

Introduction to Microeconomic Evaluation

SS 2011

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**UNI
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1. Endogeneity Condition of Exogeneity



1. Endogeneity
2. Simultaneity
3. Missing Variables

- Börsch-Supan, Axel und Jens Köke (2002), An Applied Econometricians' View of Empirical Corporate Governance Studies, *German Economic Review*, 3 (3), S. 295-326

1. Endogeneity

Condition of Exogeneity



- True Model (1) $z = \beta x + \varepsilon$
(2) $x = \gamma z + \eta$

whereas

$$E(\varepsilon) = 0 \quad E(\eta) = 0 \quad Cov(\varepsilon, \eta) = \sigma_{\varepsilon\eta}$$

OLS estimation of (1):

$$\begin{aligned} \hat{\beta} &= \frac{Cov(x, z)}{Var(x)} && \text{z from (1)} \\ &= \frac{Cov(x, \beta x + \varepsilon)}{Var(x)} \end{aligned}$$

1. Endogeneity

Condition of Exogeneity



$$\text{I } \text{Cov}(x, x) = \text{Var}(x)$$

$$\text{II } \text{Cov}(z, ax + by) = a \text{Cov}(x, z) + b \text{Cov}(y, z)$$

Example:

$$\hat{\beta} = \frac{\text{Cov}(x, \beta x + \varepsilon)}{\text{Var}(x)} = \frac{\beta \text{Cov}(x, x) + 1 \text{Cov}(\varepsilon, x)}{\text{Var}(x)}$$

$$= \frac{\beta \text{Var}(x)}{\text{Var}(x)} + \frac{\text{Cov}(\varepsilon, x)}{\text{Var}(x)}$$

$$= \beta + \frac{\text{Cov}(x, \varepsilon)}{\text{Var}(x)} \quad (3)$$

Rule
II

Rule
I

1. Endogeneity



$$\begin{aligned} &Cov(x, \varepsilon) \\ &= Cov(\gamma z + \eta, \varepsilon) \\ &= Cov(\gamma(\beta x + \varepsilon) + \eta, \varepsilon) \\ &= \gamma Cov(\varepsilon, (\beta x + \varepsilon)) + 1 Cov(\varepsilon, \eta) \\ &= \gamma [\beta Cov(x, \varepsilon) + \underbrace{1 Cov(\varepsilon, \varepsilon)}_{\sigma_{\varepsilon\varepsilon}}] + \sigma_{\varepsilon\eta} \\ &\quad = Var(\varepsilon) \\ &= \gamma\beta Cov(x, \varepsilon) + \gamma\sigma_{\varepsilon}^2 + \sigma_{\varepsilon\eta} \end{aligned} \tag{4}$$

Rule II

Rule II

Rule I

1. Endogeneity



Solving for $\text{Cov}(x, \varepsilon)$:

$$\text{Cov}(x, \varepsilon) - \beta \gamma \text{Cov}(x, \varepsilon) = \gamma \sigma_{\varepsilon}^2 + \sigma_{\varepsilon \eta}$$

$$(1 - \beta \gamma) \text{Cov}(x, \varepsilon) = \gamma \sigma_{\varepsilon}^2 + \sigma_{\varepsilon \eta}$$

$$\text{Cov}(x, \varepsilon) = \frac{\gamma \sigma_{\varepsilon}^2 + \sigma_{\varepsilon \eta}}{1 - \beta \gamma}$$

$$\hat{\beta} = \beta + \frac{\text{Cov}(x, \varepsilon)}{\text{Var}(x)}$$

1. Endogeneity

Problem of Endogeneity, if



$$\text{Cov}(x, \varepsilon) \neq 0$$

Case 1

$$\gamma \neq 0$$

Case 2

$$\sigma_{\varepsilon\eta} \neq 0$$

→ OLS estimators are biased and inconsistent

1. Endogeneity

Notation Analysis of Endogeneity



1. Covariance

$$\text{Cov}(x, \varepsilon) = 0$$

$$\text{Cov}(u_i, x_i) = 0$$

2. Expected Value

$$E(u_i x_i) = 0$$

3. Conditional Expected Value

$$E(\varepsilon | x) = 0$$

1. Endogeneity

Relation between Covariance and Expected Value



$$\text{Cov}(u_i, x_i)$$

$$= E \left[\left(u_i - \underbrace{E[u_i]}_{=0} \right) (x_i - E[x_i]) \right]$$

