Econometrics with Observational Data

Introduction and Identification

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HEALTH SERVICES RESEARCH & DEVELOPMENT

Goals for Course

- To enable researchers to conduct careful analyses with existing VA (and non-VA) datasets.

- We will
  - Describe econometric tools and their strengths and limitations
  - Use examples to reinforce learning

Goals of Today's Class

- Understanding causation with observational data
- Describe elements of an equation
- Example of an equation
- Assumptions of the classic linear model

Terminology

- Confusing terminology is a major barrier to interdisciplinary research
  - Multivariable or multivariate
  - Endogeneity or confounding
  - Interaction or Moderation
  - Right or Wrong
- Maciejewski ML, Weaver ML and Hebert PL. (2011) *Med Care Res Rev 68 (2): 156-176*

Polls

Understanding Causation:
Randomized Clinical Trial

- RCTs are the gold-standard research design for assessing causality
- What is unique about a randomized trial?
  - The treatment / exposure is randomly assigned
- Benefits of randomization:
  - Causal inferences

Randomization

- Random assignment distinguishes experimental and non-experimental design
- Random assignment should not be confused with random selection
  - Selection can be important for generalizability (e.g., randomly-selected survey participants)
  - Random assignment is required for understanding causation

Limitations of RCTs

- Generalizability to real life may be low
  - Exclusion criteria may result in a select sample
- Hawthorne effect (both arms)
- RCTs are expensive and slow
- Can be unethical to randomize people to certain treatments or conditions
- Quasi-experimental design can fill an important role

Can Secondary Data Help us understand Causation?

Study: Coffee may make you lazy

Coffee not linked to psoriasis

Coffee, exercise may decrease risk of skin cancer

Coffee: An effective weight loss tool

Coffee poses no threat to hearts, may reduce diabetes risk: EPIC data

Coffee may make high achievers slack off

Observational Data

- Widely available (especially in VA)
- Permit quick data analysis at a low cost
- May be realistic/ generalizable

- Key independent variable may not be exogenous – it may be endogenous

Endogeneity

- A variable is said to be **endogenous** when it is correlated with the error term (assumption 4 in the classic linear model)
- If there exists a loop of causality between the independent and dependent variables of a model leads, then there is endogeneity

Endogeneity

- Endogeneity can come from:
  - Measurement error
  - Autoregression with autocorrelated errors
  - Simultaneity
  - Omitted variables
  - Sample selection

Elements of an Equation

Maciejewski ML, Diehr P, Smith MA, Hebert P. Common methodological terms in health services research and their synonyms. *Med Care.* Jun 2002;40(6):477-484.

Terms

- Univariate– the statistical expression of one variable
- Bivariate– the expression of two variables
- Multivariate– the expression of more than one variable (can be dependent or independent variables)

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

Covariate, RHS variable,
Predictor, independent
variable

Intercept

Dependent variable
Outcome measure

Error Term

Note the similarity to the equation of a line (y=mx+B)

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

“i” is an index.

If we are analyzing people, then this typically refers to the person

There may be other indexes

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 Z_i + \varepsilon_i$$

Two covariates

Intercept

DV

Error Term

Different notation

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 Z_i + \sum_j B_{ij} X_{ij} + \varepsilon_i$$

j covariates

Intercept

DV

Error Term

Error term

- Error exists because
  1. Other important variables might be omitted
  2. Measurement error
  3. Human indeterminacy
- Understand error structure and minimize error
- Error can be additive or multiplicative

