Econometrics with Observational Data

Introduction and Identification

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Health Economics Resource Center

HSR&D
HEALTH SERVICES RESEARCH & DEVELOPMENT

Goals for Course

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

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

Course Schedule

	Date	Presenter	Title
1	*1/23/19*	Todd Wagner	Econometrics Course: Introduction & Identification
2	*1/30/19*	Wei Yu	Research Design
3	*2/6/19*	Todd Wagner	Propensity Scores
4	*2/13/19*	Jean Yoon	Natural Experiments & Difference-in-Differences
5	*2/20/19*	Liam Rose	Regression Discontinuity
6	*2/27/19*	Wei Yu	Instrumental Variables
7	*3/6/19*	Jo Jacobs	Fixed Effects and Random Effects
8	*3/13/19*	Ciaran Phibbs	Specifying the Regression Model
9	*3/27/19*	Ciaran Phibbs	Limited Dependent Variables
10	*4/3/19*	Paul Barnett /Jo Jacobs	Cost as the Dependent Variable (Part I)
11	*4/10/19*	Paul Barnett /Jo Jacobs	Cost as the Dependent Variable (Part II)

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

- Maciejewski ML, Weaver ML and Hebert PL. (2011) *Med Care Res Rev 68 (2): 156-176*

Polls

- What is your background with analyzing observational data?
  1. Beginner. Understand averages, medians and variance, but don't run regression
  2.
  3. Modest experience. Familiar with linear or logistic regression
  4.
  5. Reasonably advanced. Have used statistical methods to control for unobserved heterogeneity or endogeneity.

Do you have advanced training in Economics?

- Yes
- No
- It was so long ago, I can’t remember

Years since last degree

- 1
- 2-3
- 3-4
- 5-7
- 8+

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 *plausible* loop of causality between the independent and dependent variables, then there is endogeneity

Endogeneity

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

Example of Endogeneity: smoking

- People's decision to smoke or not smoke is affected by many factors.
  - Family, friends, genetics

- Imagine running a regression

$$\text{Heart attacks}_i = \alpha + \text{smoking}_i + \varepsilon_i$$

Smoking

- Endogeneity isn’t a problem if you observe everything and can control for it.
- Different approaches
  - Control for observables as best we can (propensity scores)
  - Focus on variation that is exogenous (instrumental variables, regression discontinuity)

Econometrics v Statistics

- Often use different terms
- Cultural norms–if it seems endogenous, it probably is
- Underlying data generating model is economic. Rational actors concerned with
  - Profit maximization
  - Quantity maximization
  - Time minimization

Elements of an Equation

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

$$Y_i = \beta_0 + \underbrace{\beta_1 X_i + \beta_2 Z_i}_{\text{Two covariates}} + \varepsilon_i$$

Intercept

DV

Error Term

Different notation

$$Y_i = \beta_0 + \underbrace{\beta_1 X_i + \beta_2 Z_i + \sum_j B_{ij} X_{ij}}_{\text{j covariates}} + \varepsilon_i$$

Intercept

DV

Error Term

Error term

- Error exists because
  1. Other important variables might be omitted
  2. Measurement error
  3. Human indeterminacy