$$= E[u_i (x_i - E[x_i])]$$

$$= E[u_i x_i] - \underbrace{E[u_i] E[x_i]}_{=0}$$

$$= E[u_i x_i]$$

1. Endogeneity

Conditional Expected Value



$$E(\varepsilon|x) = 0$$

In case x and y are independent, then:

$$E(y|x) = E(y)$$

conditional	unconditional
expected	expected
value	value

$$\Rightarrow E(\varepsilon|x) = E(\varepsilon) = 0$$

if ε and x are independent

(assumption of exogeneity).

1. Endogeneity

Condition of Exogeneity



Emphasis of this lesson is the assumption of exogeneity:

- Independence of residual and explaining variables
- All missing variables are captured by a disturbance term

1. Endogeneity

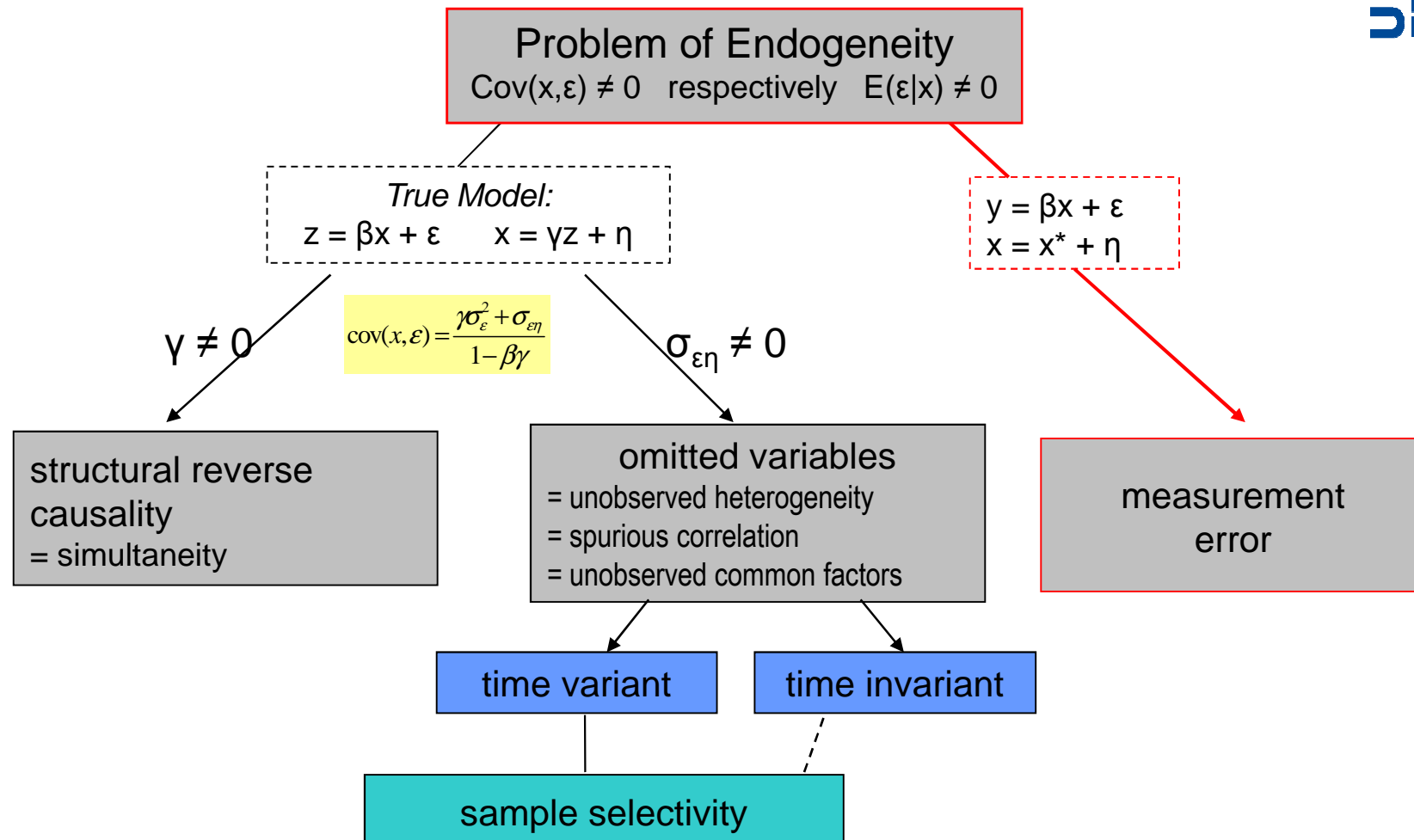
Condition of Exogeneity



If the assumption of exogeneity is violated then OLS is

- biased
