Selection bias and Heckman two-stage estimation

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Disclaimer

- This presentation and its content represent a **work in progress** and are **still subject to peer review – your feedback is very welcome here**
- The basic assumption and examples are given in the context of **secondary panel data**
- Feel free to use our materials – if you decide to do so, **we ask you to cite our work**

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Introduction

- In his seminal paper, James J. Heckman (1979) pioneered a method that helps **identify and mitigate sample-induced endogeneity**: the Heckman two-stage estimation
- With the **rising relevance of selection bias** in the prevalent research and the **attention scientific journals pay** to the choices and implementation of econometric techniques, we notice an **increasing number of methodological errors** in applying the Heckman two-stage estimation
- Scholars and practitioners **may be challenged to stay in touch with this development**: For these reasons we developed a **practical and comprehensible step-by-step guide** with this presentation and the respective discussion paper
- These resources **aim to enable applying the Heckman two-stage estimation to any research model** in entrepreneurship, innovation, and other research streams

Sources: Certo et al., 2016; Heckman, 1979; Ullah et al., 2021; Wolfolds & Siegel, 2019

Problem

- **Selection bias** occurs when a sample is not randomly generated and, thus, **does not represent the population**
- An example is **corporate venture capital (CVC)** investments, where researchers can only observe a firm's final investment decision. However, the strategic decision of CVC may be based on characteristics that researchers cannot observe
- **Consequence**: "The problem of selection bias [...] arises when a rule other than simple random sampling is used to sample the underlying population that is the object of interest. The distorted representation of a true population as a consequence of a sampling rule is the essence of the selection problem." (Heckman, 2018, p. 12131)

Sources: Bushway et al., 2007; Greene, 2018; Heckman, 2018; Hill et al., 2021

Methodology

- The Heckman two-stage estimation supports **identifying and mitigating a potential selection bias**
- This technique **consists of two consecutively applied stages** that separate the selection process from the primary relationship of interest
  - In the **first stage**, the selection process of the underlying relationship is estimated
  - The **second stage** analyzes the primary relationship of interest
  - The connection between the two stages is a **unique selection parameter** induced from the first stage and inserted in the second-stage regression
  - The selection parameter **captures unobservable characteristics** found in the primary regression’s error term that lead to endogenous covariates

Sources: Certo et al. 2016; Clougherty et al., 2015; Hamilton & Nickerson, 2003; Heckman, 1979; Hill et al., 2021

Application in Stata (1|5)

First stage: Selection equation (1|2)

- The Selection Equation analyzes whether **observations from the population appear in the selected sample**
- A probit regression is performed, where a **binary selection variable** is chosen as the dependent variable
- In addition, **matching instruments** must be selected that **meet two requirements**: The instruments must
  1. **Influence the binary selection variable of the second stage**
  2. **Not influence the dependent variable of the second stage**

```
xtprobit Selection_Variable Independent_Variables Controls Instruments
```

Example for panel data: Depending on the data structure, a pooled probit regression may be useful

Sources: Clougherty et al., 2015; Hill et al., 2021; Wolfolds & Siegel, 2019

Application in Stata (2|5)

First stage: Selection equation (2|2)

- The Inverse Mills Ratio (IMR) correction variable is then determined to **retrieve the IMR as a selection parameter** and captures the significant unobserved characteristics that affect the underlying relationship
- The IMR can be calculated by **dividing the normal density function (PDF) by the normal cumulative distribution**

```
predict xb, xb
generate PDF = normalden(xb)
generate CDF = normal(xb)
generate IMR = PDF / CDF
```


Sources: Certo et al., 2016; Clougherty et al., 2015; Wolfolds & Siegel, 2019

Application in Stata (3|5)

Second stage: Outcome equation (1|3)

- The outcome equation is estimated **using a linear regression model (OLS)**
- The **Inverse Mills Ratio (IMR) correction variable** is used in the outcome equation
- The **standard least squares estimator may be downward biased** → One possible way to correct this biased variance may be to **bootstrap the standard errors** of the first and second stages

Sources: Clougherty et al., 2015; Hamilton & Nickerson, 2003; Heckman, 1979, Hill et al., 2003

Application in Stata (4|5)

Second stage: Outcome equation (2|3)

```
program heckman_2_stage
    xtprobit Selection Variable Independent_Variables Controls Instruments
    predict xb, xb
    gen PDF = normalden(xb)
    gen CDF = normal(xb)
    gen IMR = PDF / CDF
    xtreg Dependent_Variable Independent_Variables Controls IMR
    drop xb PDF CDF IMR
end

bootstrap: heckman_2_stage
```

Application in Stata (5|5)

Second stage: Outcome equation (3|3)

- The level of significance and sign of the IMR's beta coefficient suggests the magnitude of the correlation between the error terms of the selection equation and the outcome equation → represents the level of endogeneity present in the research model

➢ A **significantly positive** (**negative**) **beta coefficient** suggests that unobserved factors **positively** (**negatively**) **affect the estimated relationship**

