# Econometrics with Observational Data

Introduction and Identification

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HERC
Health Economics Resource Center

VA
U.S. Department of Veterans Affairs
Veterans Health Administration
*Health Services Research & Development Service*

# Goals for Course

- VA researchers have access to large datasets (millions and billions of records)
- Turning these data from information to wisdom requires careful analyses
- In this course, we will
  - Describe econometric tools and their strengths and limitations
  - Use examples to reinforce learning

# Course Schedule

| Date | Title | Presenter(s) |
|---|---|---|
| 1/11/23 | Econometrics Seminar Series: Introduction & Identification | Todd Wagner, Ph.D. |
| 1/18/23 | Research Design | Laura Graham, Ph.D., M.P.H. |
| 1/25/23 | Propensity Scores | Todd Wagner, Ph.D. |
| 2/1/23 | Instrumental Variables | Kritee Gujral, Ph.D. |
| 2/15/23 | Regression Discontinuity | Liam Rose, Ph.D. |
| 2/22/23 | Natural Experiments & Difference-in-Difference | Jean Yoon, Ph.D. |
| 3/1/23 | Interval regression | Clara Dismuke-Greer, Ph.D. |
| 3/8/23 | Quantile regression | Diem Tran, Ph.D., M.P.P. |
| 3/15/23 | Multipart models of continuous outcomes | Peter Veazie, PhD |
| 3/22/23 | Right-hand Side Variables | Ciaran Phibbs, Ph.D. |
| 3/29/23 | Limited Dependent Variables | Ciaran Phibbs, Ph.D. |
| 4/5/23 | Fixed Effects and Random Effects | Josephine Jacobs, Ph.D. |
| 4/19/23 | Empirical Bayes | David Chan, M.D., Ph.D. |
| 4/26/23 | Cost as the Dependent Variable | Mark Bounthavong, Pharm.D., Ph.D. |

https://www.herc.research.va.gov/include/page.asp?id=course-econometrics

# Goals of Today's Class

- Are there ways to think about causation with observational data?
- Describe elements of an equation with an example
- 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
  - Hierarchical models or clustering

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

# 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
  - The exposure is exogeneous

- Benefits of (good) 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

- RCTs are expensive and slow
- Generalizability to real life may be low
  - https://www.precis-2.org/
- Hawthorne effect (both arms)
- Can be unethical to randomize people to certain treatments or conditions

- Quasi-experimental design can fill an important role

# *One Perspective:*

FULL TEXT ARTICLE

## Real-world studies no substitute for RCTs in establishing efficacy

Hertzel C Gerstein, John McMurray and Rury R Holman

Lancet, The, 2019-01-19, Volume 393, Issue 10168, Pages 210-211, Copyright © 2019 Elsevier Ltd

"In the absence of randomisation, analyses of most observational data from the real world, regardless of their sophistication, can only be viewed as hypothesis generating."

Study: Coffee may make you lazy

Coffee not linked to psoriasis

Coffee: An effective weight loss tool

Coffee exercise may decrease risk of skin cancer

# Can secondary data be used to understand causation?

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

Coffee may make high achievers slack off

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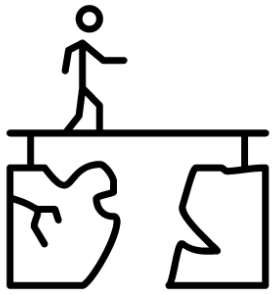
# Observational Data

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

- Key covariate may not be exogenous – it may be endogenous



# Endogeneity

- A variable is **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

# Example of Endogeneity: Testosterone Injections

- Research has correlated bone density and testosterone in men.
- Men generate different levels of testosterone.
  - This is endogenous testosterone.
  - There may be many reasons why a man's internal testosterone is low/high
- Giving men exogenous testosterone (an injection) may lead to very different effects from those studies that examine endogenous testosterone.

# Testosterone

- Endogeneity isn't necessarily 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)
- But, there is no way to control for everything