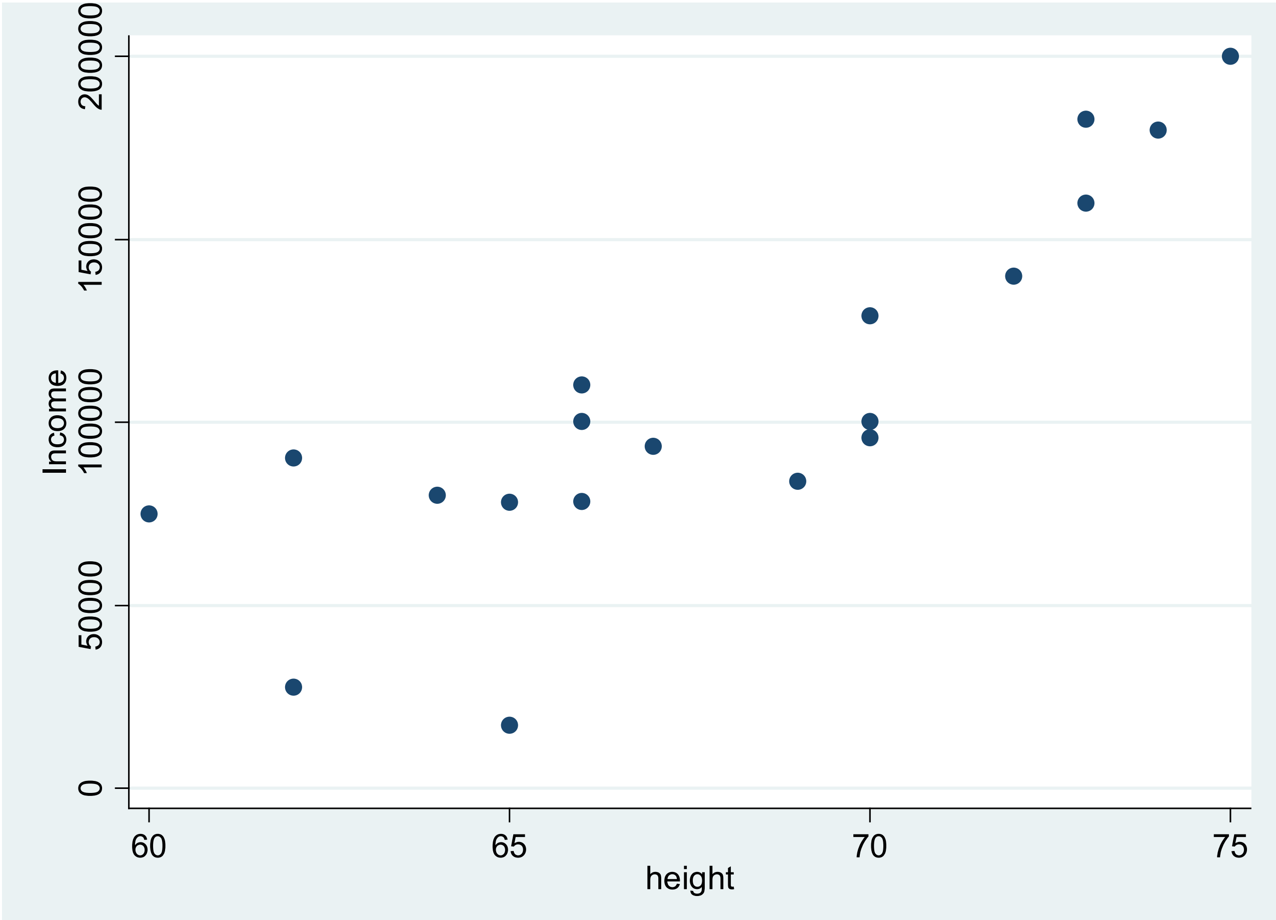
- Your goal
  - Understand error structure
  - minimize error