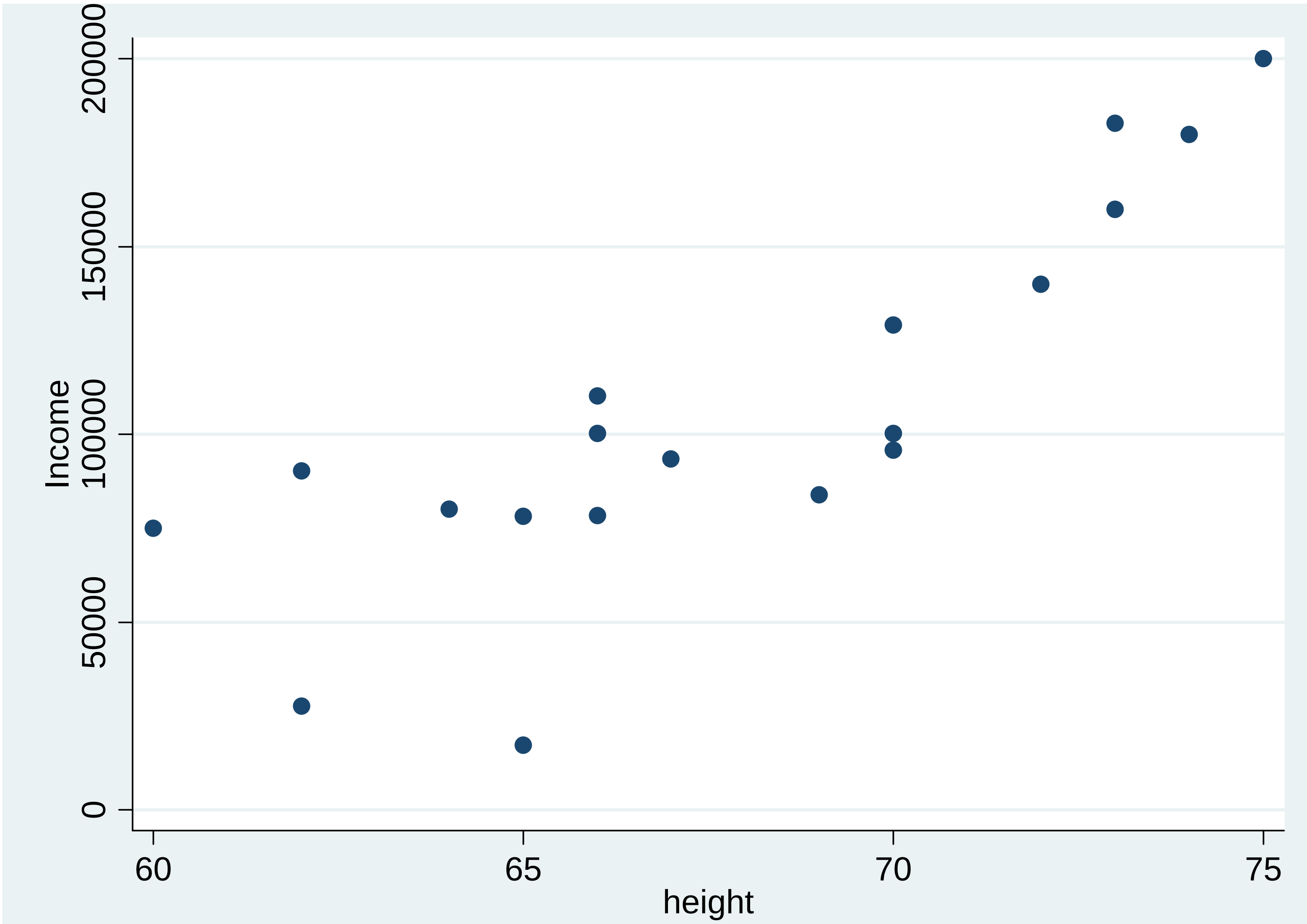
See Kennedy, P. <u>A Guide to Econometrics</u>

Example: is height associated with income?

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

- Y=income; X=height
- Hypothesis: Height is not related to income (B_1=0)
- If B_1=0, then what is B_0?