# Endogeneity

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

# Econometrics vs Statistics

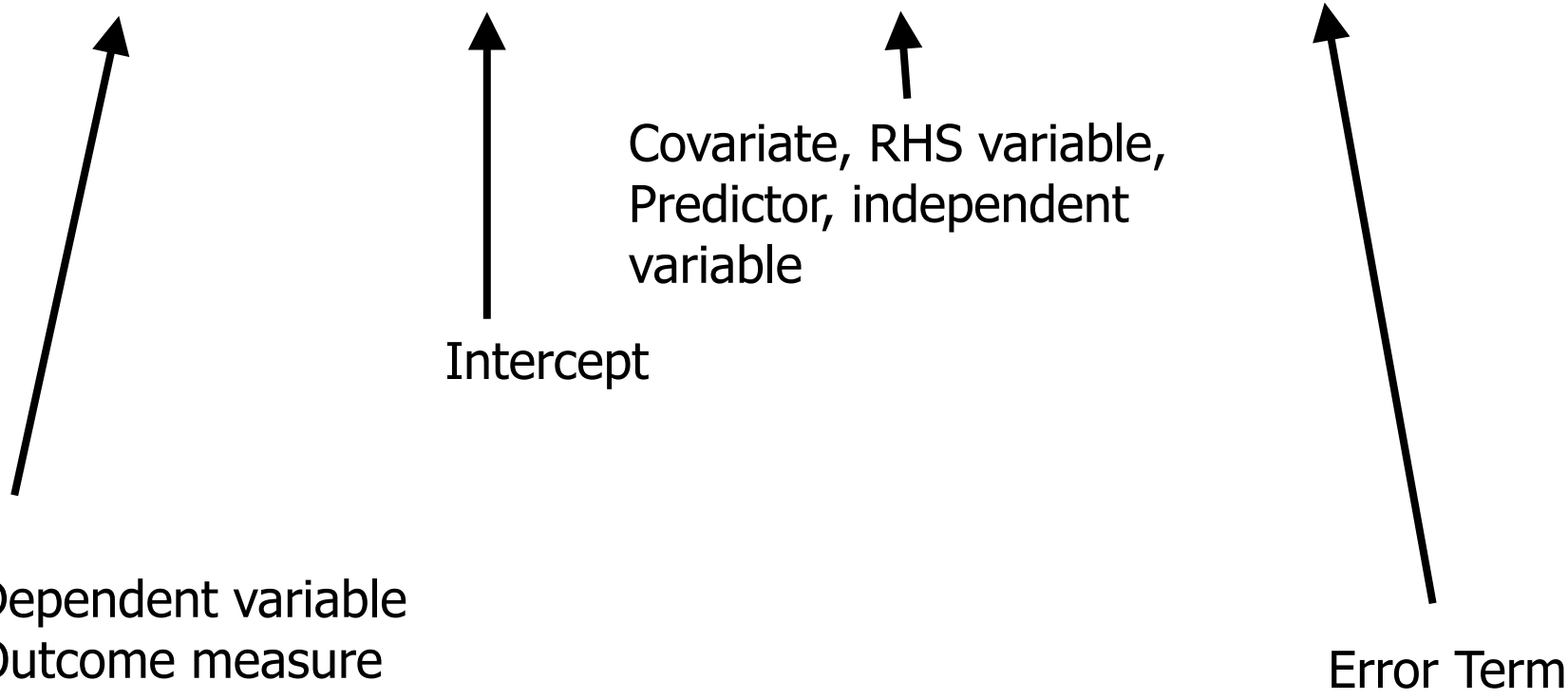
- Often use different terms
- Cultural norms
  - In health economics if it seems endogenous, it probably is
  - Underlying data generating model is economic. Rational actors concerned with
    - Profit maximization
    - Quantity maximization
    - Time minimization
  - Random and fixed effects
  - Propensity scores

# 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)

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




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

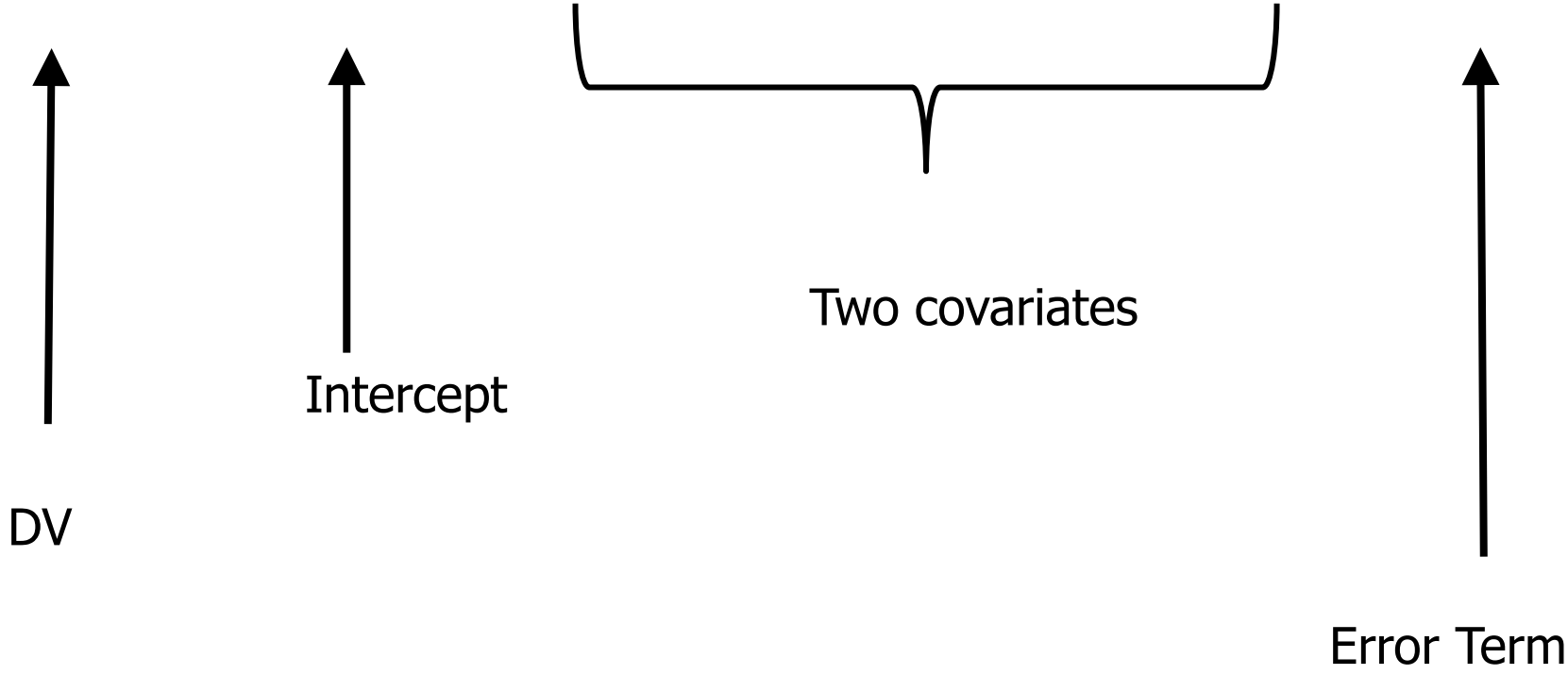
$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

"i" is an index.