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

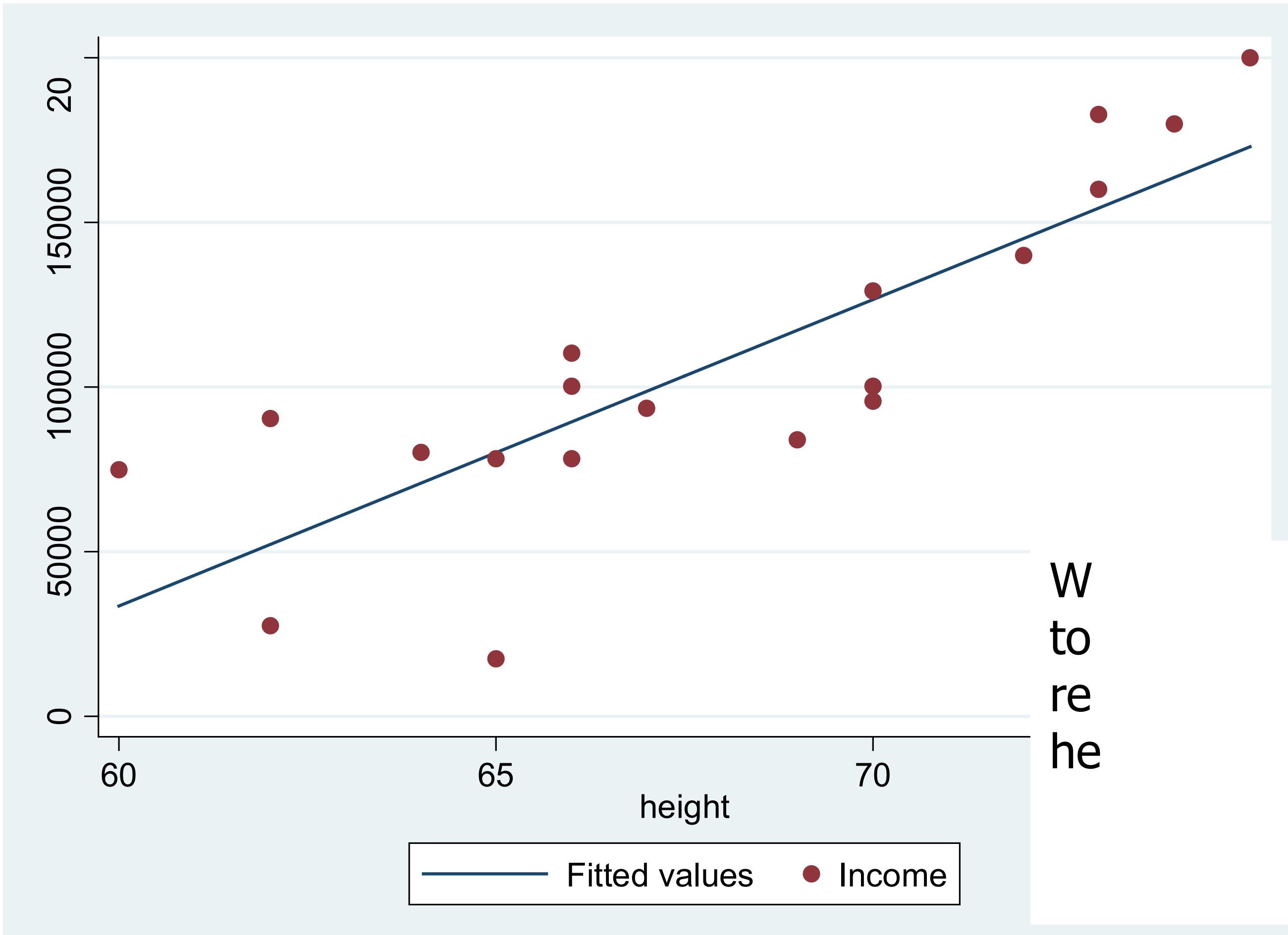


How do we want to describe the data?

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)



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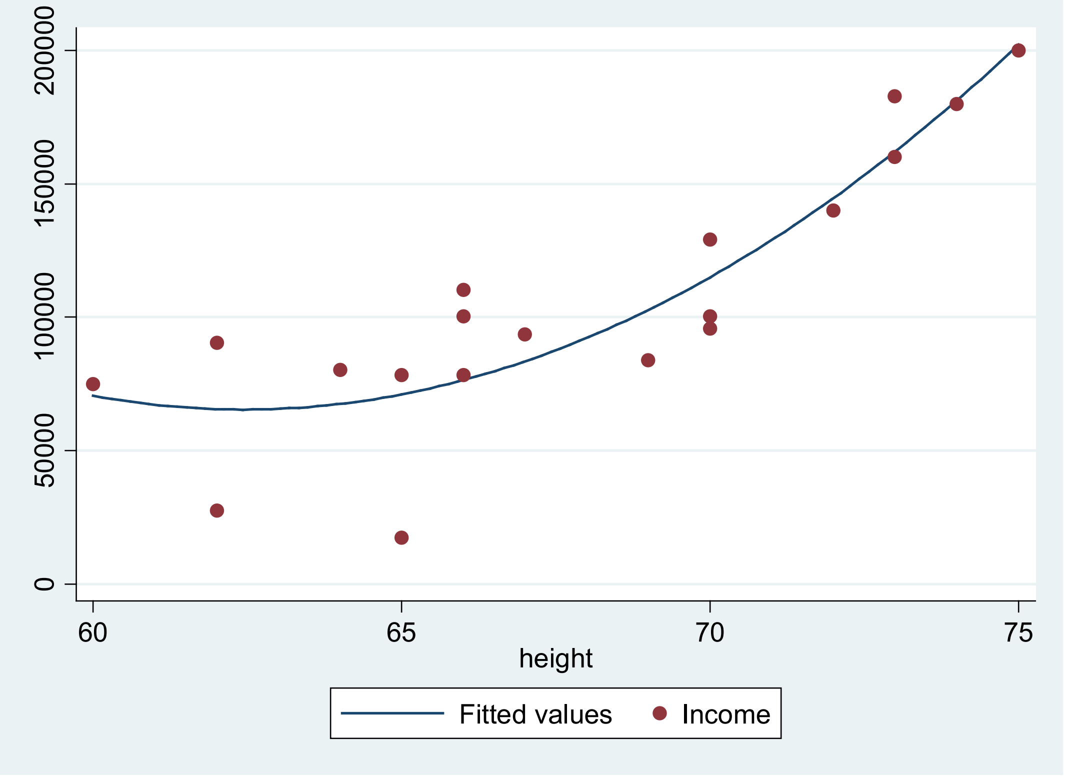
Other estimators