Height and Income

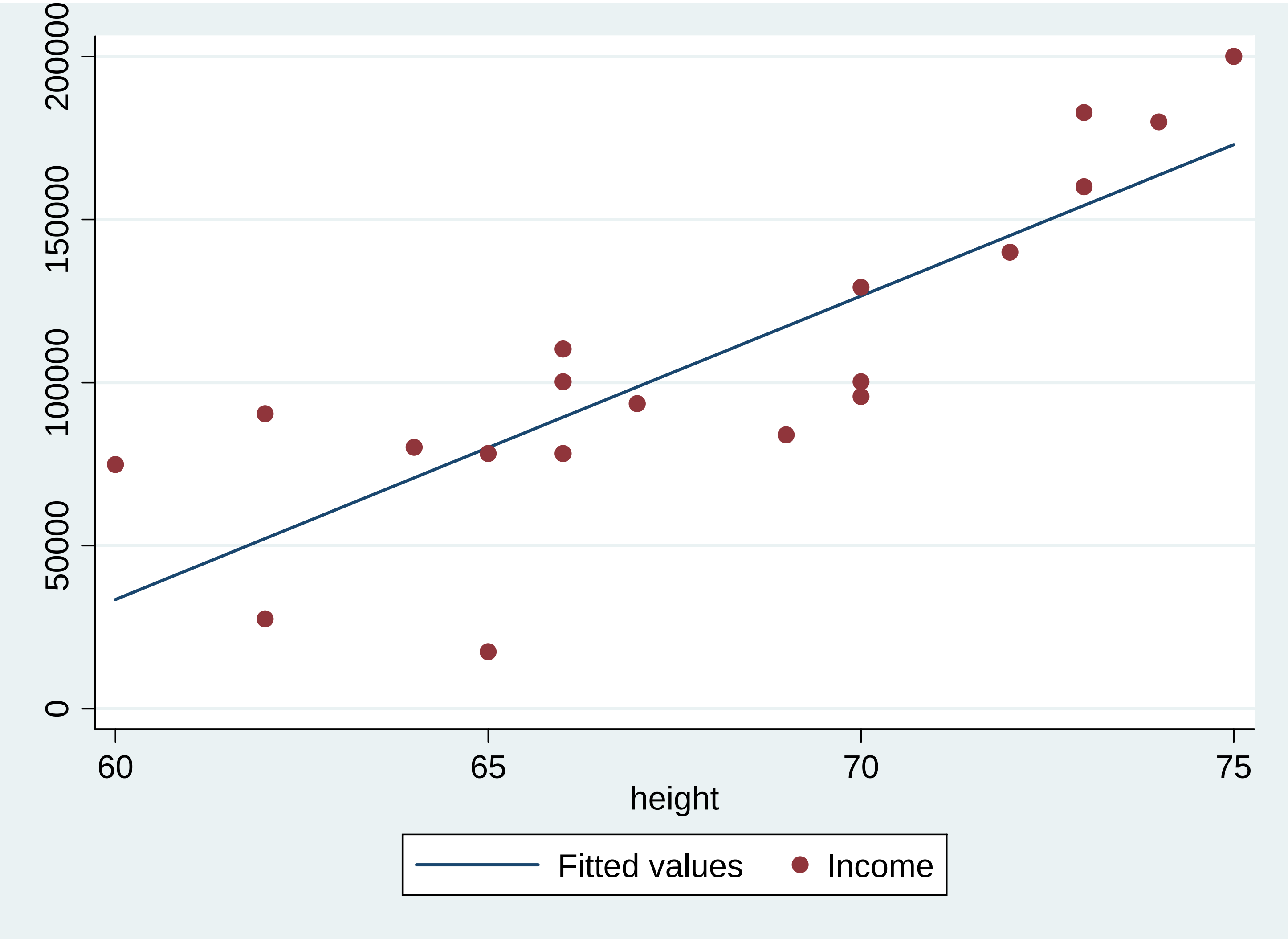


How do we want to describe the data?