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

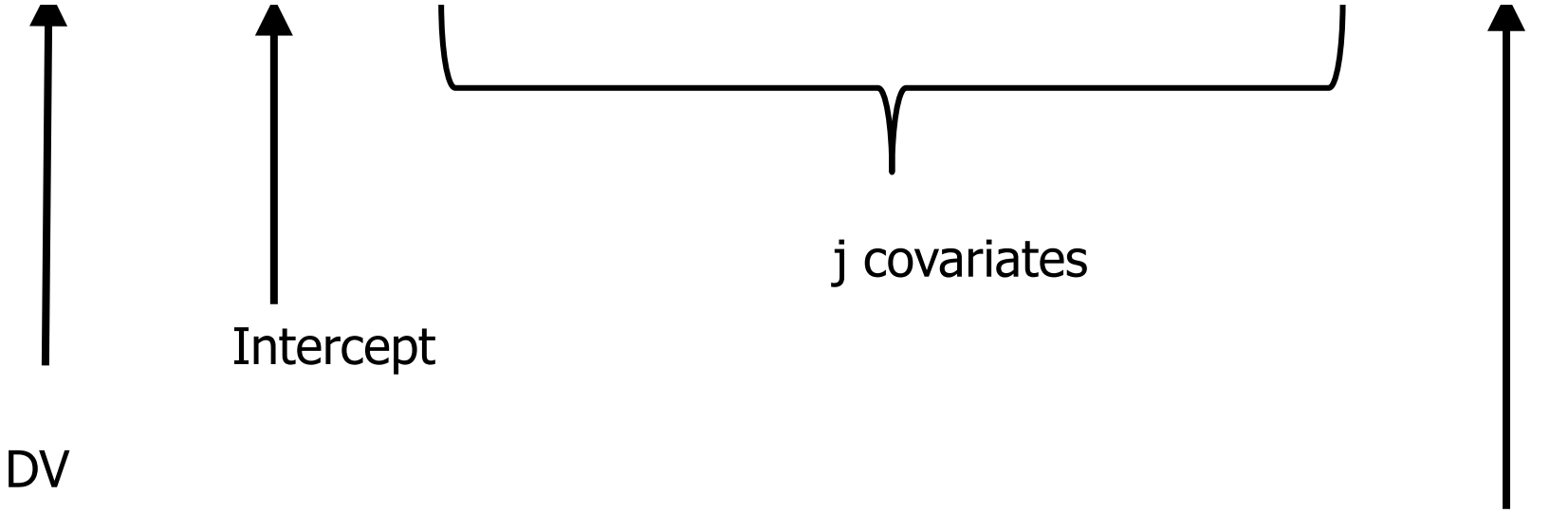
There may be other indexes

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



# Different notation

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



