Research Design

Jean Yoon

December 15, 2010

HERC
Health Economics Resource Center

HSR&D
HEALTH SERVICES RESEARCH & DEVELOPMENT

Outline

- Causality and study design
- Quasi-experimental methods for observational studies
  - Covariate matching
  - Differences-in-differences
  - Regression discontinuity

Outline

- Causality and study design
- Quasi-experimental methods for observational studies
  - Covariate matching
  - Differences-in-differences
  - Regression discontinuity

Causality

- Want to be able to understand impact of implementing new program or intervention.
- Ideally, would estimate causal effect of treatment on outcomes by comparing outcomes under counterfactual
  - Treatment effect=$Y_i(1)$-$Y_i(0)$
  - Observe outcome Y when patient gets treatment, t=1 and when same patient does not get treatment, t=0
  - Compare difference in outcomes to get impact of treatment
  - In reality we don't observe same patients with and without treatment

Randomized Experiment

- Randomize who gets treatment T

  R T O

  R O

- Compare outcome between treated and untreated groups to get impact of treatment
- Because treatment was randomized, there are no <u>systematic</u> differences between treated and untreated groups.
- Differences in outcomes can be attributed to causal effect of treatment

Causality and Observational Studies

- Most health services research is observational and cross sectional
  - Causality difficult to show because of confounding also referred to as selection and endogeneity
    - Omitted variables bias
    - Selection
    - Reverse causality
    - Measurement error

Observational Study Example

- Observe some patients with diabetes in primary care clinic participate in phone-based, disease management program, others don't.
  - Compare A1c, cholesterol, other outcomes between groups of patients at end of program
  - If patients who participated in the program had better outcomes than those who didn't, can we conclude the program caused the better outcomes?

whiteboard

- What other factors could have led the program participants to have better outcomes than the non-participants?

Bias of Treatment Effect

- Characteristics not be balanced between groups
  - Enrolled had better outcomes to start with
- Patients selected into treatment
  - Enrolled would have improved over time b/c more motivated to improve
- Changes over time occurred that were unrelated to intervention
- Enrolled also engaged in other activities (not part of program), e.g. reading diabetes info online

Outline

- Causality and study design
- <u>Quasi-experimental methods for observational studies</u>
  - Covariate matching
  - Differences-in-differences
  - Regression discontinuity

Quasi-experimental Methods

- Observational studies do not have randomized treatment, so use methods to make like experimental study.
  - Identify similar control group
  - Try to eliminate any systematic differences between treatment and control groups
- Compare (change in) outcomes between treatment and control groups

Outline

- Causality and study design
- Quasi-experimental methods for observational studies
  - Covariate matching
  - Differences-in-differences
  - Regression discontinuity

Covariate Matching

- To estimate causal effect of treatment, want to compare treated group with similar cohort
- Matches observations in treatment group with observations in control group on selected variables
- Computes difference in outcome within matches, then mean of difference across all matches

  = average treatment effect

Covariate Matching

- Matching addresses bias in treatment effect caused by selection (into treatment) based on observable characteristics
- Matching procedures involve calculating distance between observations using selected covariates
- Can match on more than one variable, match the joint distribution of all observed covariates
- Observations can be used more than once (with replacement) for better matching

Covariate Matching

- Stata nnmatch estimates the average treatment effect using nearest neighbor matching across defined variables
- Can also match on propensity to receive treatment using propensity scores (topic of future lecture)

Covariate Matching

- Strengths
  - Uses nonparametric methods and does not rely on parametric modeling assumptions
  - Can use with other methods like D-D
- Weaknesses
  - Does not address selection based on unobservable characteristics
  - If all patients with same characteristics get treatment, then no comparison group

Matching Example

- McConnell KJ, Wallace NT, Gallia CA, Smith JA. Effect of eliminating behavioral health benefits for selected medicaid enrollees. *Health Serv Res. Aug 2008;43(4):1348-1365.*
- Compare medical expenditures for
  - Patients who previously used behavioral health services
  - Patients who did not use behavioral health services
- Matched patients in target group with patients from control group on demographics, risk factors, prior medical expenditures

Matching Example

- McConnell et al. results

Table 2: Descriptive Characteristics for Outpatient Mental Health Service Users and Comparison Group