Estimator

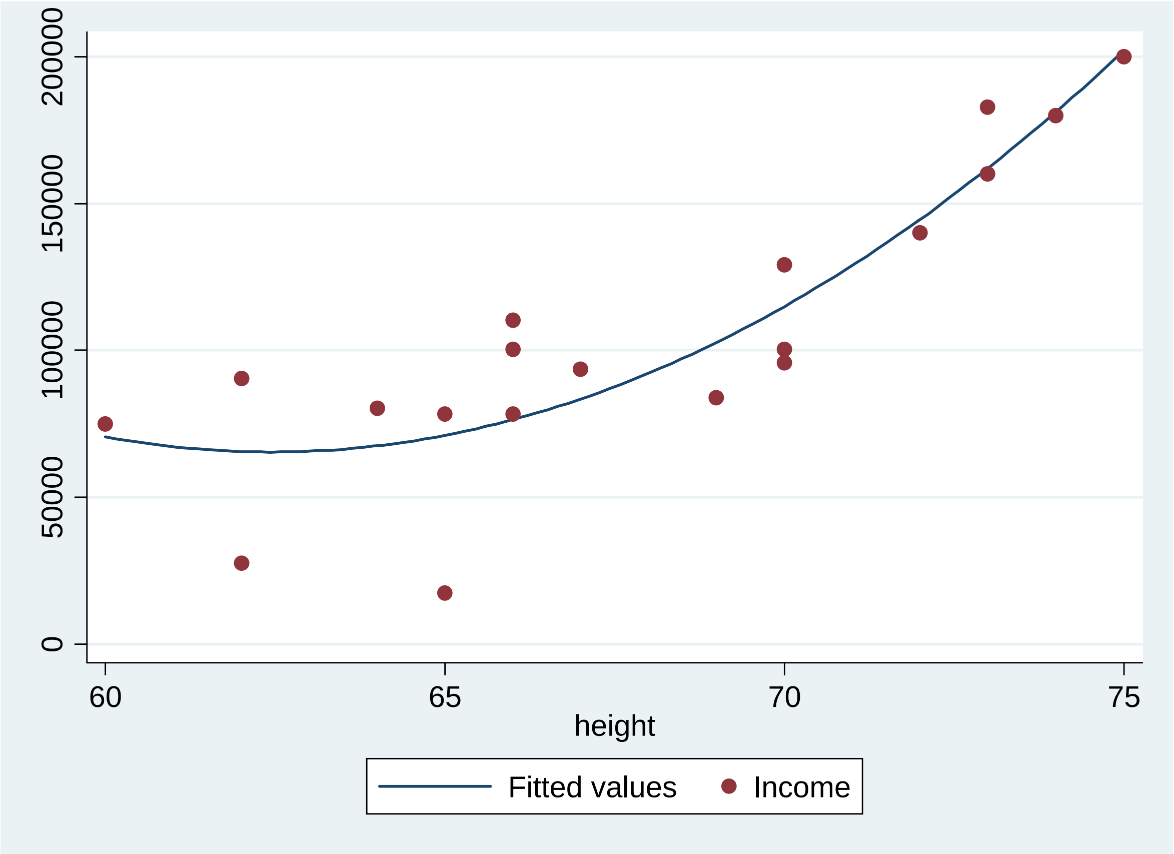
- A statistic that provides information on the parameter of interest (e.g., height)
- Generated by applying a function to the data
- Many common estimators
  - Mean and median (univariate estimators)
  - Ordinary least squares (OLS) (multivariate estimator)

Ordinary Least Squares (OLS)