# 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

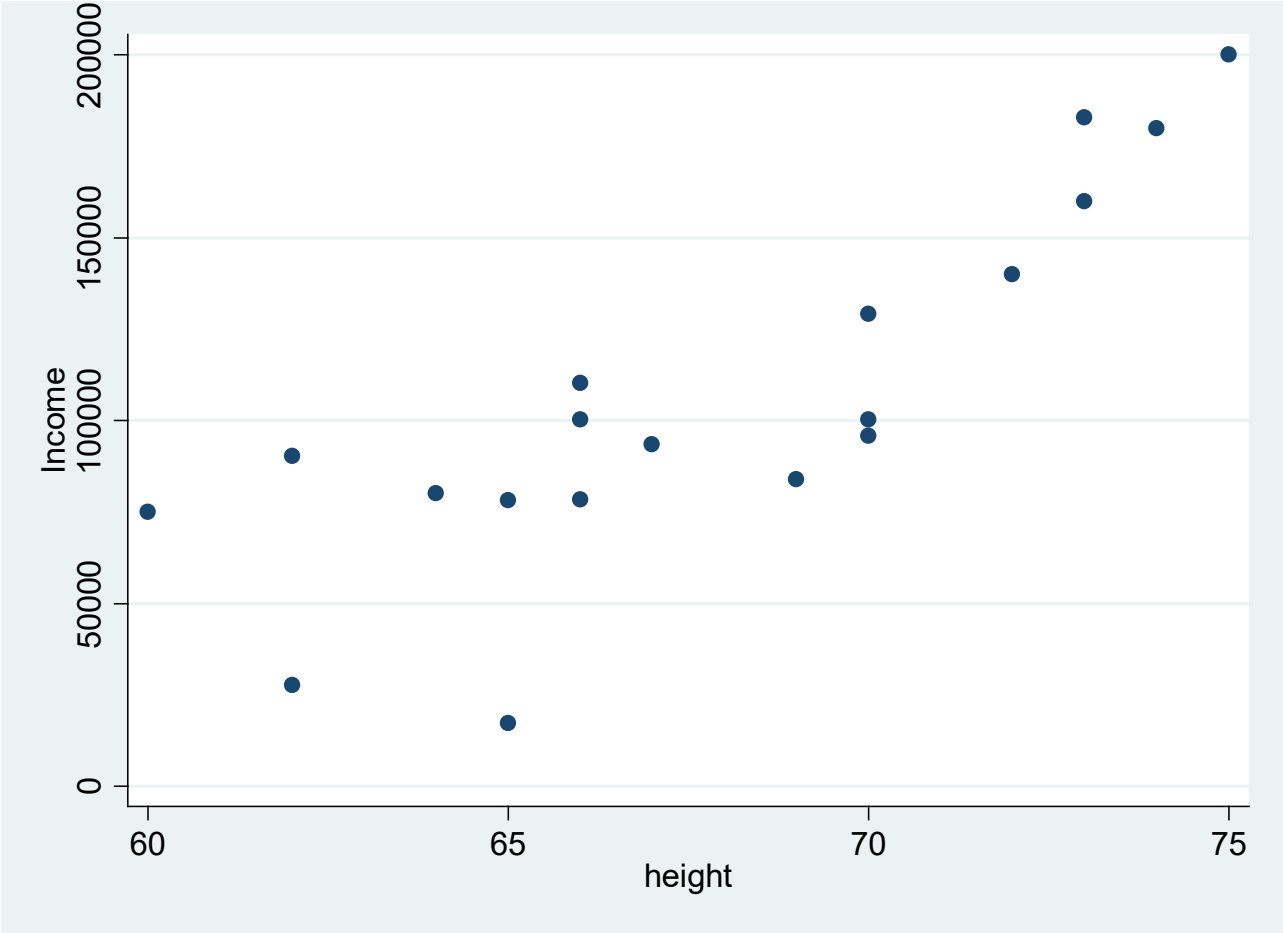
See Kennedy, P. A Guide to Econometrics

# 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

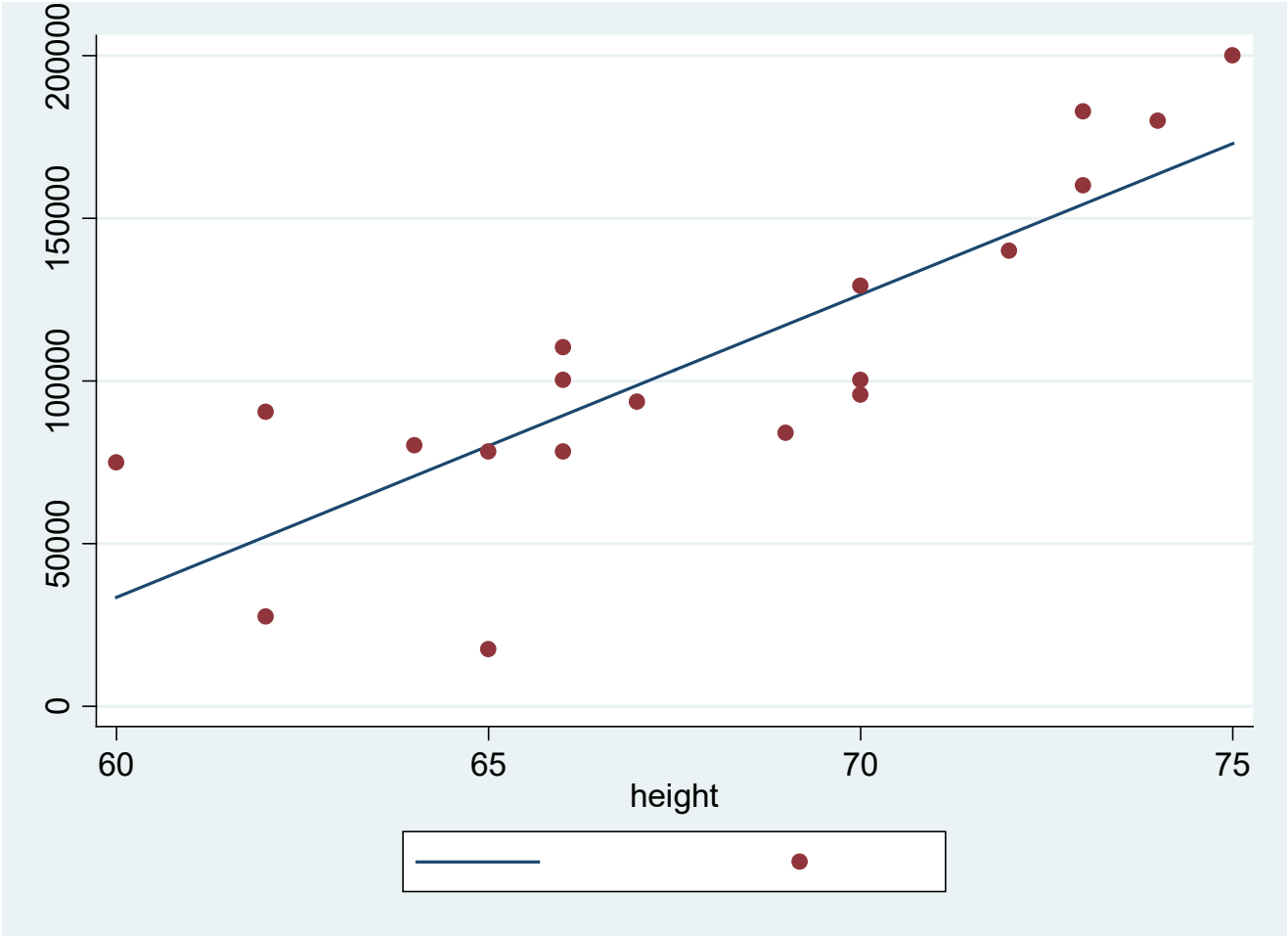



How do we want to describe the data?

