}_B)[\gamma + \delta\frac{Cov(X, D)}{Var(X)}]$$

- Note: δ,the discrimination parameter,which belongs to the **unexplained** parts of the gap,now attributes to the **explained** part of the gap.

Oaxaca-Blinder Decomposition: Weighted

- To address the OVB problem in decomposition, **Jann(2008)** suggested estimate a pooled regression over both groups but controlling group membership(a dummy variable D), that is

$$Y = \beta^* X + \delta D + \varepsilon$$

- In this case,

$$\hat{\beta}^* = ((X, D)'(X, D))^{-1}(X, D)'Y$$

- And the **coefficient effect** or **unexplained part** of the difference is $\hat{\delta}$, which is the the coefficient of D in the pooled regression now.
- The most widely used weighted method for OB decomposition right now.

Reference group: Wrap up

- On the different circumstances, the value could be quite different.
    - One reference group: A or B
    - Weighted reference group
        - simple weight: 0.5
        - weighted in matrix: Omega and Pooled
- In practice
    1. We could use one reference group method but both A and B. If the two result are similar, then it is OK.
    2. If the simple method does not work(not similar), then we have to adjusted the weight.

Section 4

Detailed Decomposition

Introduction

- The detailed contributions of the **single** predictors or sets of predictors are subject to investigation.
- For example, one might want to evaluate *how much of the gender wage gap is due to differences in* ***education*** and *how much is due to differences in* ***work experience***.
- Similarly, it might be informative to determine how much of the unexplained gap is related to differing **returns to education** and how much is related to differing **returns to work experience**.

Detailed Decomposition: the explained part

- Identifying the contributions of the individual predictors to the explained part of the differential is realtive easy.
- Because the total component is a simple sum over the individual contributions.Thus

$$(\bar{X}_A - \bar{X}_B)'\hat{\beta}_A = (\bar{X}_{1A} - \bar{X}_{1B})\hat{\beta}_{1A} + (\bar{X}_{2A} - \bar{X}_{2B})\hat{\beta}_{2A} + ...$$

- The first summand reflects the contribution of the group differences in X_1; the second, of differences in X_2; and so on.

Detailed Decomposition: the unexplained part

- the individual contributions to the **unexplained** part are the summands in

$$\bar{X}'_B(\hat{\beta}_A - \hat{\beta}_B) = (\hat{\beta}_{0A} - \hat{\beta}_{0B}) + (\hat{\beta}_{1A} - \hat{\beta}_{1B})\bar{X}_{1B} + (\hat{\beta}_{2A} - \hat{\beta}_{2B})\bar{X}_{2B}...$$

Detailed Decomposition: sets of covariates

- Furthermore, it is easy to subsum the detailed decomposition by sets of covariates
- the **explained part** of every set

$$(\bar{X}_A-\bar{X}_B)'\hat{\beta}_A=\sum_{k=1}^{a}\hat{\beta}_{kA}(\bar{X}_{kA}-\bar{X}_{kB})+\sum_{j=a+1}^{b}\hat{\beta}_{jA}(\bar{X}_{jA}-\bar{X}_{jB})+\ldots$$

- the **unexplained part** of every set

$$\bar{X}_B'(\hat{\beta}_A-\hat{\beta}_B)=(\hat{\beta}_{0A}-\hat{\beta}_{0B})+\sum_{k=1}^{a}(\hat{\beta}_{kA}-\hat{\beta}_{kB})\bar{X}_{kB}+\sum_{j=a+1}^{b}(\hat{\beta}_{jA}-\hat{\beta}_{jB})\bar{X}_{j}$$

Section 5

Standard Errors

Introduction

- The computation of the decomposition components is straight forward:
  - Estimate OLS models and insert the coefficients and the means of the regressors into the formulas.
- For a long time, results from OB decompositions were reported **without** information on statistical inference (standard errors, confidence intervals).
- Without reporting s.e. or C.I is problematic
  - because it is hard to evaluate the significance of reported decomposition results without knowing anything about their sampling distribution.