Other estimators

- Least absolute deviations
- Maximum likelihood

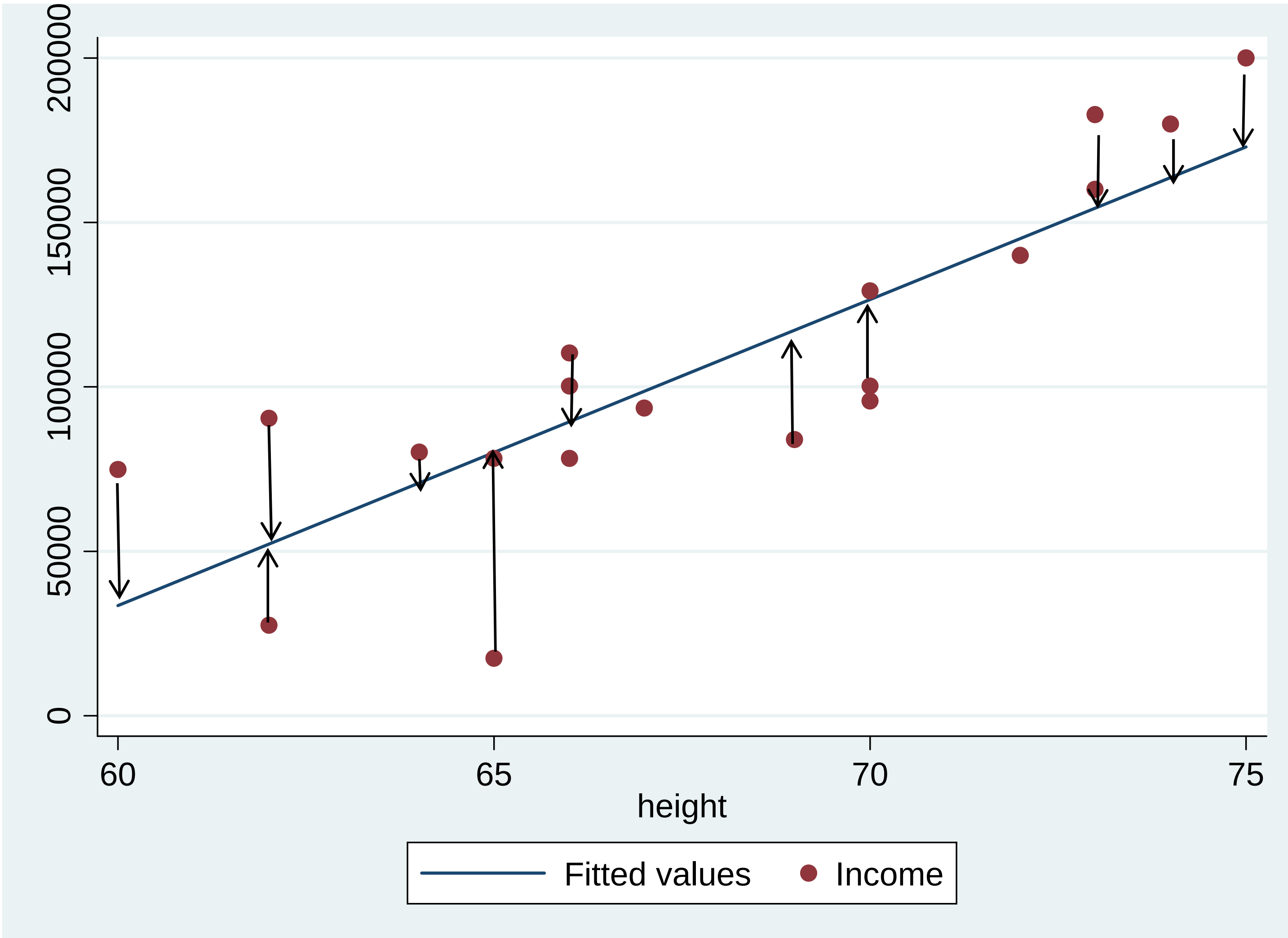


Choosing an Estimator

- Least squares
- Unbiasedness
- Efficiency (minimum variance)
- Asymptotic properties
- Maximum likelihood
- Goodness of fit

- We'll talk more about identifying the "right" estimator throughout this course.

How is the OLS fit?



What about gender?

- How could gender affect the relationship between height and income?
  - Gender-specific intercept
  - Interaction