# 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 / median of income (univariate)
  - Mean of income and by height (bivariate)
  - Mean of and by height controlling for other variable (multivariate)

# Ordinary Least Squares (OLS)

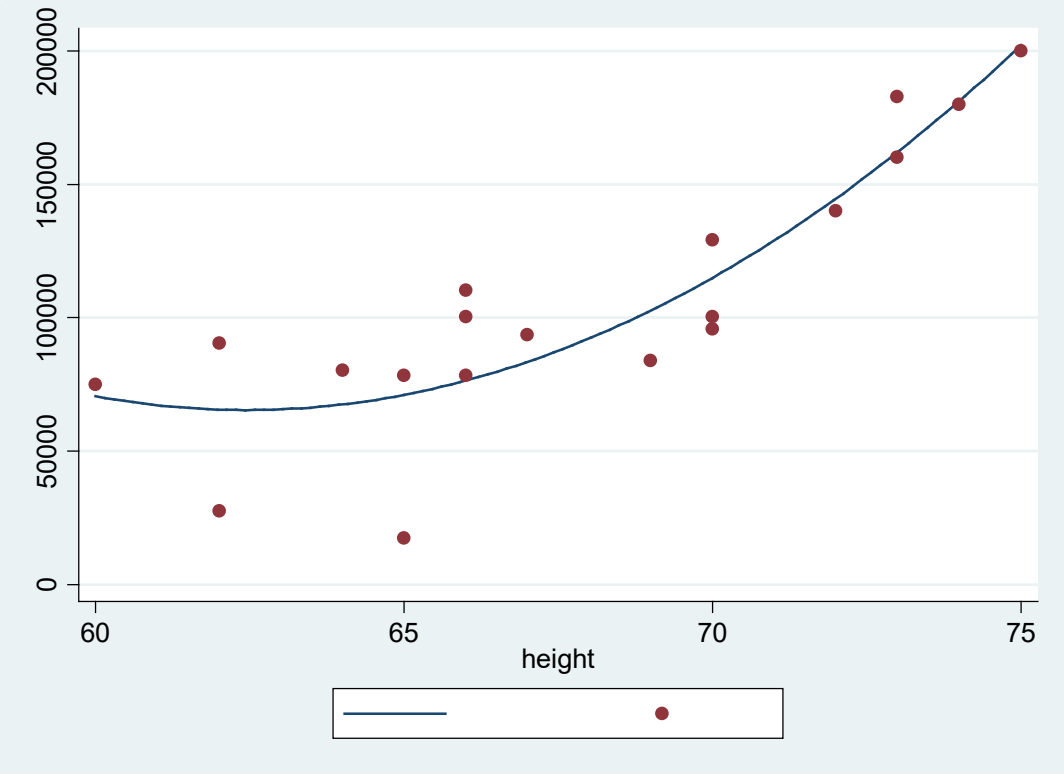



We are using this line to represent a relationship between height and income

Is this linear relationship correct?