- Least absolute deviations
- Maximum likelihood

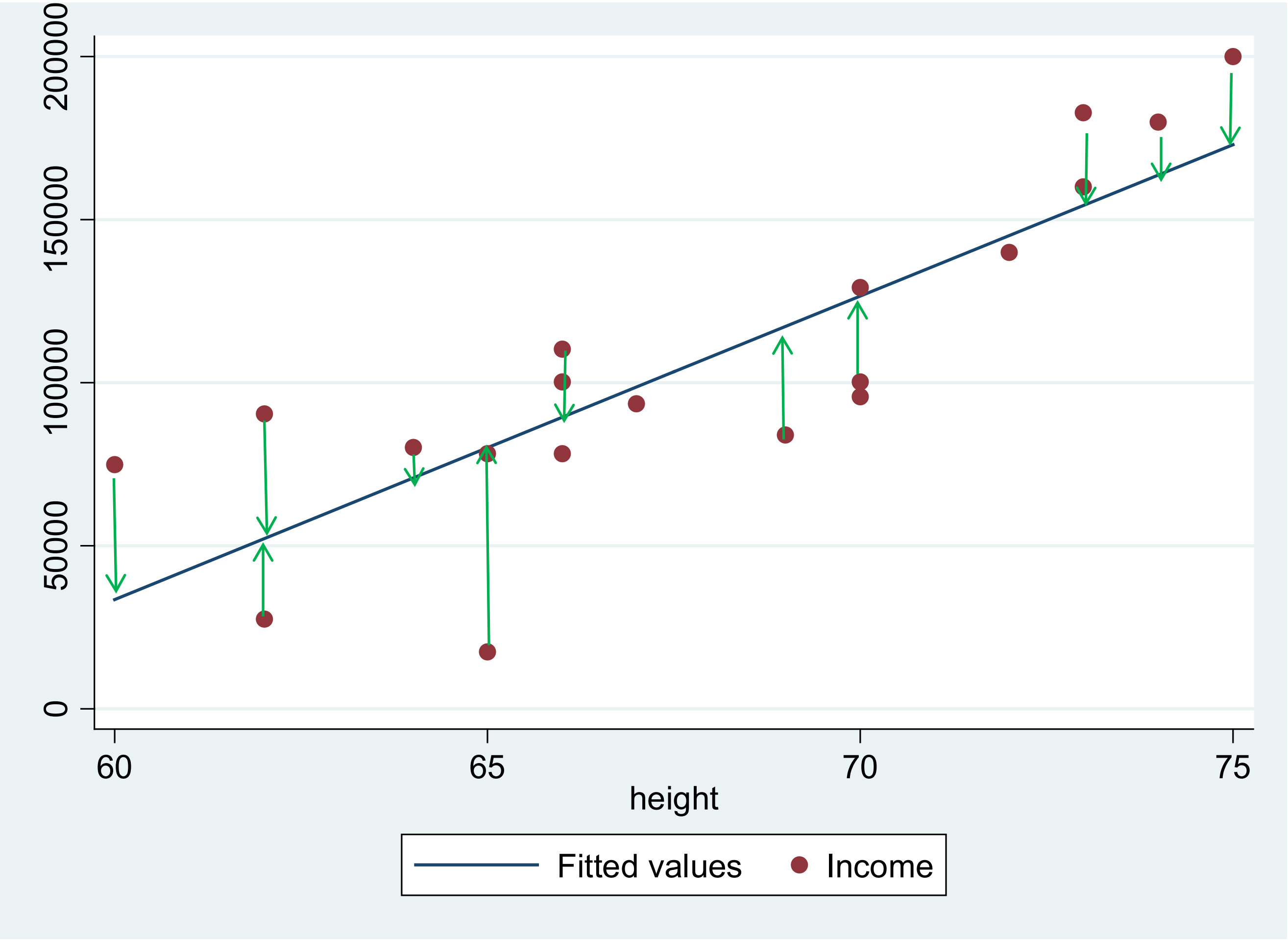


Choosing an Estimator

- 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

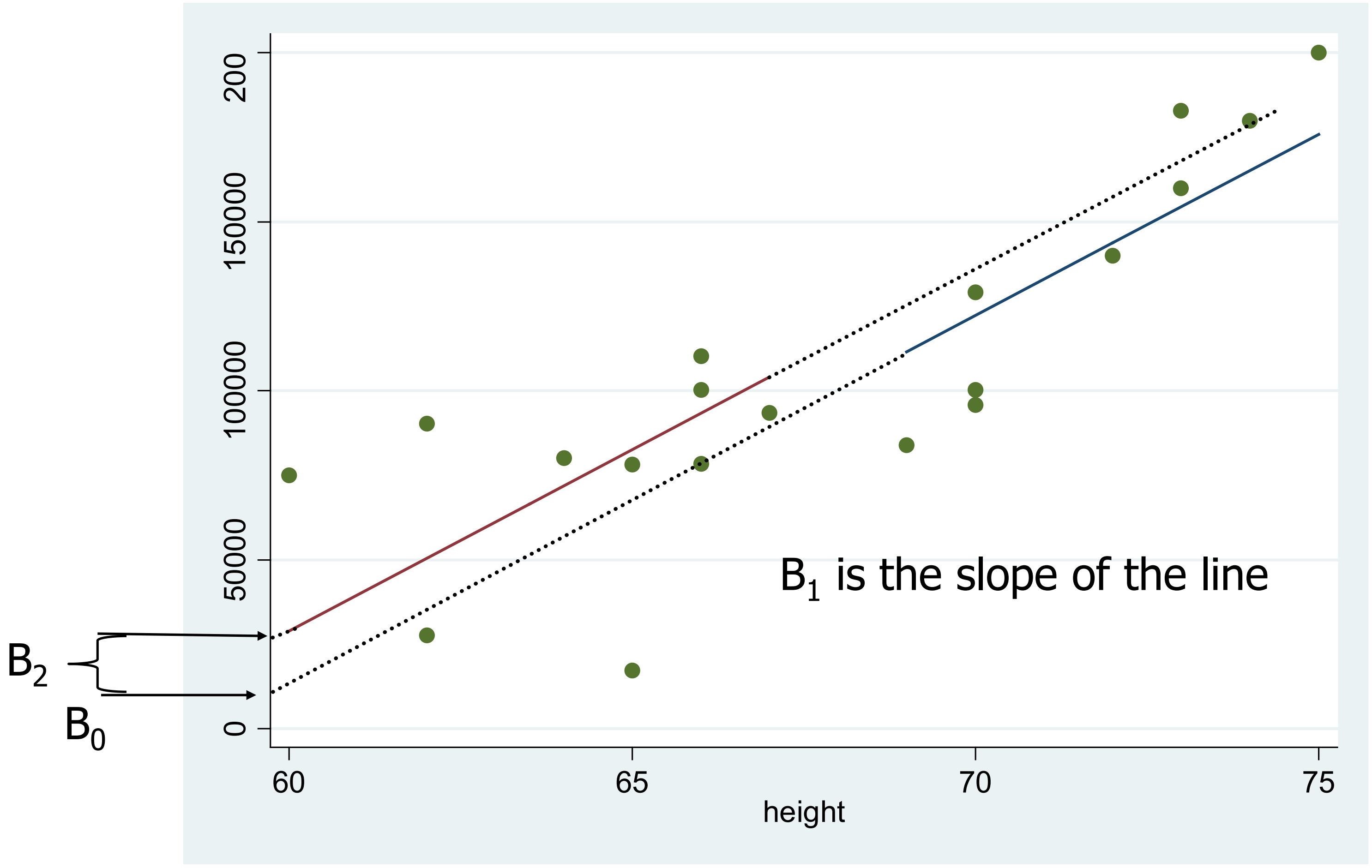
Gender Indicator Variable

height

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

Gender Intercept

Gender-specific Indicator

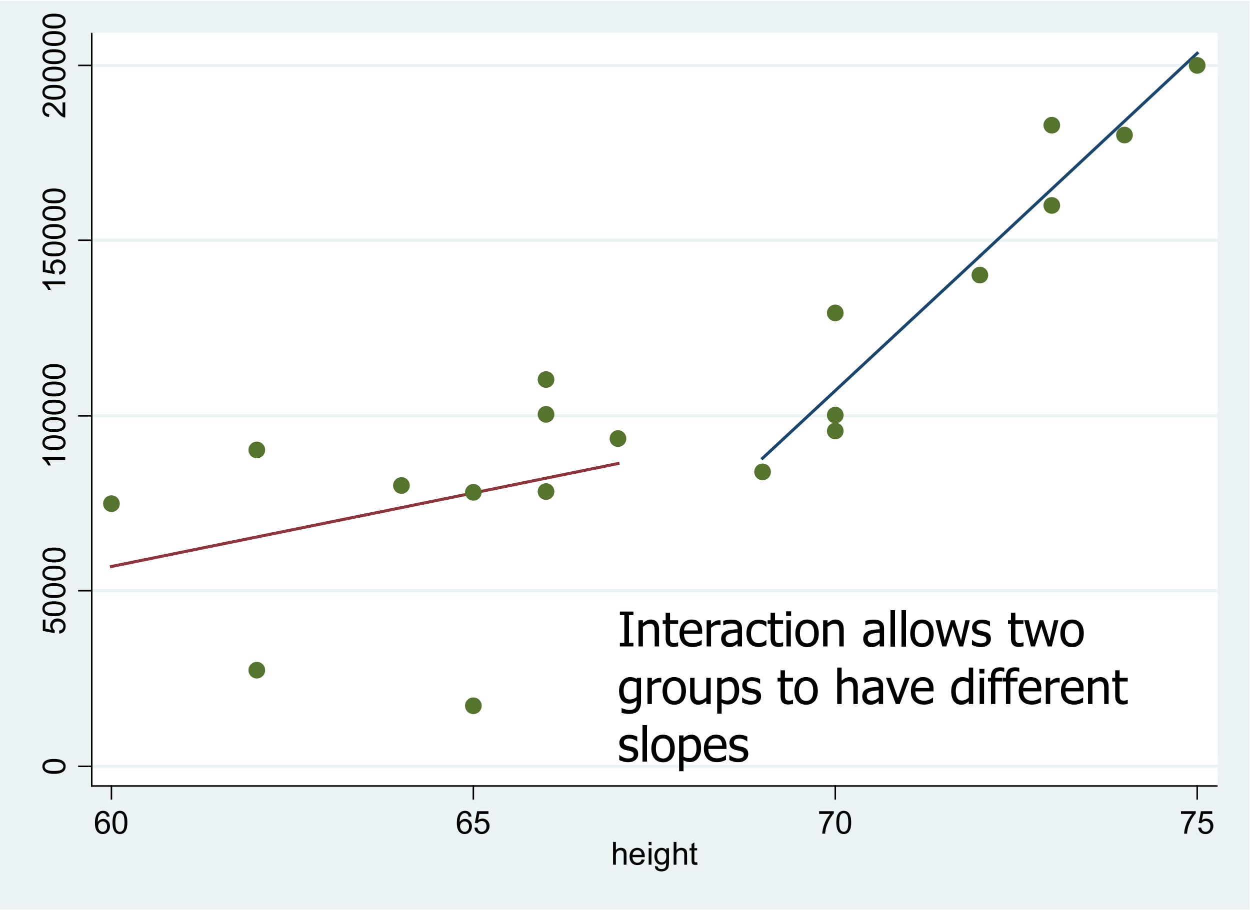


Interaction

$$Y_i = \beta_0 + \overset{\text{height}}{\beta_1 X_i} + \overset{\text{gender}}{\beta_2 Z_i} + \underbrace{\beta_3 X_i Z_i}_{\substack{\text{Interaction Term,} \\ \text{Effect modification,} \\ \text{Modifier}}} + \varepsilon_i$$

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

Gender Interaction



Identification

- Is an association meaningful?
- Should we change behavior or make policy based on associations?
- For many, associations are insufficient and we need to identify the **causal** relationship
- Identification requires that we meet all 5 assumptions in the classic linear model

Bad science can lead to bad policy

- Example: Bicycle helmet laws
- In laboratory experiments, helmets protect the head
- This may not translate to the real road
  - Do bikers behave differently when wearing a helmet?
  - Do drivers behave differently around bikers with/without helmets?
  - Do helmet laws have unintended consequences? (low uptake of bike share)

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 (e.g., Cobb-Douglas production)
- 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.