- inconsistent

1. Endogeneity



2. Simultaneity Classification



Problem of Endogeneity
 $\text{Cov}(x, \varepsilon) \neq 0$ respectively $E(\varepsilon|x) \neq 0$

True Model:
 $z = \beta x + \varepsilon \quad x = \gamma z + \eta$

$\gamma \neq 0$

$$\text{cov}(x, \varepsilon) = \frac{\gamma \sigma_{\varepsilon}^2 + \sigma_{\varepsilon \eta}}{1 - \beta \gamma}$$

structural reverse
causality
= simultaneity

2. Simultaneity



Basic Problem:

Direction of causal effects between variables is ambiguous.

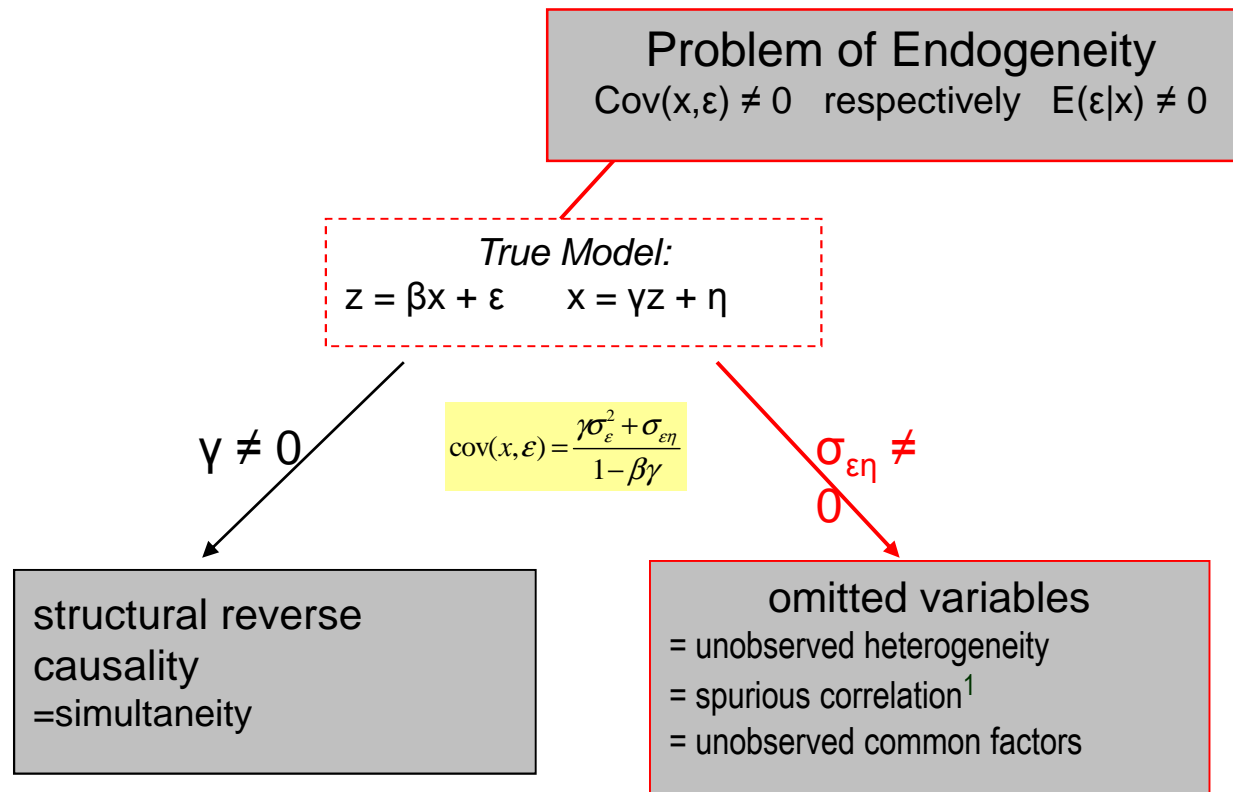
Example:	y	\longleftrightarrow	x
	Rate of criminality	\longleftrightarrow	No. of policemen
	GDP	\longleftrightarrow	Consumption
	Unemployment	\longleftrightarrow	Application of active labour market policy

