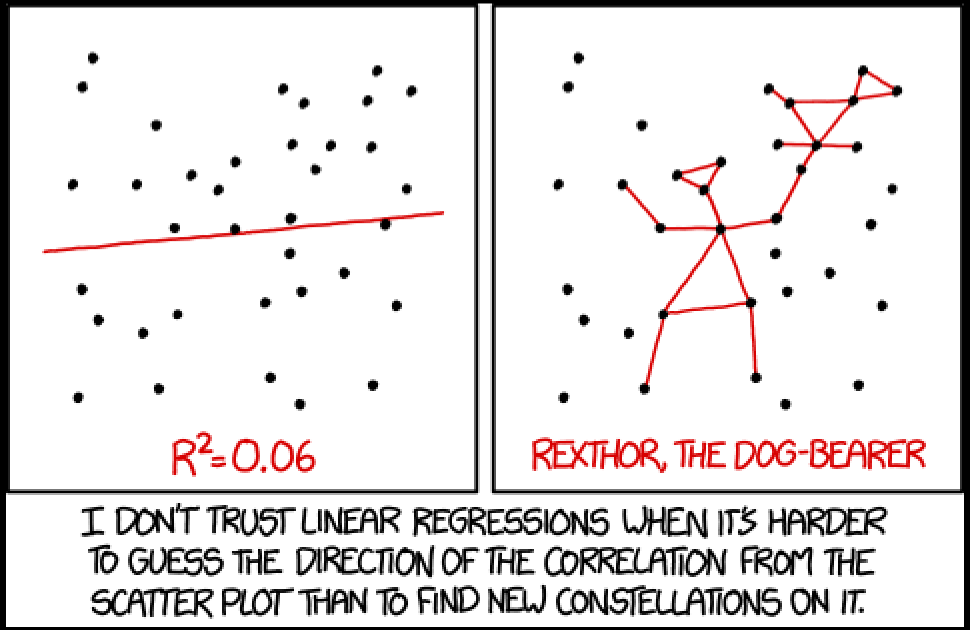


INFO 251: Applied Machine Learning

Regression and Impact Evaluation, part 2

Announcements

- Enrollment updates
  - Roster is close to final!

Outline

- Regression and Impact Evaluation
- Heterogeneous treatment effects
- Double-Difference via Regression
- Fixed effects and Normalization

Key Concepts (last lecture)

- Randomization pitfalls
  - Spillovers
  - Non-compliance
  - Non-random attrition
- Progresa
  - Motivation
  - Program design and roll-out
  - Different approaches to impact evaluation
- Interpreting regression coefficients
- Dummy variables, "one-hot" vectors

Key Concepts (this lecture)

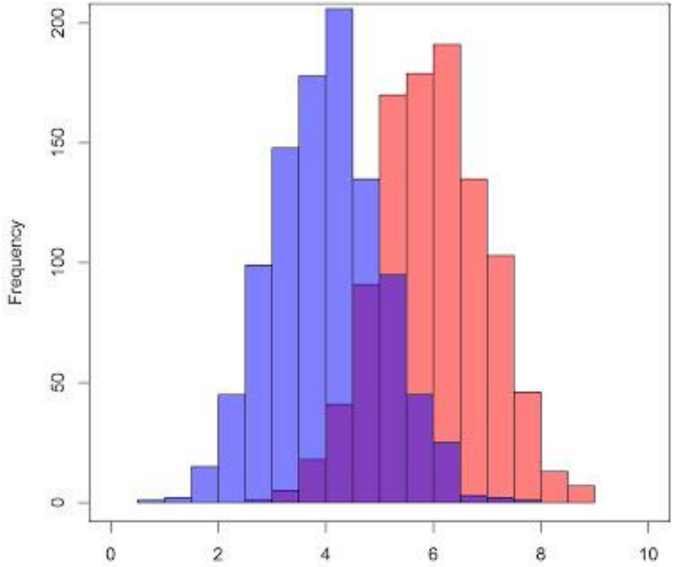
- Regression for impact evaluation
- Control variables
- Interaction variables
- Heterogeneous treatment effects
- Double difference estimation
- Fixed effects (revisited)

Regression and Impact: Basics

- How to measure effect of a binary treatment T on outcome Y via regression?
  - The regression equation:
$$Y_i = \alpha + \beta T_i + \epsilon_i$$
  - Example:
    - Y_i indicates # classes attended (1-10)
    - T_i indicates whether the student received an email encouraging attendance
    - We estimate $\hat{\alpha} = 4.1, \hat{\beta} = 1.3$. What does this mean?