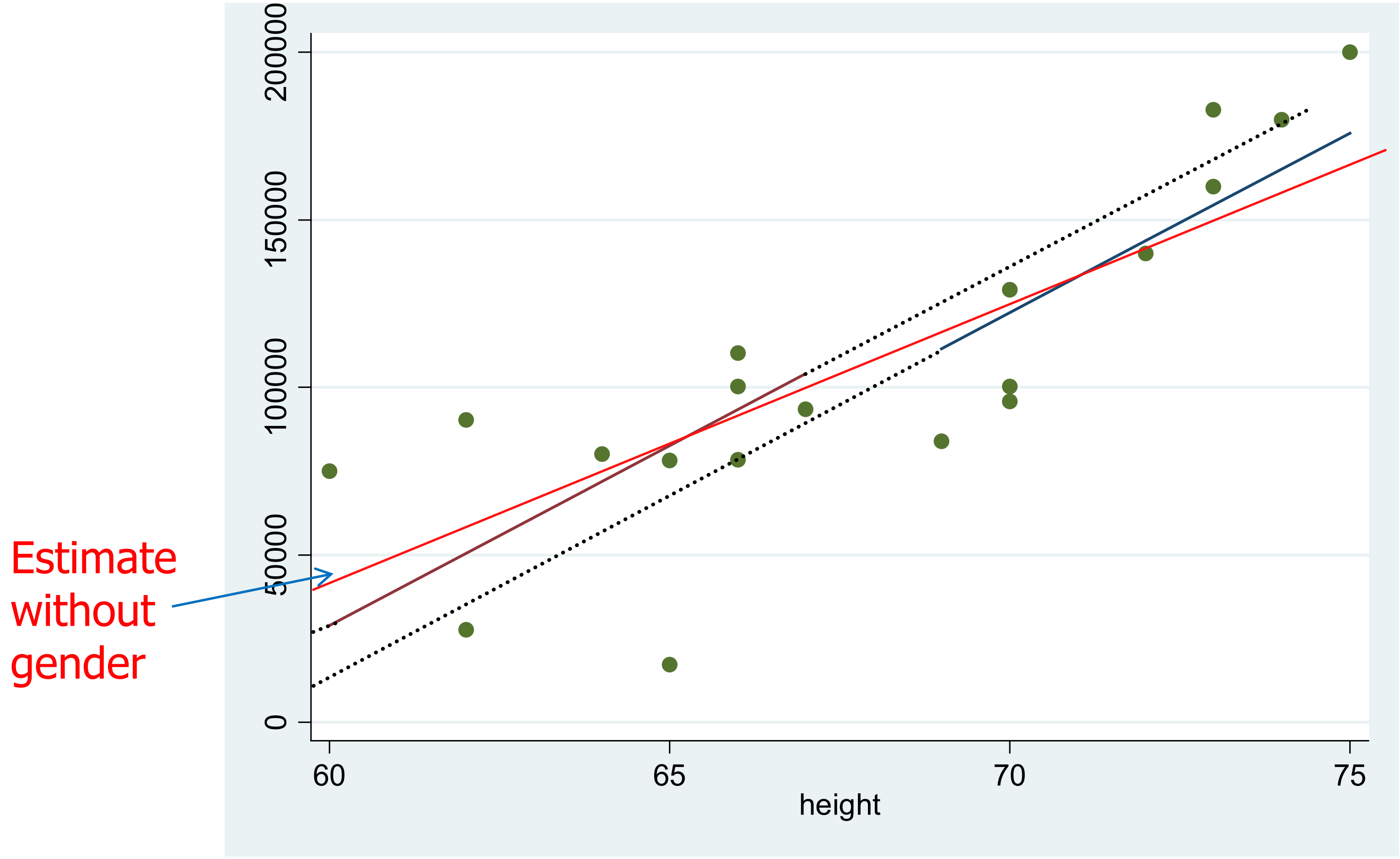
Pregibon D. Logistic regression diagnostics. *Annals of Statistics.* 1981;9(4):705-724.