$$(1) y = \beta x + \varepsilon$$

$$(2) x = \gamma y + \eta$$

Estimation of (1) with OLS \rightarrow Estimated coefficients biased, if $\gamma \neq 0$, as $\text{Cov}(x, \varepsilon) \neq 0$.

3. Omitted Variables Classification



¹ The denomination is deceptive; a better denomination would be „spurious causality“

3. Omitted Variables



- **Classification:** Omission of variables leads to an endogeneity bias and thus to misleading regression results
- In case the incorrect specification $y = x_1\beta_1 + \varepsilon$ is assumed instead of $y = x_1\beta_1 + x_2\beta_2 + \varepsilon$, then the effect of the omitted variable is captured in the residual
- If either $\text{Cov}(x_1, x_2) \neq 0$ or $\beta_2 \neq 0$ is violated, then the disturbance term is correlated with $x_1 \rightarrow$ endogeneity bias

3. Omitted Variables = unobserved heterogeneity



1) Unobserved Heterogeneity

= unobservable individual effect

Examples:

- Motivation
- Intelligence
- Management Skills

3. Omitted Variables = „spurious correlation“/ „spurious causality“



2) Spurious Correlation / Spurious Causality

Due to an omitted variable, a pseudo-correlation between regressor x and regressand y emerges

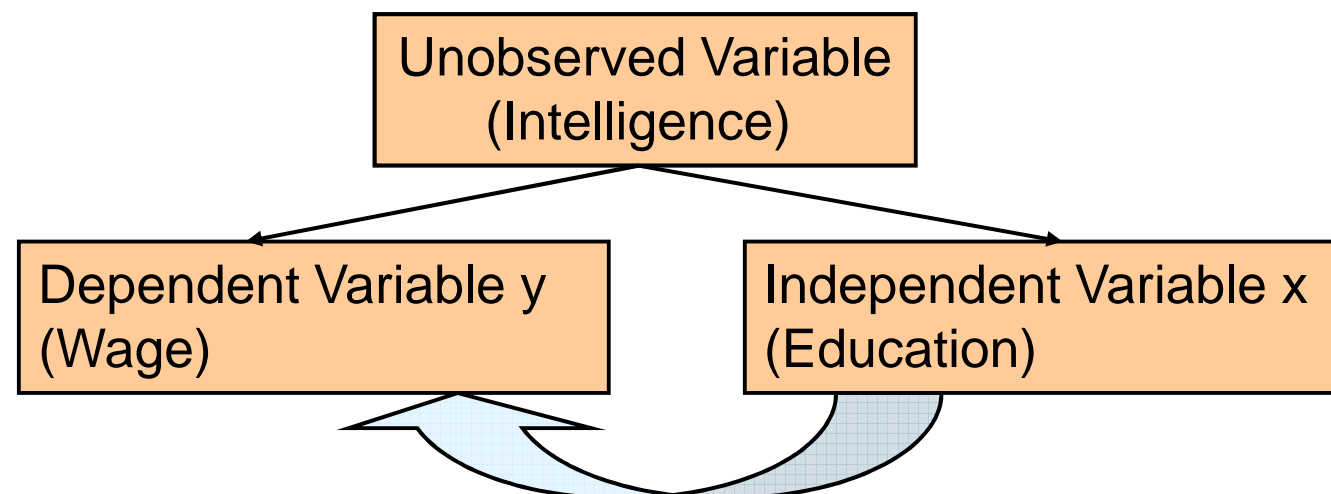
Example: Estimation of the effect of education on wages: Individuals A and B differ in regard to their intelligence