	Unmatched Comparison Group (No Use of Behavioral Health Services)	*Mental Health Service Users*	*Comparison Group (Weighted by Propensity Score)*	*Comparison Group (One-to-One Matching on Covariates)*
Patient demographics				
Male (%)	41.2	32.2	32.2	32.1
White (%)	81.5	90.4	90.4	90.4
Single (%)*	53.5	71.2	71.3	71.3
CCI**	53.1	64.4	64.5	64.8
Rural*	51.4	47.5	47.6	47.4
Enrolled in FFS (%)*	33.0	35.0	35.0	33.7
Age* (mean)	41.9	40.2	40.1	40.5
Months enrolled* (mean)	10.4	10.5	10.5	10.6
Monthly income* (mean)	$503	$339	$337	$333
Monthly expenditures				
Expenditures before behavioral health benefit elimination (11/01–10/02)***	$182	$403	$218	$320
Expenditures following behavioral health benefit elimination (5/03–4/04)***	$208	$372	$247	$294
Sample size	9,500	1,135	9,442	1,135

Matching Example

- McConnell et al. results

Table 3: Estimated Change in Expenditures for Covered Services after Behavioral Health Benefit Elimination

	Benefit Group	
	Substance Abuse Treatment Users	*Outpatient Mental Health Users*
Model specification		
Two-part model with propensity score weighting	$70 ($13, $128)	– $74 (– $104, – $39)
Covariate matching	$127 ($20, $234)	– $5 (– $48, $38)

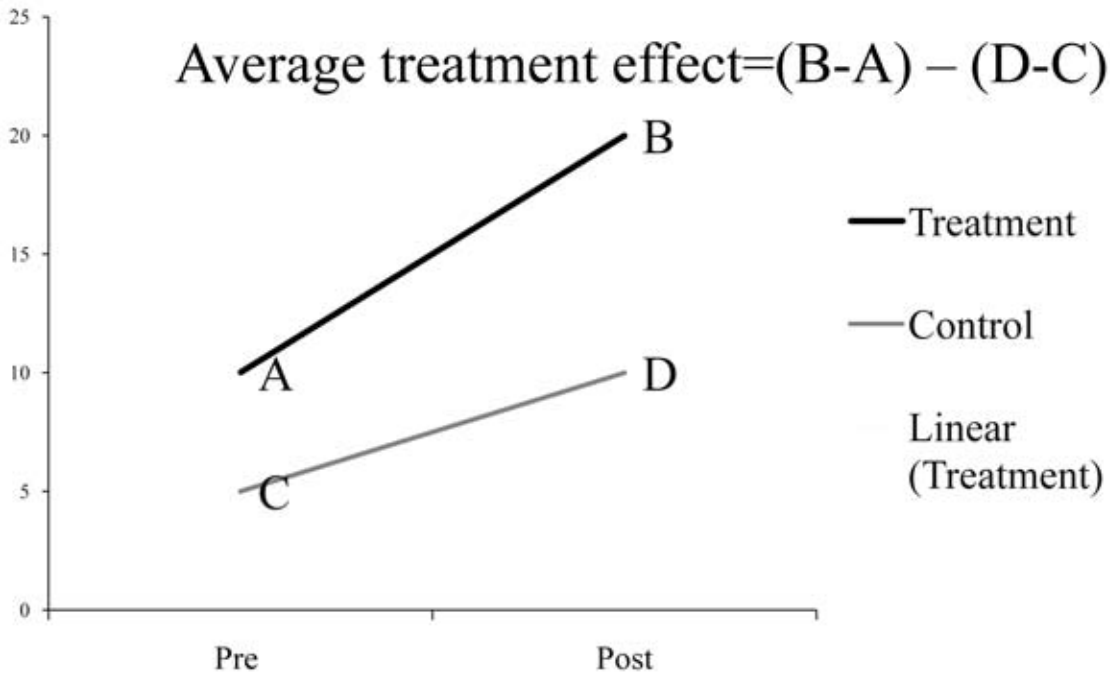
Outline

- Causality and study design
- Quasi-experimental methods for observational studies
  - Covariate matching
  - <u>Differences-in-differences</u>
  - Regression discontinuity

Differences-in-Differences

- Can exploit natural experiment with D-D
- Need longitudinal data or observe outcome at different time points for treatment and control groups
- Subtract out differences between treatment and control groups and differences over time