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

Bias if Gender is Ignored



Assumption 2

- Expected value of the error term is 0

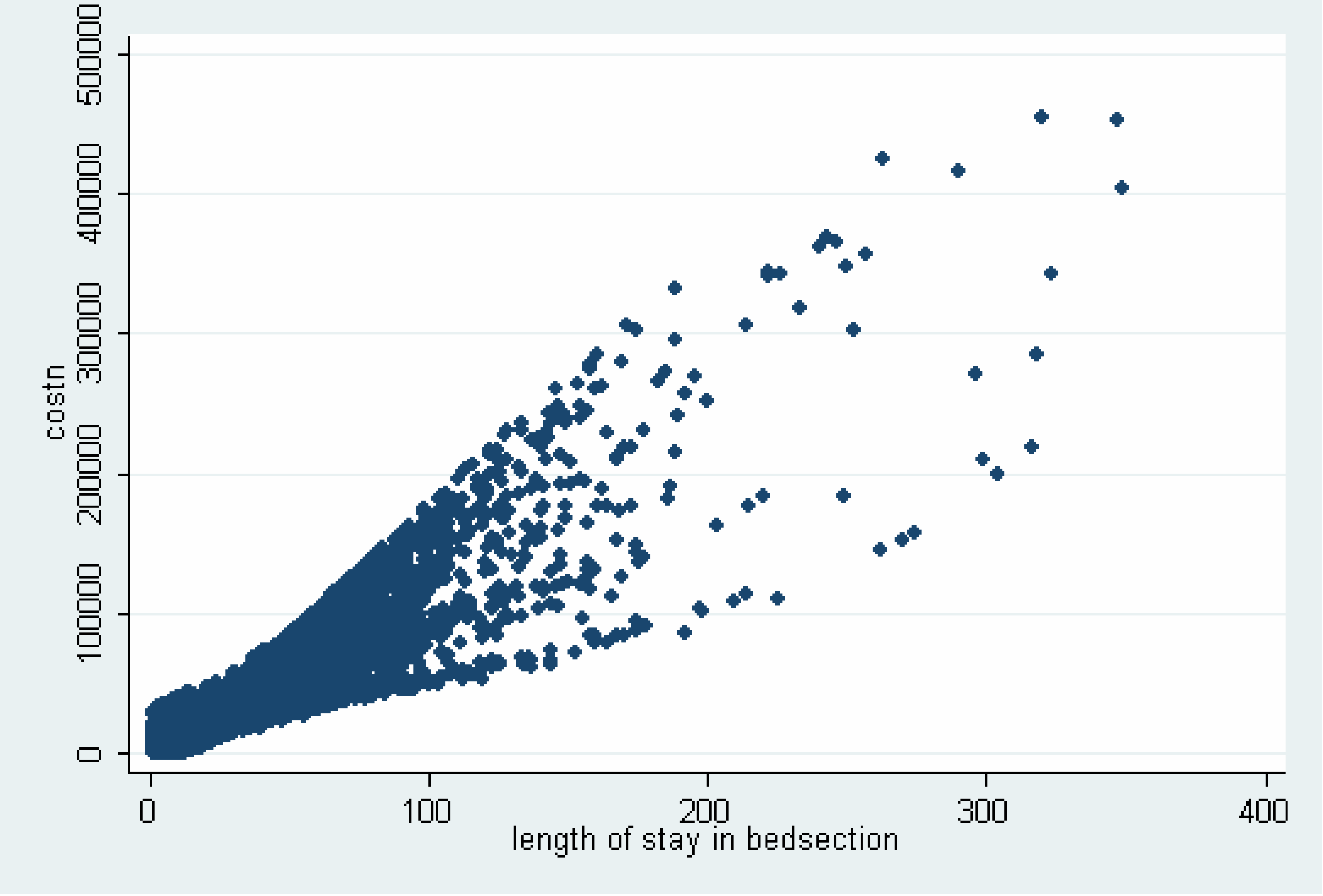
$$E(u_i)=0$$

- Violations lead to biased intercept
- A concern when analyzing cost data (Smearing estimator when working with logged costs)

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
- $E(x_i u_i | x) = 0$
- 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

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.

Any Questions?