- If T is not randomly assigned, $\hat{\beta}$ tells us about the correlation between T on Y

- If T is randomly assigned, $\hat{\beta}$ is an estimate of the *causal impact* of T on Y



Regression: "Control" variables

- How to simultaneously estimate the effect of a randomized treatment T and a non-random control variable X on an outcome Y?

$$Y_i = \alpha_1 + \beta_1 T_i + \gamma X_i + e_i$$

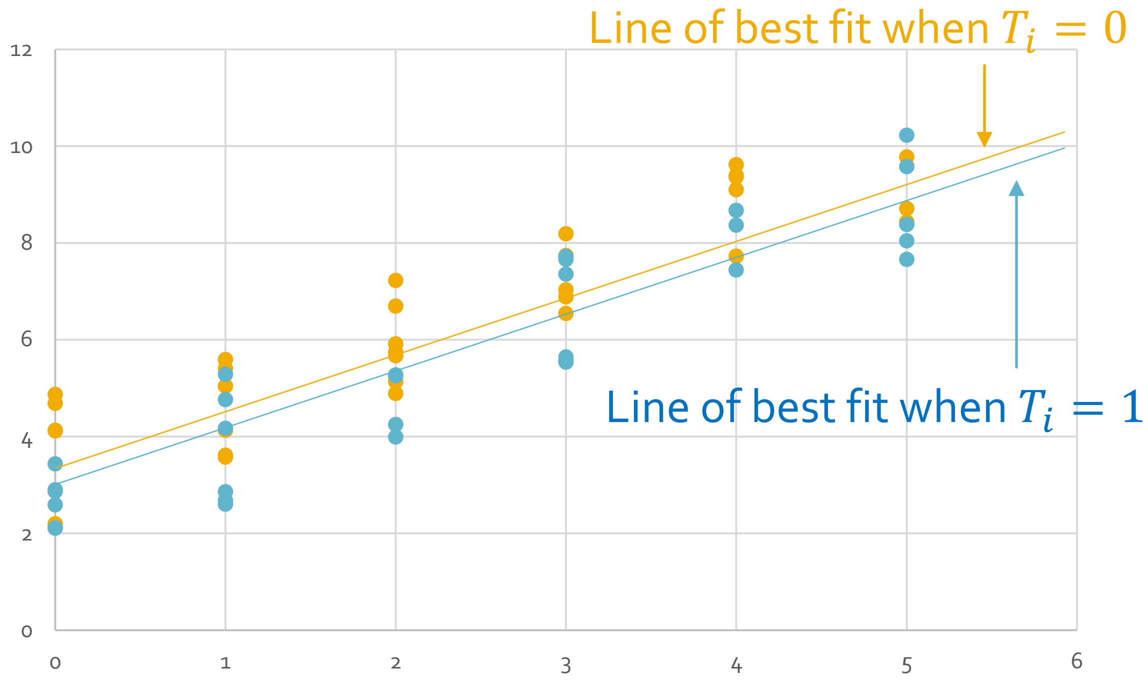
- How is this different from a version without control variables?

$$Y_i = \alpha_2 + \beta_2 T_i + \epsilon_i$$

- If T is perfectly randomized…
  - What, if anything, can we say about $Cor(T_i, X_i)$?
  - What, if anything, can we say about our estimates of β_1 and β_2?
  - What, if anything, can we say about γ?

Control variables: Example

- Example: We are estimating the effect of receiving an email (T_i) on attendance (Y_i), while controlling for years in grad school (X_i)
- Regression equation:
  - $Y_i = \alpha + \beta T_i + \gamma X_i + \epsilon_i$
- Coefficient estimates
  - $\hat{\alpha} = 3.4, \hat{\beta} = -0.5, \hat{\gamma} = 1.2$
  - What do these results mean?
- How to visualize?



Outline

- Regression and Impact Evaluation
- **Heterogeneous treatment effects**
- Double-Difference via Regression
- Fixed effects and Normalization

Treatment effect heterogeneity

- How to simultaneously measure the effect on an outcome *Y* of: (i) a randomized treatment *T*; and (ii) a non-random control variable *X*; and (iii) *allow for the treatment effect to vary with the control variable?*
  - Example: Phd students may respond differently to emails than MA students
  - The treatment effect is different for different types of people (where "type" is measured with X_i)

- We can estimate this with a regression:

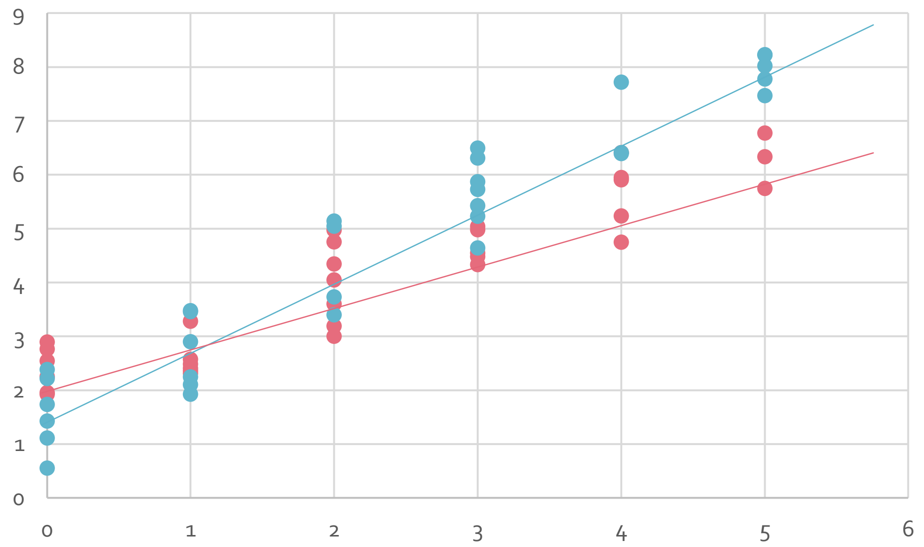
$$Y_i = \alpha + \beta T_i + \gamma X_i + \delta(T_i * X_i) + \epsilon_i$$

Treatment effect heterogeneity: Binary X

- Example 1: We want to estimate the effect of receiving and email (T) on attendance (Y), while controlling for PhD (X) and the interaction (T*X)
  - $Y_i = \alpha + \beta T_i + \gamma X_i + \delta(T_i * X_i) + \epsilon_i$
  - $\hat{\alpha} = 1.4, \hat{\beta} = -1.0, \hat{\gamma} = 0.8, \hat{\delta} = 0.6$
    - What do these results mean?
  - What is the expected happiness for:
    - A PhD student with a cookie
    - An MA student with a cookie
    - A PhD student without a cookie
    - An MA student without a cookie

Treatment effect heterogeneity: Continuous X

- Example 2: We want to estimate the effect of receiving an email (T) on attendance (Y), while controlling for years in grad school (X) (a continuous variable), and the interaction effect (T*X)
  - Note: this is identical to the last example, except now our X variable is continuous, not binary
- $Y_i = \alpha + \beta T_i + \gamma X_i + \delta(T_i * X_i) + \epsilon_i$
- $\hat{\alpha} = 1.4, \hat{\beta} = -1.0, \hat{\gamma} = 0.8, \hat{\delta} = 0.6$
- What do these results mean?
- How to visualize?



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- **Double-Difference via Regression**
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Regression and Impact: Diff-in-Diff

- In a typical double-difference setting, data is collected at baseline (pre-treatment) and at endline (post-treatment)
- Very similar to a situation where you have a treatment *T* **and** a non-experimental binary control variable *X* **and** a differential effect of treatment by a binary control variable
- In this case, the control variable is time!
  - Instead of a binary X_i (in previous example, X=PhD), we have a binary $Post_i$

Regression and Impact: Diff-in-Diff

- For example, our data look like this:

ID	Y	Post?	Treatment?	Post * Treat	...
1	12	0 (PRE)	1 (Treat)	0	...
1	14	1 (POST)	1 (Treat)	1	...
2	11	0 (PRE)	0 (Control)	0	...
2	11	1 (POST)	0 (Control)	0	...
3	24	0 (PRE)	0 (Control)	0	...
...	...	...	...	...	...
12419	...	...	...	...	...

	Control	Treat
Pre	A	B
Post	C	D

- This is the regression equation:

$$Y_i = \alpha + \beta T_i + \gamma Post_i + \delta(T_i * Post_i) + \epsilon_i$$

Regression and Impact: Diff-in-Diff

- Let's return to Progresa (Shultz, 2004: page 209)

$$S_i = \alpha_0 + \alpha_1 P_i + \alpha_2 E_i + \alpha_3 P_i E_i + \sum_{k=1}^{K} \gamma_{ki} C_{ki} + \sum_{j=1}^{J} \beta_j X_{ji} + e_i \quad i = 1, 2 \ldots, n \qquad (1)$$

- P_i = Progresa village ("T")
- E_i = Eligible (poor) household ("X")
- P_iE_i = Difference-in-difference estimator
- C_{ki} = Dummy variable for grade of child
  - Controls for fact that enrollment rates vary across grades
- X_{ji} = Other control variables (I think?)