# Other estimators

- Least absolute deviations
- Maximum likelihood
- Non-linear

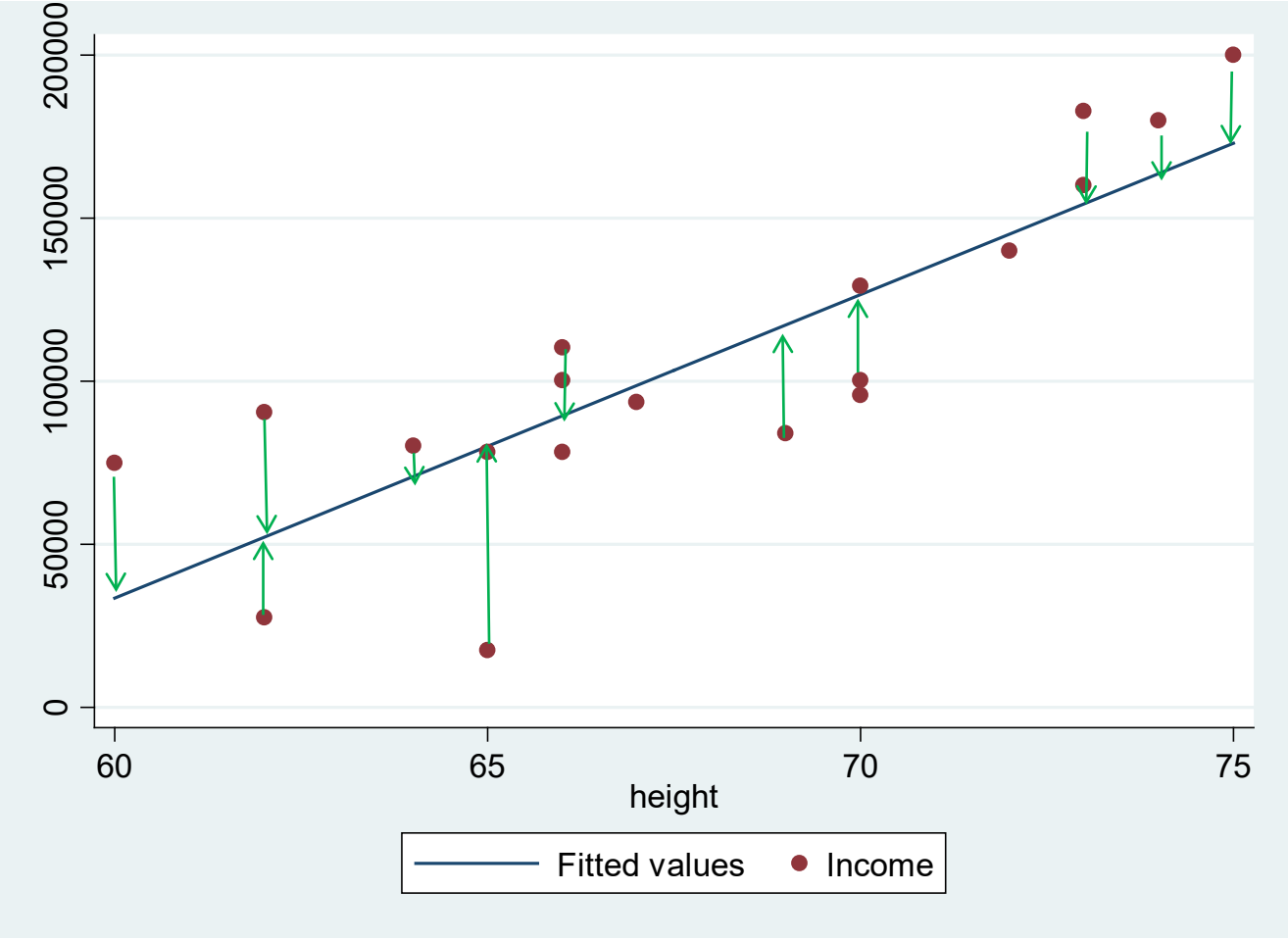


# Choosing an Estimator

- 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

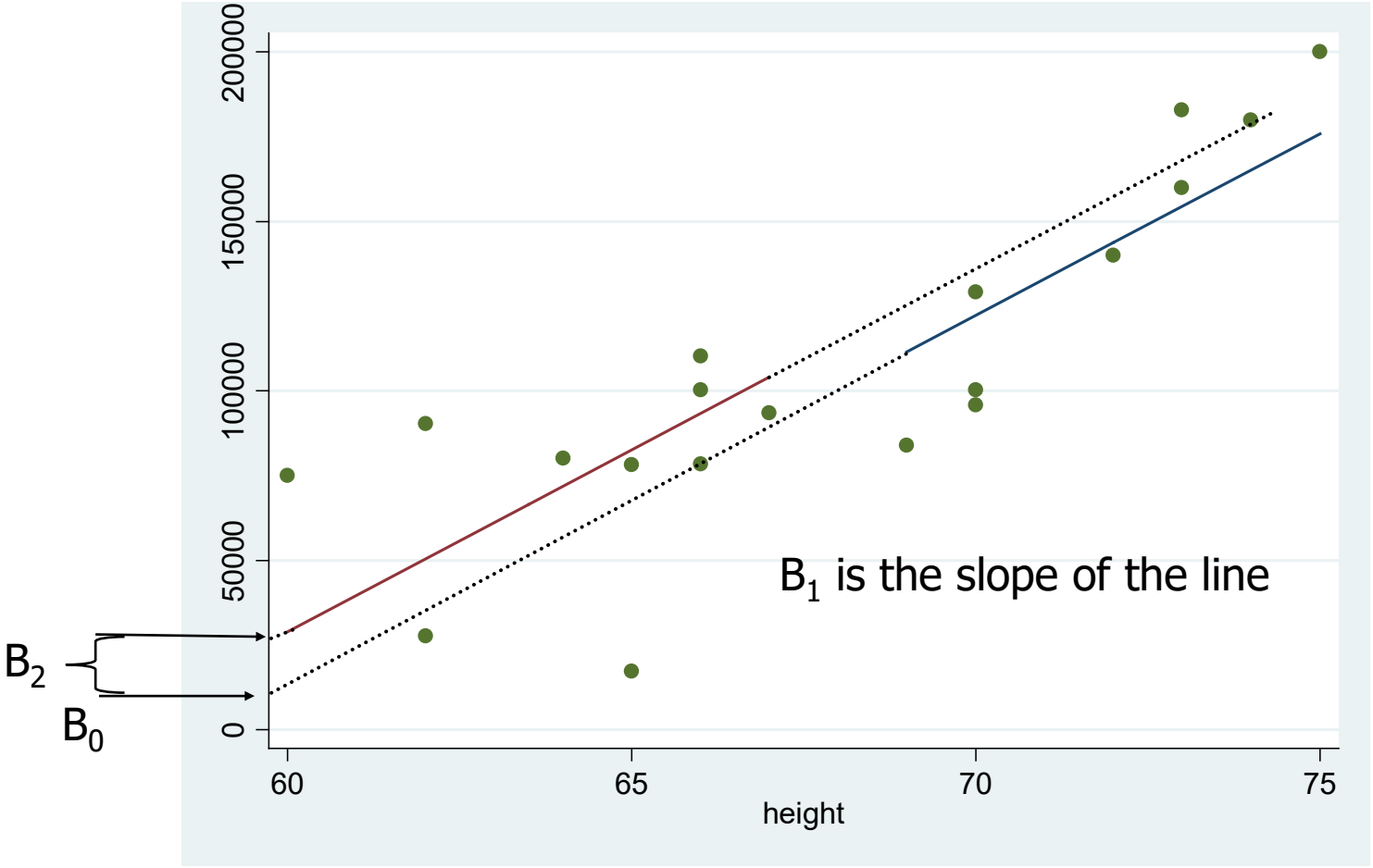
$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 Z_i + \varepsilon_i$$