Standard Errors: Jan(2005)

- Think of a term such as $\bar{X}\hat{\beta}$,where $\bar{X}$ is a row vector of sample means and $\hat{\beta}$ is a column vector of regression coefficients (the result is a scalar).
  - How can its sampling variance,$V(\bar{X}\hat{\beta})$ be estimated?
- Following Jann(2005), the sampling variance is

$$Var(\bar{X}\hat{\beta}) = \bar{X}Var(\hat{\beta})\bar{X}' + \hat{\beta}'Var(\bar{X})\hat{\beta} + trace[Var(\bar{X})Var(\hat{\beta})]$$

Standard Errors: Jan(2005)

- The last term, $trace[Var(\bar{X})Var(\hat{\beta})]$,will be asymptotically vanishing and can be ignored when n is enough large.
- To estimate $Var(\bar{X}\hat{\beta})$, plug in estimates for $Var(\hat{\beta})$ (the variance-covariance matrix of the regression coefficients) and $Var(\bar{X})$ (the variance-covariance matrix of the means), which are readily available.

Standard Errors: Jan(2005)

- Recall OB decomposition:

$$\bar{Y}_A - \bar{Y}_B = \bar{X}_A(\hat{\beta}_A - \hat{\beta}_B) + (\bar{X}_A - \bar{X}_B)\hat{\beta}_B$$

- So corresponding the first term's variance is as follows

$$\begin{aligned} Var[\bar{X}_A(\hat{\beta}_A - \hat{\beta}_B)] &= Var[\bar{X}_A\hat{\beta}_A - \bar{X}_A\hat{\beta}_B] \\ &= Var[\bar{X}_A\hat{\beta}_A] - Var[\bar{X}_A\hat{\beta}_B] \\ &\approx \bar{X}_A[V(\hat{\beta}_A) + V(\hat{\beta}_B)]\bar{X}'_A + \\ &(\hat{\beta}_A - \hat{\beta}_B)'V(\bar{X}_A)(\hat{\beta}_A - \hat{\beta}_B) \end{aligned}$$

- Similarly,

$$Var[(\bar{X}_A - \bar{X}_B)\hat{\beta}_B] \approx (\bar{X}_A - \bar{X}_B)V(\hat{\beta}_B)(\bar{X}_A - \bar{X}_B)' + \\ \hat{\beta}'_B V(\bar{X}_A + \bar{X}_B)\hat{\beta}_B$$

- Equations for other variants of the decomposition, for elements of the detailed decomposition, and for the covariances among components

Section 6

Representative Applications

Examples

1. Labor Economics: Wage or Income Gaps
   - Gender: Male-Female
   - Urban-Rural(or Urban-Migrant)
   - Minority-Majority(Racial Gaps)
   - Poor-Nonpoor
   - Public-Private Sectors gaps
   - Union-NonUnion gaps

章莉等 (2014): 中国劳动力市场上工资收入的户籍歧视

表 4 工资户籍差异 Oaxaca-Blinder 分解结果 (CHIPs2007)

(1)		(1)标准分解	(2)反向分解	(3)Omega分解	(4)全样本分解
(2)	$E[\ln(w_u)]-E[\ln(w_m)]$	0.6456	0.6456	0.6456	0.6456
		(0.0130)	(0.0130)	(0.0130)	(0.0130)
可解释部分					
A	年龄	−0.0458	−0.0444	−0.0291	−0.0490
		(0.0094)	(0.0084)	(0.0065)	(0.0067)
B	教育	0.1652	0.1598	0.2071	0.1710
		(0.0105)	(0.0112)	(0.0088)	(0.0089)
C	工作经验	0.1246	0.0376	0.1354	0.1209
		(0.0093)	(0.0210)	(0.0074)	(0.0073)
D	性别	−0.0079	−0.0050	−0.0057	−0.0065
		(0.0021)	(0.0014)	(0.0015)	(0.0017)
E	民族	−0.0001	0.0005	0.0005	0.0004
		(0.0005)	(0.0004)	(0.0003)	(0.0003)
F	婚姻状况	0.0240	0.0177	0.0232	0.0231
		(0.0056)	(0.0044)	(0.0037)	(0.0036)
G	地区	−0.0184	−0.0121	−0.0150	−0.0153
		(0.0044)	(0.0029)	(0.0036)	(0.0036)
H	行业	0.0645	−0.0064	0.0388	0.0274
		(0.0087)	(0.0091)	(0.0060)	(0.0060)
I	职业	0.1099	−0.0207	0.1107	0.0908
		(0.0108)	(0.0148)	(0.0086)	(0.0086)
J	所有制	0.0458	0.0451	0.0779	0.0513
		(0.0117)	(0.0141)	(0.0088)	(0.0089)
(3)	全部可解释部分	0.4621	0.1721	0.5438	0.4142
		(0.0180)	(0.0311)	(0.0112)	(0.0155)
(4)	贡献率	72%	27%	84%	64%