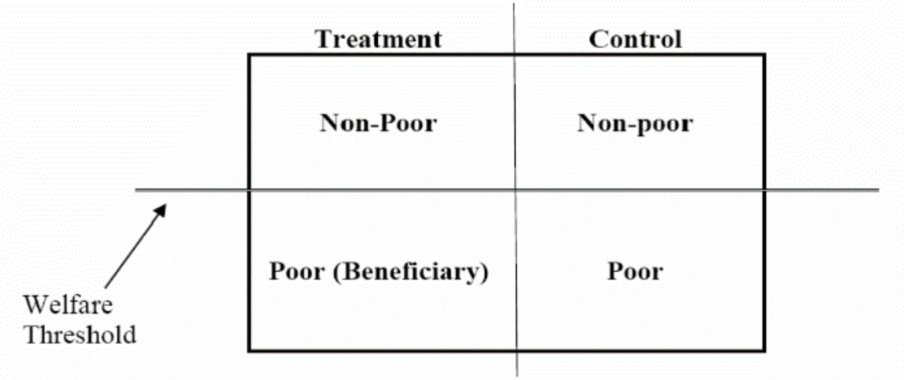

Figure 1: Program Evaluation Design

Regression and Impact: Summary

- Double Difference

$$Y_i = \alpha + \beta T_i + \gamma Post_i + \delta(T_i * Post_i) + \epsilon_i$$

- Simple difference

$$Y_i = \alpha + \beta T_i + \epsilon_i$$

  - (Estimated only in Post period)

- Pre vs. Post

$$Y_i = \alpha + \gamma Post_i + \epsilon_i$$

  - (Estimated only on treatment group)

Outline

- Regression and Impact Evaluation
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- **Fixed effects and Normalization**

Fixed Effects and Normalization

- **Cross-sectional data:** Data from several units at a single point in time
  - Schooling outcomes in 1998
  - Happiness of students on Jan 20
  - Number of logins per person in March

- **Time series (panel) data:** Multiple observations for each unit over time
  - Schooling outcomes in 1997 and 1998
  - Happiness of students on Jan 20 and Jun 20
  - Number of logins per person in each month of 2010

Between and Within Variation

- **Cross-sectional data:**
  - Variation is between/across units

Location	Year	Price	Quantity sold (per capita)
Chicago	2003	$75	2.0
Seattle	2003	$50	1.0
Milwaukee	2003	$60	1.5
Madison	2003	$55	0.8

- What do you notice about relationship between price and quantity?
  - Across the four cities, price and quantity are positively correlated
  - This is not what we would expect – omitted variables likely matter

Between and Within Variation

- **Panel data:**
  - Variation is between/across units *and* **within units over time**

- What do you notice about relationship between price and quantity?
  - Within each of the four cities, price and quantity are inversely correlated (as expected with downward sloping demand)

Location	Year	Price	Quantity
Chicago	2003	$75	2.0
Chicago	2004	$85	1.8
Seattle	2003	$50	1.0
Seattle	2004	$48	1.1
Milwaukee	2003	$60	1.5
Milwaukee	2004	$65	1.4
Madison	2003	$55	0.8
Madison	2004	$60	0.7

Exploiting Within-Unit Variation

- How to isolate changes in outcomes correlated with changes *within* a unit ?
  - e.g., Changes in demand caused by changes in price *within* a given city (over time)

Exploiting Within-Unit Variation

- One (familiar?) approach: “difference” regressions
  - Isolate differences over time in X and Y
  - Instead of: $Y_{it} = \alpha + \beta X_{it} + \epsilon_{it}$
  - $(Y_{it} - Y_{i(t-1)}) = \alpha + \beta(X_{it} - X_{i(t-1)}) + \epsilon_{it}$
    - Are *changes* in *Y* related to *changes* in *X*?

- Another approach: normalization
  - Instead of: $Y_{it} = \alpha + \beta X_{it} + \epsilon_{it}$
  - $(Y_{it} - \overline{Y}_i) = \alpha + \beta(X_{it} - \overline{X}_i) + \epsilon_{it}$

Exploiting Within-Unit Variation

- A third (closely related) approach: **Fixed effects**
- Basic idea (refer to lecture notes for details)
  - Instead of: $(Y_{it} - \bar{Y_i}) = \alpha + \beta(X_{it} - \bar{X_i}) + \epsilon_{it}$
  - Add "dummy" variables for each *i*: $Y_{it} = \alpha + \beta X_{it} + (\mu_i + \cdots + \mu_N) + \epsilon_{it}$
    - Conceptually the same as the "country fixed effect" example from previous lecture
    - More formally: $Y_{it} = \alpha + \beta X_{it} + \sum_{j=2}^{N} \mu_j \, \mathbf{1}(ID_i = j) + \epsilon_i$
    - Equivalent to adding an intercept for each *i*
  - Shorthand: $Y_{it} = \alpha + \beta X_{it} + \mu_i + \epsilon_{it}$
- Note: we can also "normalize" for time FE's
  - $Y_{it} = \alpha + \beta X_{it} + \mu_i + \pi_t + \epsilon_{it}$

Fixed Effects: Digging Deeper

- Key advantage of Fixed Effects
  - Fixed effects control for *unobserved heterogeneity*
  - They remove the effect of time-invariant characteristics to assess the net effect of the predictors on the outcome

- Extensions
  - Time trends
  - Region-specific slopes

Additional Resources

Beginner → Advanced