income

height

Gender Intercept

# Gender-specific Indicator



# Interaction

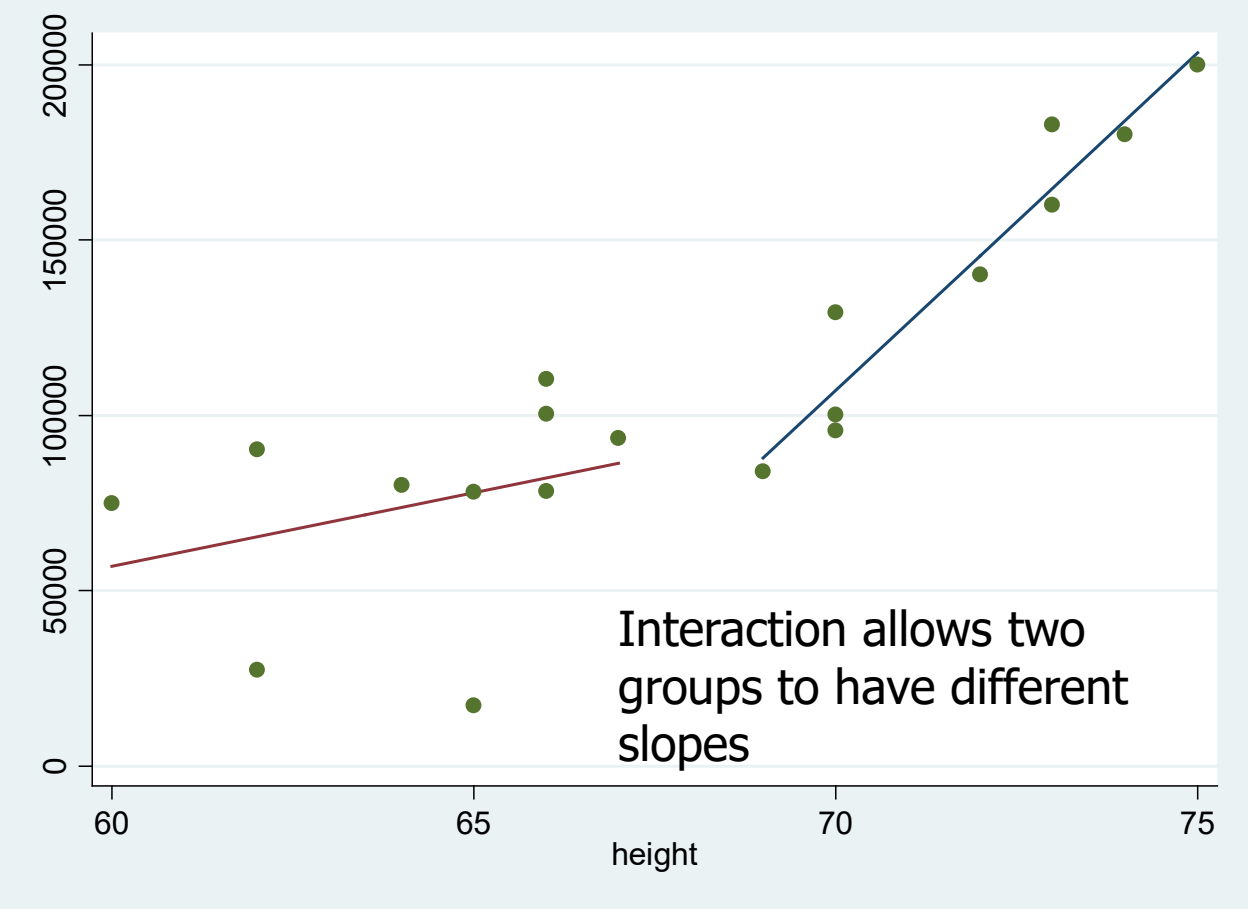
height gender

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

Interaction Term,
Effect modification,
Modifier

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

# Gender Interaction



# Identification

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

# Questionable science can lead to questionable 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

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# Classic Linear Regression

- No “superestimator”
- CLR models are often used as the starting point for analyses
- 5 assumptions for the CLR
- Variation in these assumptions 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.

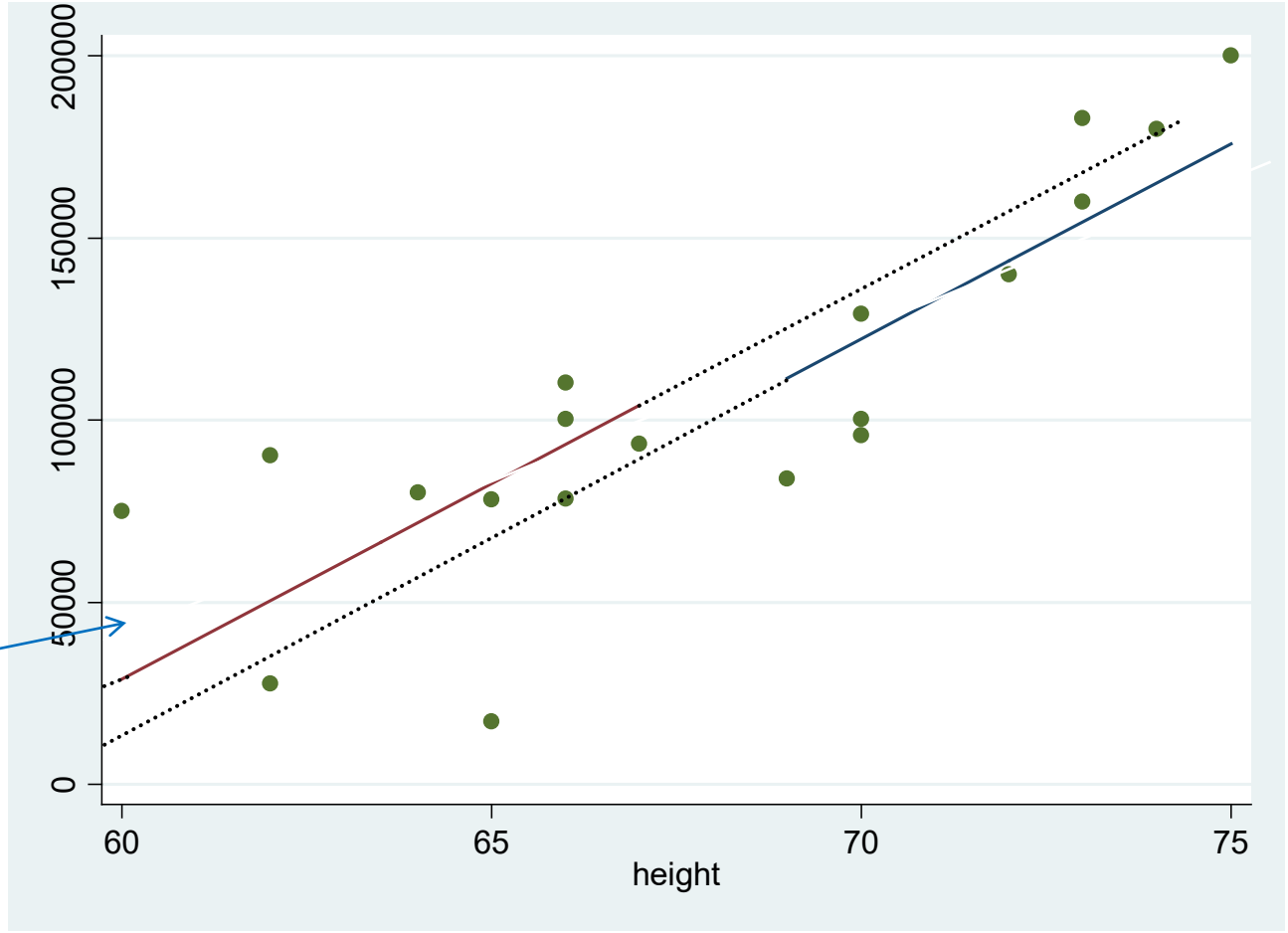
Pregibon D. Logistic regression diagnostics. *Annals of Statistics.* 1981;9(4):705-724.