➢ Note that an **insignificant Inverse Mills Ratio** at the second-stage level **does not entirely rule out a selection bias**; The power of the Heckman two-stage estimation of determining a selection bias is affected by the strength of the exclusion restriction and the sample size

Sources: Bushway et al., 2007; Certo et al., 2016; Hill et al., 2021

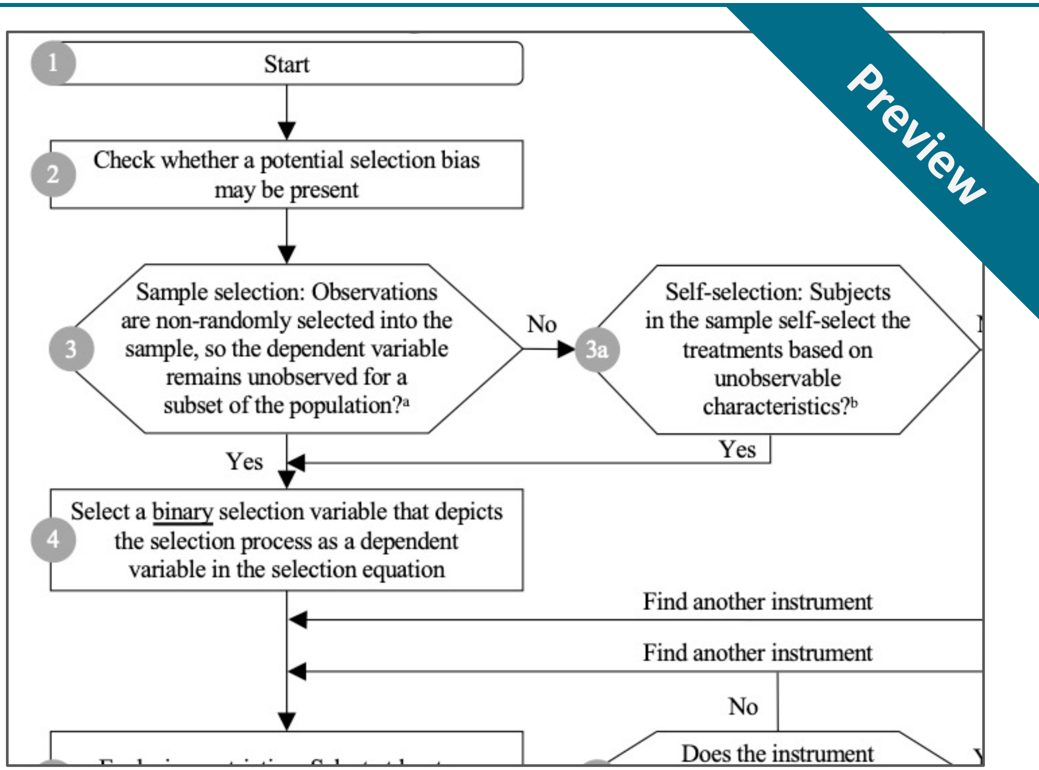
Critical factors and methodological pitfalls to avoid

- The regression analyses of the first and second stages should contain the **same independent and control variables** – do not forget time fixed-effects for panel data
- The **regression types used in the two stages are essential** for the Heckman two-stage estimation since the error terms of both stages should follow a bivariate normal distribution
  - The **first stage** must be a **probit regression**
  - The **second stage** should be **either a probit or an OLS regression**, and "since the derivation of the Heckman two-step method relies on the normality of errors, we are hesitant to suggest that the use of other estimation techniques is appropriate" (Wolfolds & Siegel, 2019, p. 452)
- The Heckman two-stage estimation is not suitable for count data as it **requires a full parametric specificity** → regression error specification test (RESET) by Ramsey (1969) to indicate whether the normality assumption can be found in the errors terms

Sources: Arregle et al., 2012; Bushway et al., 2007; Ramsey, 1969; Wolfolds & Siegel, 2019

Preview of our Heckman flowchart

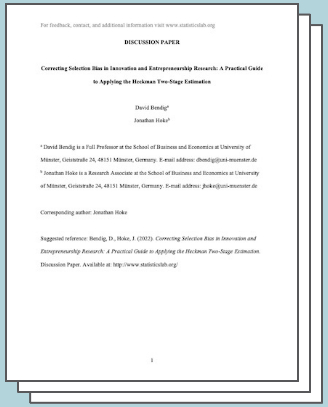
- We developed a **graphical representation** of the Heckman two-stage estimation in a flowchart
- The flowchart helps **better understand the theoretical assumptions and application** of the technique by **showing the process steps** and **ensuring that no step is omitted**
- Each step in the flowchart is **numbered to indicate the flow's direction**



➢ **Access a virtual version of the flowchart or download the PDF file on www.statisticslab.org**

Recommended literature

- Our discussion paper addresses the theoretical assumptions and methodological fundamentals of Heckman’s technique in more detail
  Download from www.statisticslab.org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DISCUSSION PAPER

Correcting Selection Bias in Innovation and Entrepreneurship Research: A Practical Guide to Applying the Heckman Two-Stage Estimation

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Access here

Further literature recommendations addressing the Heckman two-stage estimation:

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