章莉等 (2014): 中国劳动力市场上工资收入的户籍歧视

不可解释部分					
a	年龄	−0.0059 (0.0526)	−0.0073 (0.0651)	−0.0226 (0.0605)	−0.0027 (0.0605)
b	教育	0.0139 (0.0384)	0.0192 (0.0532)	−0.0281 (0.0497)	0.0080 (0.0495)
c	工作经验	0.0107 (0.0129)	0.0977 (0.0287)	−0.0001 (0.0174)	−0.0144 (0.0173)
d	性别	0.0481 (0.0147)	0.0453 (0.0138)	0.0460 (0.0144)	0.0467 (0.0144)
e	民族	−0.0973 (0.1017)	−0.0979 (0.1023)	−0.0978 (0.0925)	−0.0978 (0.0925)
f	婚姻状况	0.0201 (0.0224)	0.0265 (0.0294)	0.0210 (0.0268)	0.0210 (0.0268)
g	地区	0.0738 (0.0247)	0.0675 (0.0238)	0.0704 (0.0238)	0.0707 (0.0238)
h	行业	−0.1421 (0.0423)	−0.0711 (0.0340)	−0.1163 (0.0409)	−0.1049 (0.0409)
i	职业	−0.2503 (0.0319)	−0.1197 (0.0140)	−0.2511 (0.0250)	−0.2311 (0.0250)
j	所有制	−0.0132 (0.0309)	−0.0125 (0.0133)	−0.0453 (0.0235)	−0.0187 (0.0236)
	常数项	0.5257 (0.1443)	0.5257 (0.1443)	0.5257 (0.1419)	0.5257 (0.1419)
(5)	全部不可解释部分	0.1835 (0.0201)	0.4734 (0.0329)	0.1018 (0.0085)	0.2314 (0.0185)
(6)	贡献率	28%	73%	16%	36%

Fortin and Lemiux(2011)