# Assumption 1 and Stepwise

- Statistical software allows for creating models in a “stepwise” fashion

- Don’t use it
  - Little penalty for adding a nuisance variable
  - BIG penalty for missing an important covariate
- There are better methods for model building

# Bias if Gender is Ignored



# Assumption 2

- Expected value of the error term is 0

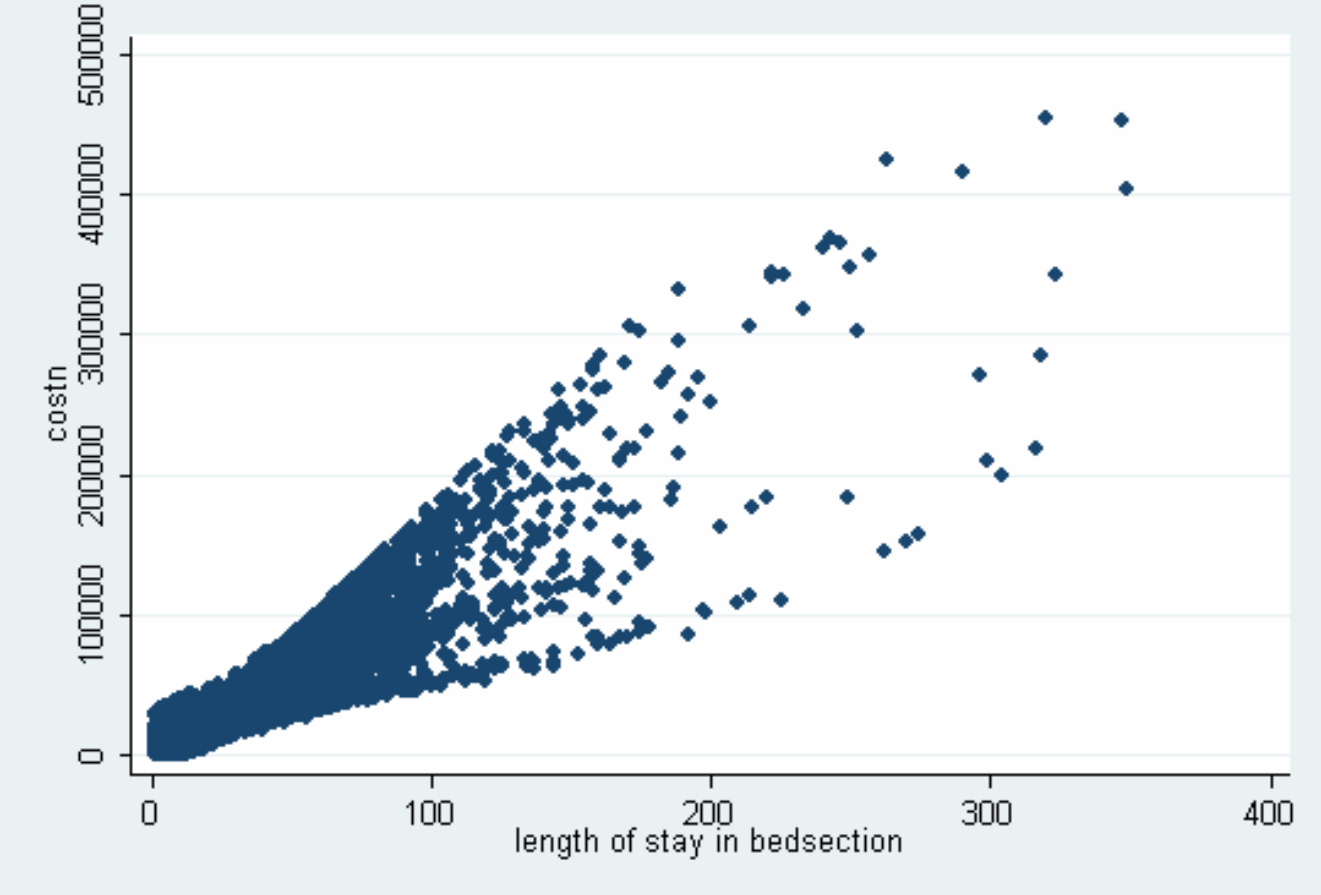
$$E(u_i)=0$$

- 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)
- Potential solutions: instrumental variables, regression discontinuity (discussed in future classes)

# 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.

# Any Questions?

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