- Due to higher intelligence, A has more years of education
- Due to higher intelligence, A receives higher wages

3. Omitted Variables = „unobserved common factors“



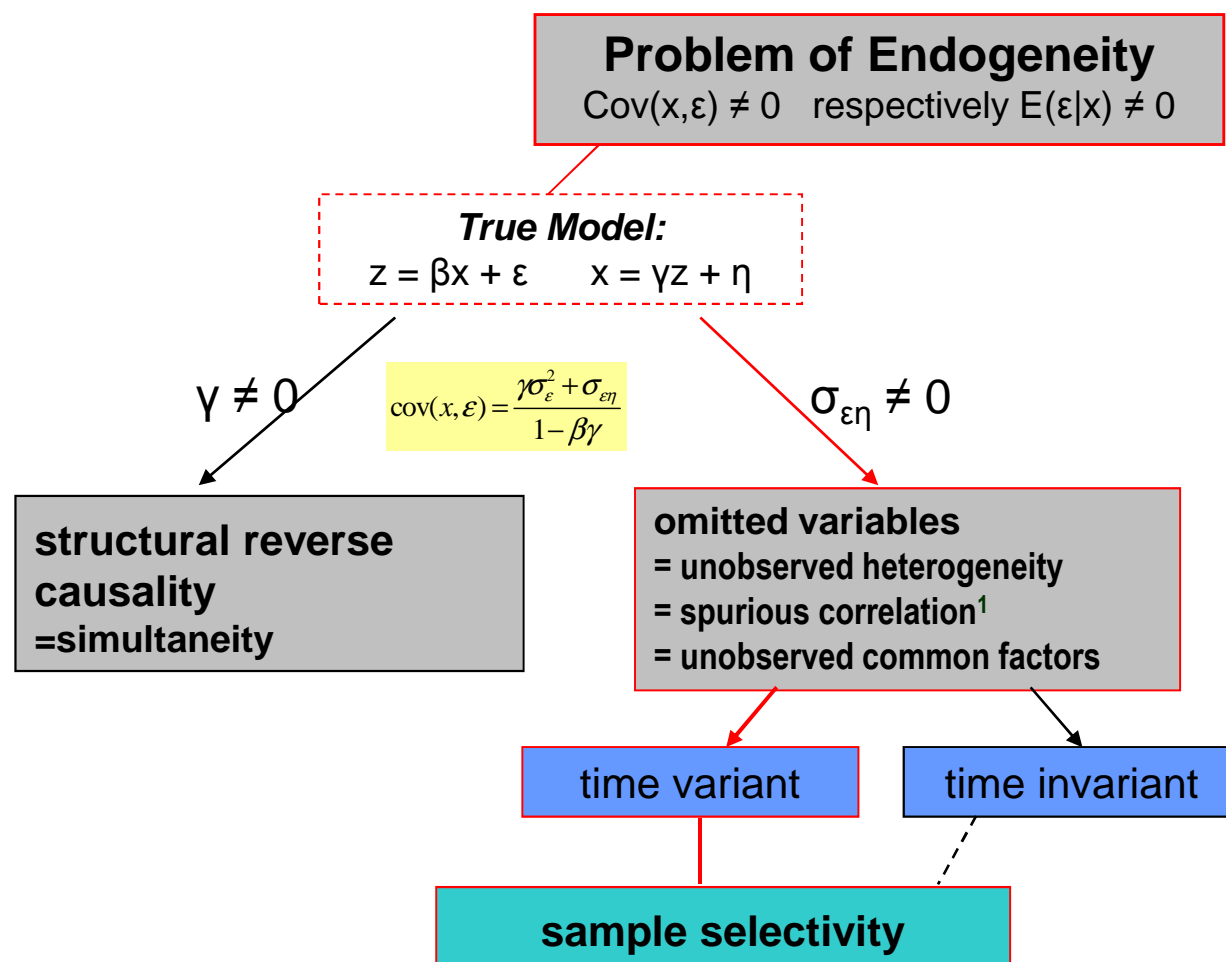
3) Unobserved Common Factors



In case intelligence is not specified within the model: Regression overestimates the real effect of education on wages because of a positive correlation between intelligence and education.