Differences-in-Differences



Differences-in-Differences

- Program P: 0=no, 1=yes
- Time T: 0=pre, 1=post

  $Y = \beta_0 + \beta_1 T + \beta_2 P + \beta_3 P*T + \varepsilon$
- So β_3 is the differences-in-differences estimate

$$\beta_3 = (\Delta \overline{Y}_{P=1}) - (\Delta \overline{Y}_{P=0})$$

Differences-in-Differences

- Strengths
  - Difference out time trend
  - Addresses omitted variables bias if unmeasured time invariant factors
- Weaknesses
  - If unobserved factors that change over time, can have biased estimates

Differences-in-Differences

- Unobserved factors often cause omitted variables bias
- Panel analysis with time invariant characteristics δ_i for individual (observed and unobserved)

  $Y_{it} = \beta_0 + \beta_1 T_t + \beta_2 P_{it} + \delta_i + \varepsilon_{it}$
- Difference model

  $Y_{i1} - Y_{i0} = \beta_1 + (P_{i1} - P_{i0t}) * \beta_2 + \varepsilon_{i1} - \varepsilon_{i0}$
- β_1 is time trend
- β_2 is treatment effect
- Time invariant δ_i drops out of model

Differences-in-Differences

- Fixed effects estimate of "within estimator" same as first differencing with 2 time periods
- Cannot estimate effect of time invariant factors in FE model
- Can estimate effect of time invariant factors if δ_i not parameter to be estimated but part of ε_{it} using random effects, same as clustering
- Stata command xtreg will run FE and RE

D-D Example

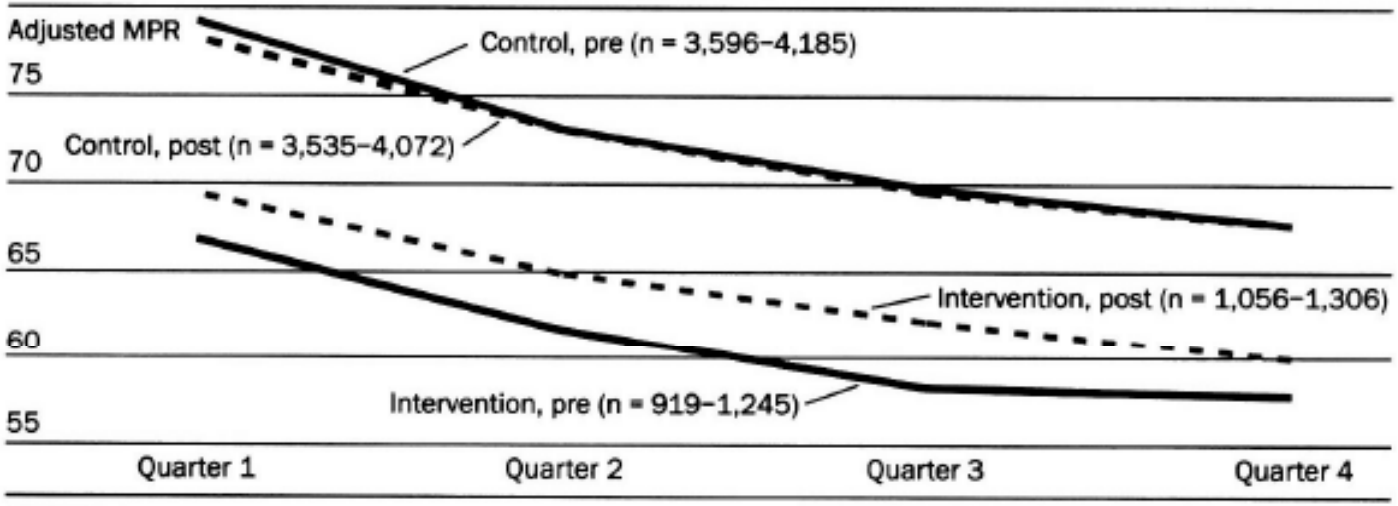
- Chernew ME et al. Impact Of Decreasing Copayments On Medication Adherence Within A Disease Management Environment. *Health Affairs; Jan/Feb 2008; 27, 1;103-112.*
- Two health plans implemented disease management programs, but only one reduced drug copayments
- Drug adherence for two groups of patients compared pre-post implementation of disease management and reduction in drug copays

D-D Example

- Chernew et al.