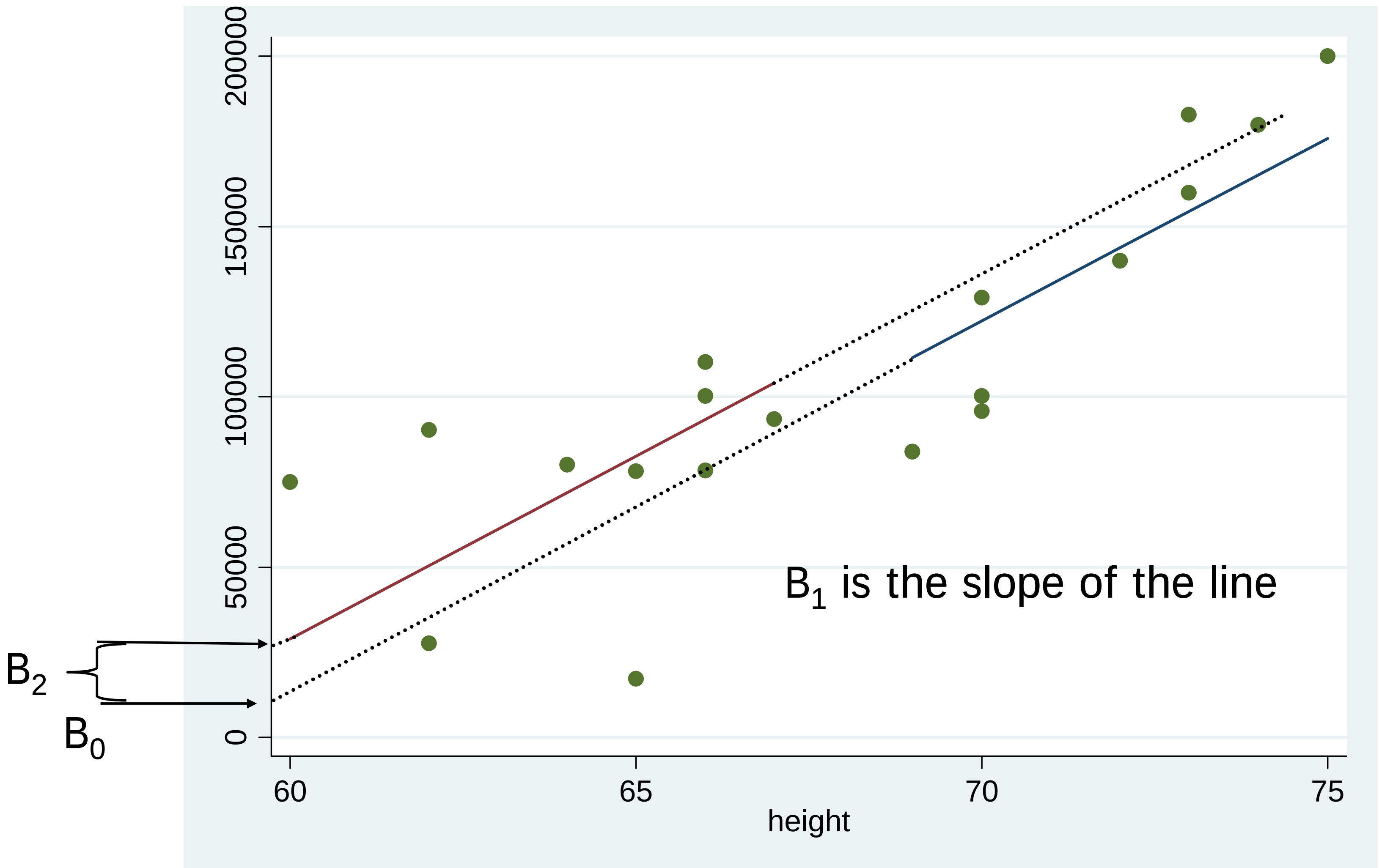
Gender Indicator Variable

height

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 Z_i + \varepsilon_i$$

Gender Intercept

Gender-specific Indicator



Interaction

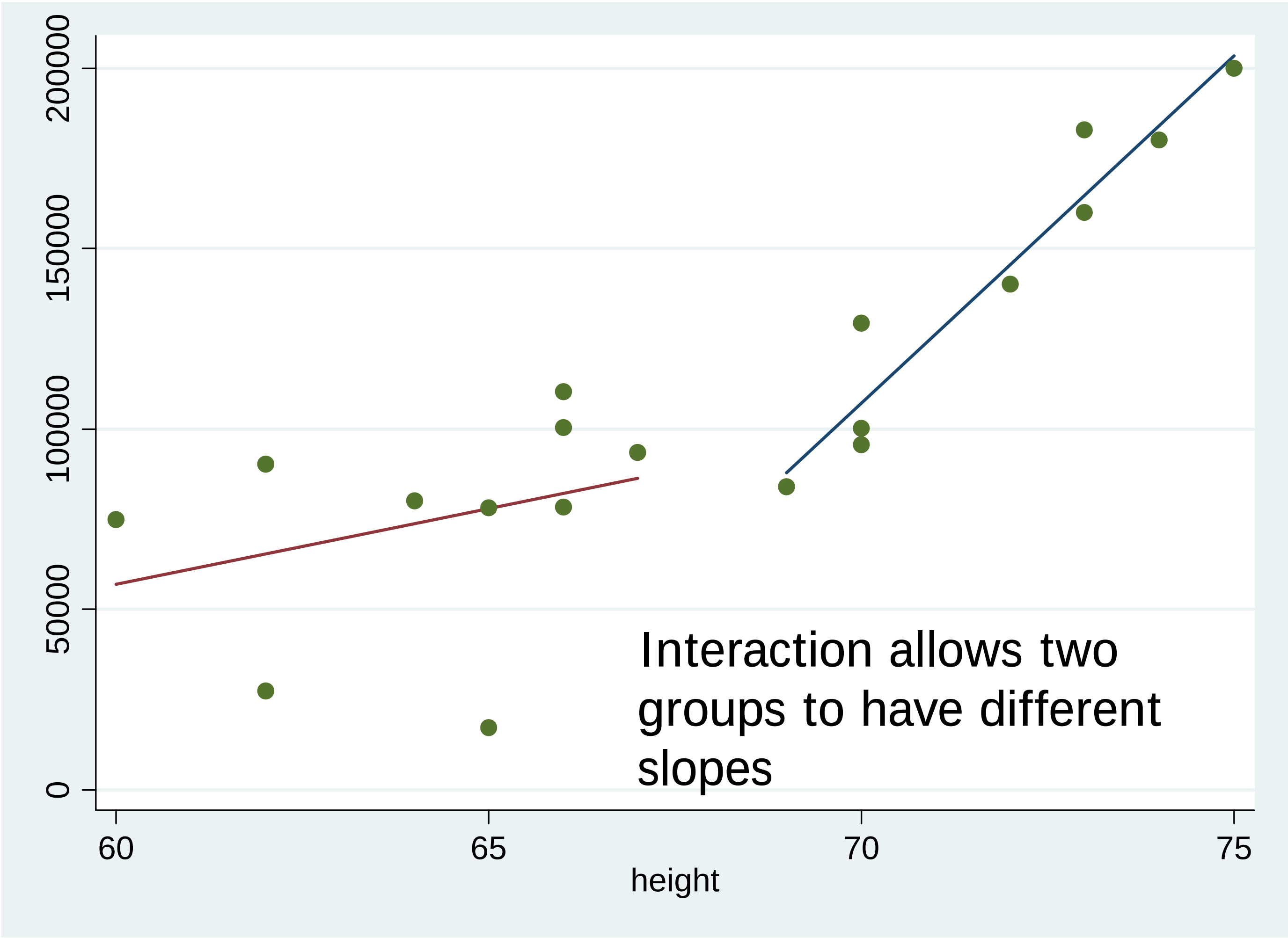
height gender

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 Z_i + \beta_3 X_i Z_i + \varepsilon_i$$

Interaction Term,
Effect modification,
Modifier

Note: the gender "main effect" variable is still in the model

Gender Interaction



Classic Linear Regression (CLR)

Assumptions

Classic Linear Regression

- No “superestimator”
- CLR models are often used as the starting point for analyses
- 5 assumptions for the CLR
- Variations in these assumption will guide your choice of estimator (and happiness of your reviewers)

Assumption 1

- The dependent variable can be calculated as a linear function of a specific set of independent variables, plus an error term
- For example,

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 Z_i + \beta_3 X_i Z_i + \varepsilon_i$$

Violations to Assumption 1

- Omitted variables
- Non-linearities
  - Note: by transforming independent variables, a nonlinear function can be made from a linear function

Testing Assumption 1

- Theory-based transformations
- Empirically-based transformations
- Common sense
- Ramsey RESET test
- Pregibon Link test

Ramsey J. Tests for specification errors in classical linear least squares regression analysis. *Journal of the Royal Statistical Society*. 1969;Series B(31):350-371.

Pregibon D. Logistic regression diagnostics. *Annals of Statistics*. 1981;9(4):705-724.

Assumption 1 and Stepwise

- Statistical software allows for creating models in a "stepwise" fashion
- Be careful when using it.
  - Little penalty for adding a nuisance variable
  - BIG penalty for missing an important covariate