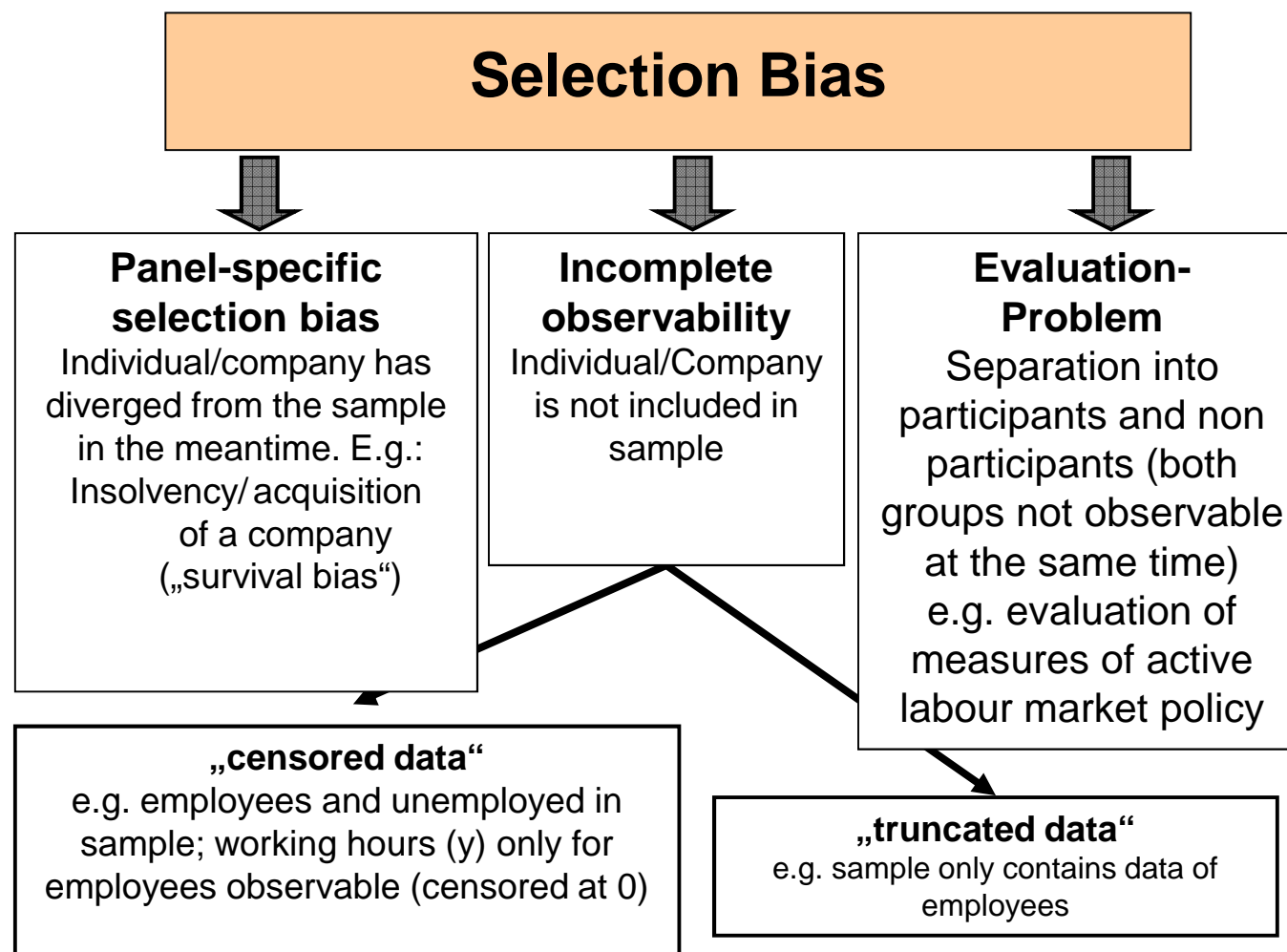
3. Omitted Variables

Classification of Selection Bias

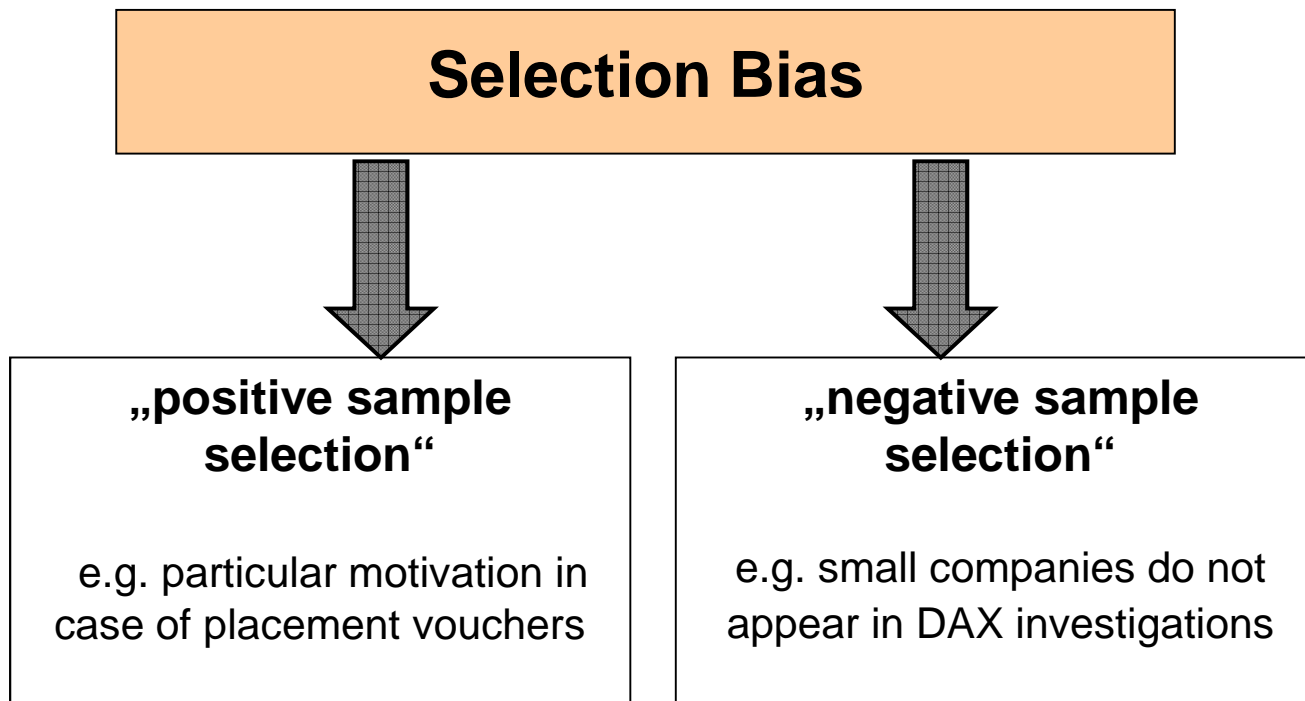