EXHIBIT 2

Adjusted Medication Possession Ratio (MPR) For Diabetic Therapy, In The Pre And Post Periods, For Intervention And Control Groups, Calendar Years 2004 And 2005



SOURCE: Authors' multivariate analysis of administrative data.
NOTE: Pre period is calendar year 2004; post period is calendar year 2005.

Outline

- Causality and study design
- Quasi-experimental methods for observational studies
  - Covariate matching
  - Differences-in-differences
  - <u>Regression discontinuity</u>

Regression Discontinuity

- Can do when treatment is not randomly assigned but based on a continuous, measured factor Z
  - Z called forcing variable
- Discontinuity at some cutoff value of Z
- Individuals cannot manipulate assignment of Z
- Only jump in outcome due to discontinuity of treatment
- Treatment effect =the expected outcome for units just above the cutoff minus the expected outcome for units just below the cutoff (otherwise identical)

Regression Discontinuity

- Strengths
  - Z can have direct impact on outcome (unlike instrumental variables)
- Weaknesses
  - Need to test functional form for effect of treatment (e.g. linear, interaction, quadratic terms) or can get biased treatment effects if model is misspecified.

RD Example

- Bauhoff, S., Hotchkiss, D. R. and Smith, O. , The impact of medical insurance for the poor in Georgia: a regression discontinuity approach. Health Economics, n/a. doi: 10.1002/hec.1673
- Effect of medical insurance program for poor in republic of Georgia on utilization
- Eligibility for program limited to residents below means test score (SSA)
- Compare outcomes for eligible residents versus low income residents who are not eligible

RD Example

- Bauhoff et al

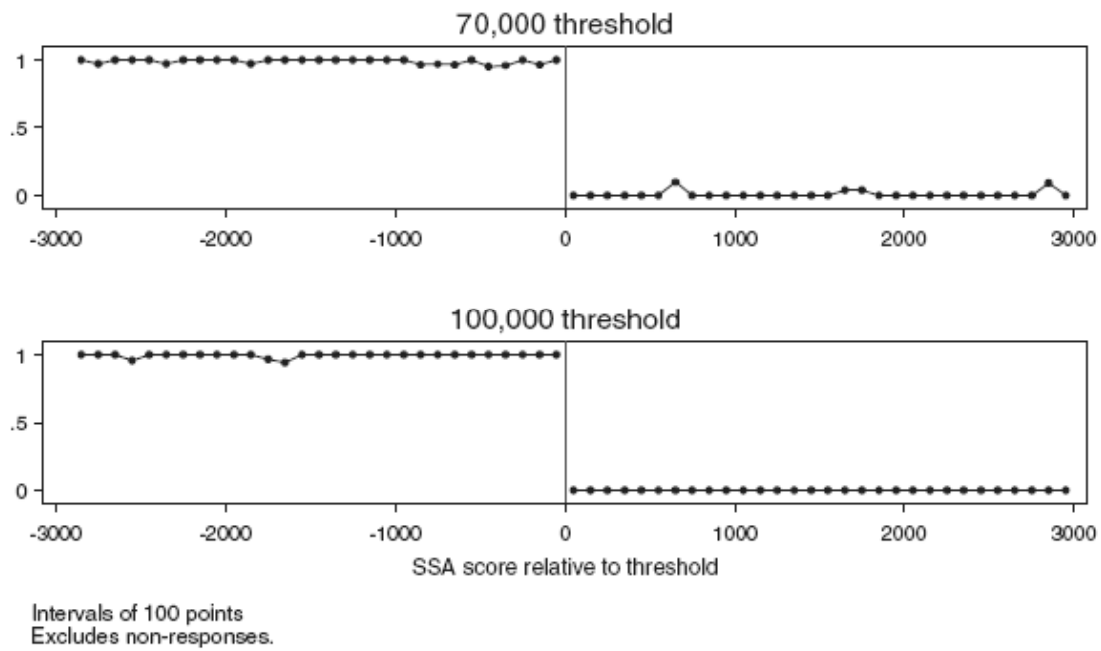


Figure 2. Share of households enrolled in MIP

RD Example

Bauhoff et al

$$Y=\beta_0+\beta_1 MIP+\beta_2 f(score\text{-}cutoff)+\beta_3 MIP*f(score\text{-}cutoff)+\beta_4 X+\varepsilon$$