Reference Group:	(1) Using Male Coef. from col. 2, Table 2		(2) Using Male Coef. from col. 4, Table 2		(3) Using Female Coef.		(4) Using Weighted Sum		(5) Using Pooled from col. 5, Table 2	
Unadjusted mean log wage gap :										
$E[\ln(w_m)]-E[\ln(w_f)]$	0.233	(0.015)	0.233	(0.015)	0.233	(0.015)	0.233	(0.015)	0.233	(0.015)
Composition effects attributable to										
Age, race, region, etc.	0.012	(0.003)	0.012	(0.003)	0.009	(0.003)	0.011	(0.003)	0.010	(0.003)
Education	-0.012	(0.006)	-0.012	(0.006)	-0.008	(0.004)	-0.010	(0.005)	-0.010	(0.005)
AFQT	0.011	(0.003)	0.011	(0.003)	0.011	(0.003)	0.011	(0.003)	0.011	(0.003)
L.T. withdrawal due to family	0.033	(0.011)	0.033	(0.011)	0.035	(0.008)	0.034	(0.007)	0.028	(0.007)
Life-time work experience	0.137	(0.011)	0.137	(0.011)	0.087	(0.01)	0.112	(0.008)	0.092	(0.007)
Industrial sectors	0.017	(0.006)	0.017	(0.006)	0.003	(0.005)	0.010	(0.004)	0.009	(0.004)
Total explained by model	0.197	(0.018)	0.197	(0.018)	0.136	(0.014)	0.167	(0.013)	0.142	(0.012)
Wage structure effects attributable to										
Age, race, region, etc.	-0.098	(0.234)	-0.098	(0.234)	-0.096	(0.232)	-0.097	(0.233)	-0.097	(0.24)
Education	0.045	(0.034)	0.045	(0.034)	0.041	(0.033)	0.043	(0.034)	0.043	(0.031)
AFQT	0.003	(0.023)	0.003	(0.023)	0.003	(0.025)	0.003	(0.024)	0.002	(0.025)
L.T. withdrawal due to family	0.003	(0.017)	0.003	(0.017)	0.001	(0.004)	0.002	(0.011)	0.007	(0.01)
Life-time work experience	0.048	(0.062)	0.048	(0.062)	0.098	(0.067)	0.073	(0.064)	0.092	(0.065)
Industrial sectors	-0.092	(0.033)	0.014	(0.028)	-0.077	(0.029)	-0.085	(0.031)	-0.084	(0.032)
Constant	0.128	(0.213)	0.022	(0.212)	0.193	(0.211)	0.128	(0.213)	0.128	(0.216)
Total wage structure - Unexplained log wage gap	0.036	(0.019)	0.036	(0.019)	0.097	(0.016)	0.066	(0.015)	0.092	(0.014)

Examples

2. Other Fields:
   - Educational Performance: Fortin, Oreopoulos and Phipps(2017)
   - Marketing: Liu et al(2016) "Movie Stars Effects"
   - Family Origins: Li,Ling and Qu(2018)
   - House Price:
   - Health Status:

Li,Ling and Qu(2018):

表 9：新、旧精英与非精英收入差距的 OB 分解

	旧精英子代		新精英子代	
	差异贡献	贡献率(%)	差异贡献	贡献率(%)
整体差异	0.138***	100	0.170***	100
	(0.040)		(0.055)	
特征效应				
个人特征	0.044*	31.92***	0.136***	79.92***
	(0.024)	(11.37)	(0.043)	(17.51)
父母特征	0.025***	17.95**	0.029**	17.19*
	(0.008)	(7.29)	(0.013)	(8.80)
合计	0.069***	49.87***	0.165***	97.12***
	(0.025)	(11.21)	(0.046)	(21.30)
系数效应				
个人特征回报	-0.065	-47.35	-0.438	-257.91
	(0.332)	(241.80)	(0.463)	(288.65)
父母特征回报	-0.096	-69.57	0.450***	264.95**
	(0.104)	(77.68)	(0.172)	(132.50)
截距项	0.230	167.05	-0.007	-4.16
	(0.362)	(266.91)	(0.454)	(267.15)
合计	0.069***	50.13***	0.005	2.88
	(0.025)	(11.21)	(0.037)	(21.30)
样本数	6941		7393	

注：1） 表中所有列的回归都包含如下变量：a)人口学特征：性别、民族和婚姻状况；b)人力资本变量：教育年限、经验、经验平方、自评健康；c)政治和社会资本：是否党员、人情往来支出占总支出比例；d)工作特征变量：行业、所有制、单位规模、职业类型和劳动合同；以及 e)城市固定效应；2）第 1 列和第 3 列表示该变量（或变量的组合）的特征或系数效应的具体数值，第 2 列和第 4 列表示该变量（或变量的组合）的特征效应或系数效应可以解释两组平均工资差异的百分比，括号中均为相应的标准误；3）*** 、**、* 分别表示 1%，5%和 10%及以下的统计显著性。

Section 7

A Summary to OB decomposition

Conclusing Remarks and Discussions:

- OB decomposition can be easily extended in some nonlinear regression models.
- But OB method decompose the gap **only on the mean**.
- The result may depends on the choice of counterfactual fact if you neglect the reference group problem.
- Intrinsically,a partial equilibrium approach to analyze **a general equilibrium question**.
- Question: how is extent to trust that the result have a **causal explanation** in the decomposition?

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