3. Omitted Variables

Selection Bias – Criteria for Differentiation I

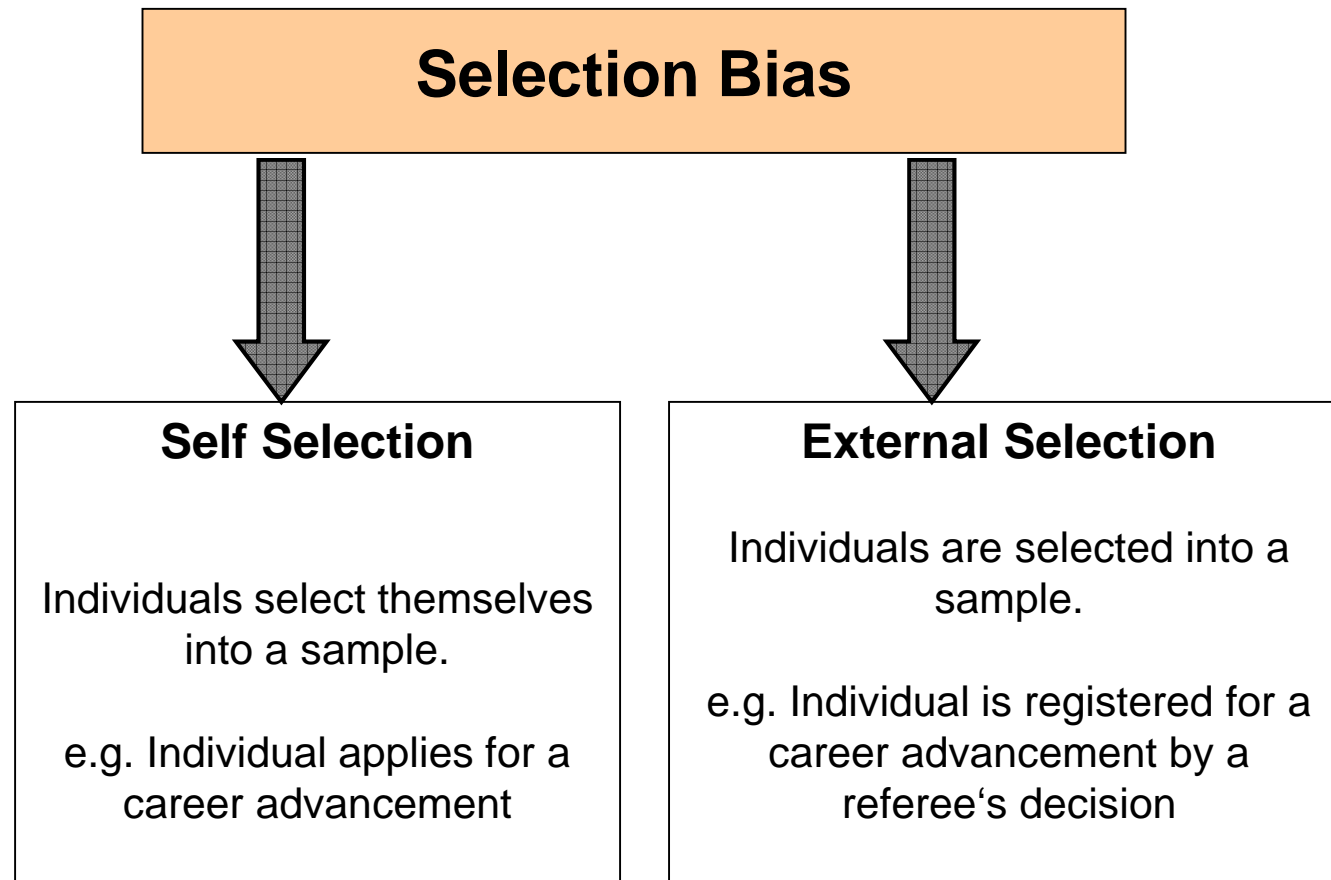


3. Omitted Variables Selection Bias – Criteria for Differentiation II



3. Omitted Variables

Selection Bias – Criteria for Differentiation III



Solution Approaches