Assumption 2

- Expected value of the error term is 0

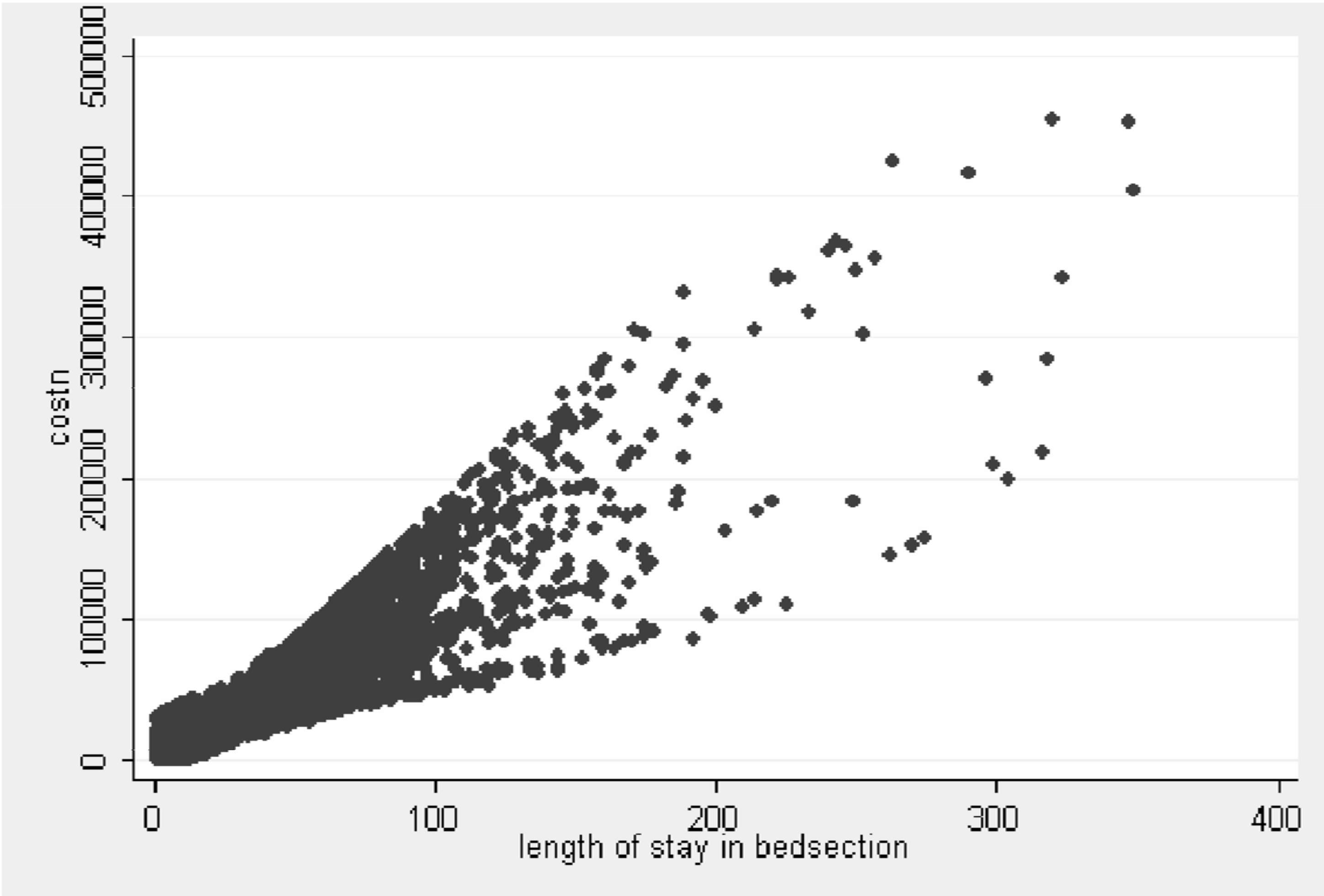
$$E(u_i)=0$$

- Violations lead to biased intercept
- A concern when analyzing cost data

Assumption 3

- IID– Independent and identically distributed error terms
  - Autocorrelation: Errors are uncorrelated with each other
  - Homoskedasticity: Errors are identically distributed

Heteroskedasticity



Violating Assumption 3

- Effects
  - OLS coefficients are unbiased
  - OLS is inefficient
  - Standard errors are biased
- Plotting is often very helpful
- Different statistical tests for heteroskedasticity
  - GWHet--but statistical tests have limited power

Fixes for Assumption 3

- Transforming dependent variable may eliminate it
- Robust standard errors (Huber White or sandwich estimators)

Assumption 4

- Observations on independent variables are considered fixed in repeated samples
- $E(x_i u_i)=0$
- Violations
  - Errors in variables
  - Autoregression
  - Simultaneity

Endogeneity

Assumption 4:
Errors in Variables

- Measurement error of dependent variable (DV) is maintained in error term.
- OLS assumes that covariates are measured without error.
- Error in measuring covariates can be problematic

Common Violations

- Including a lagged dependent variable(s) as a covariate
- Contemporaneous correlation
  - Hausman test (but very weak in small samples)
- Instrumental variables offer a potential solution

Assumption 5

- Observations > covariates
- No multicollinearity

- Solutions
  - Remove perfectly collinear variables
  - Increase sample size

Any Questions?

Statistical Software

- I frequently use SAS for data management
- I use Stata for my analyses
- Stattransfer

Regression References

- Kennedy A Guide to Econometrics
- Greene. Econometric Analysis.
- Wooldridge. Econometric Analysis of Cross Section and Panel Data.
- Winship and Morgan (1999) The Estimation of Causal Effects from Observational Data *Annual Review of Sociology*, pp. 659-706.