β_1 =treatment effect, discontinuous change at cutoff

β_2 =effect of means test on outcomes for non-beneficiaries

β_3 =effect of means test on outcomes for beneficiaries

RD Example

- Bauhoff et al

Table II. Outpatient utilization and expenditure

	Utilization MIP-70			OOP expenditure MIP-70			Utilization MIP-100			OOP expenditure MIP-100		
	Logit marginal effects [*100]			GLM			Logit marginal effects [*100]			GLM		
	Part 1a	Part 1b	Part 1c	Part 2a	Part 2b	Part 2c	Part 1a	Part 1b	Part 1c	Part 2a	Part 2b	Part 2c
MIP beneficiary	1.03	0.578	−0.0746	1.17	1.45	0.74	−0.377	−0.751	0.697	0.5***	0.454***	0.6
	(0.678)	(0.854)	(1.9)	(0.25)	(0.388)	(0.385)	(0.701)	(0.79)	(1.86)	(0.117)	(0.116)	(0.445)
Age ≥ 64		1.33	−0.477		2.24***	3.75***		1.24	−1.92		0.87	0.636
		(1.37)	(1.24)		(0.584)	(1.5)		(1.47)	(1.49)		(0.334)	(0.324)
MIP* (Age ≥ 64)		1.62	0.921		0.492*	0.443**		2.04	1.71		1.58	1.29
		(1.91)	(1.48)		(0.18)	(0.152)		(2.16)	(1.94)		(0.732)	(0.604)
Male		−0.974	−0.641		0.604***	0.576***		−1.61**	−1.04*		1.44	1.45*
		(0.649)	(0.524)		(0.108)	(0.115)		(0.627)	(0.595)		(0.351)	(0.301)
Family education		0.318	0.124		1.03	1.04		−0.144	−0.801*		0.987	1
		(0.44)	(0.383)		(0.108)	(0.115)		(0.46)	(0.466)		(0.161)	(0.151)
Age			−0.0744			1.03			−0.0411			1.04**
			(0.0585)			(0.0189)			(0.0617)			(0.0198)
Age squared			0.00102			1*			0.00104			1
			(0.000716)			(0.000238)			(0.000859)			(0.000267)

Review

- Quasi-experimental methods can help address common sources of bias of treatment effects in observational studies.
- Quasi-experimental methods attempt to reduce any systematic differences between treatment and control groups.
- Quasi-experimental methods provide stronger study designs in order to make inferences about causality.

References

- Campbell, D. T., and Stanley, J. C. Experimental and Quasi-experimental Designs for Research. Chicago: Rand McNally, 1966.
- Abadie A, Drukker D, Herr JL, Imbens GW. Implementing matching estimators for average treatment effects in Stata. The Stata Journal (2004) 4, Number 3, pp. 290–311
- Wooldridge, J. M.: Econometric Analysis of Cross Section and Panel Data. MIT Press, Cambridge, Mass., 2002.
- Trochim, William M. The Research Methods Knowledge Base, 2nd Edition. Internet WWW page, at URL: http://www.socialresearchmethods.net/kb/(version current as of 12/07/10).

More References

- McConnell KJ, Wallace NT, Gallia CA, Smith JA. Effect of eliminating behavioral health benefits for selected medicaid enrollees. *Health Serv Res. Aug 2008;43(4):1348-1365.*
- Chernew ME et al. Impact Of Decreasing Copayments On Medication Adherence Within A Disease Management Environment. *Health Affairs; Jan/Feb 2008; 27, 1;103-112.*
- Bauhoff, S., Hotchkiss, D. R. and Smith, O. , The impact of medical insurance for the poor in Georgia: a regression discontinuity approach. Health Economics, n/a. doi: 10.1002/hec.1673

HERC Sharepoint Site

- Questions and answers from today's session will be posted

http://vaww.infoshare.va.gov/sites/HERC/default.aspx

Next Lectures

Upcoming 2011

Endogeneity and Simultaneity

Mark Smith

Instrumental Variables Models

Mark Smith