Research Design

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July 11, 2012

Outline

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

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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 systematic 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?

Q&A

- Please respond using Q&A panel:
  - 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

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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

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Sample selection

- Bias arises when outcome is not observable for some people, sample selection
- Form of omitted variables bias
- Example: attrition from study collecting outcomes data from patients
  - Health outcomes only observed in respondents
  - Not possible to make inferences about determinants of health outcomes in study population as whole.
  - If reasons why patients don't respond are correlated with unobservable factors that influence outcomes, then identification problem.

Sample selection

- One solution to sample bias is a selection model called Heckman probit or heckit or generalized tobit
- First stage uses probit model for dichotomous outcome (selection equation) for whole sample
- From parameters in first stage, calculate inverse mills ratio or selection hazard for each patient
- Add inverse mills ratio as variable into second stage
- Second stage uses OLS model for linear outcome (outcome equation) for respondents in sample
- Assumption is that error terms of two equations are jointly normally distributed and correlated by ρ

Sample selection

1) $D=Z\gamma+\varepsilon$ $D=1$ participation, $D=0$ no participation

2) $w^*=X\beta+\mu$ Only have outcome w^* when $D=1$

Estimate 1) and get $\varphi(Z\gamma)/\Phi(Z\gamma)= \lambda$ inverse mills ratio

Estimate 2) adding λ as a parameter

- $E[w|X, D=1]= X\beta + \rho\delta_\mu\lambda(Z\gamma)$
- Coefficient of λ is ρ, if $=0$ then no sample selection
- Want instruments (included in Z) that are not related to outcome w

Sample selection

- If outcome is dichotomous, can use bivariate probit model.
- If outcomes data are available for all patients, then use treatment effects model.
- New, semiparametric models do not make joint normality assumptions.

Sample selection

- Strengths
  - Generalizes to population of interest
  - Addresses selection based on unobservables
- Weaknesses
  - Assumes joint normality of errors in two equations.
  - Can still be run if no instrument (unlike 2SLS) but relying on distributional assumptions of non-linearity in inverse mills ratio.

Sample selection

- Stata code

Heckman y x1 x2 x3, select (x1 x2 z1 z2) twostep

Sample Selection Example

- Zhoua A, Gaob J, Xueb Q, Yangb X, Yan J. Effects of rural mutual health care on outpatient service utilization in Chinese village medical institutions: evidence from panel data. Health Econ. 18: S129–S136 (2009)
- Compare effect of outpatient insurance program and drug policy to restrict drug prescribing on outpatient medical expenditures.
- Only some residents had outpatient visits.

Sample Selection Example

- Zhou et al. results

Table II. Outpatient visits per person, per-visit outpatient expenses and per-visit outpatient co-payments on average from 2005 to 2007

	Outpatient visits per person			Per-visit outpatient expenses			Per-visit outpatient co-payments		
Year	The insured	The uninsured	p^*	The insured	The uninsured	p^*	The insured	The uninsured	p^*
2005	0.156 (0.675)	0.098 (0.421)	0.075	10.78 (6.82)	15.58 (8.39)	<0.001	7.54 (4.78)	15.58 (8.39)	<0.001
2006	0.213 (0.707)	0.088 (0.396)	0.017	11.31 (7.49)	15.40 (8.75)	<0.001	6.80 (4.52)	15.40 (8.75)	<0.001
2007		0.096 (0.420)			14.76 (10.67)			14.76 (10.67)	
p^{**}	0.037	0.774		0.569	0.913		0.208	0.913	

Note: Standard deviations are in parentheses. p^* performs the results of the comparison tests between the insured and the uninsured for each year by using *t*-test. p^{**} performs the results of comparison tests between 2005 and 2006 for the insured and comparison tests between the three years for the uninsured by using a one-way analysis-of-variance model.

Sample Selection Example

- Zhou et al . results

Table V. Estimated results of Heckman selection model (random effect models are employed in the second stage)

	First stage (Probability of any outpatient use)	Second stage (Log of per visit expenditure)
The outpatients' coinsurance rate (nature logarithm)	–4.412 (1.570)**	–0.553 (0.256)**
The drug policy	–1.441 (0.619)**	–0.559 (0.112)**
The year of 2006	–0.262 (0.232)	–0.023 (0.292)
The year of 2007	0.054 (0.110)	–0.043 (0.156)
Male	0.004 (0.057)	0.062 (0.085)
Age 15–24	–0.367 (0.119)**	0.139 (0.220)
Age 25–34	–0.378 (0.146)**	0.524 (0.226)**
Age 35–44	–0.347 (0.147)**	0.237 (0.237)
Age 45–54	–0.344 (0.151)**	0.333 (0.249)
Age 55–64	–0.354 (0.154)**	0.262 (0.242)
Age 65+	–0.497 (0.172)**	0.258 (0.261)
Married	0.288 (0.122)**	0.066 (0.204)
Divorced	0.667 (0.284)**	0.264 (0.249)
Elementary	–0.042 (0.079)	0.027 (0.105)
Primary	–0.114 (0.092)	0.035 (0.125)
High	–0.226 (0.139)	0.121 (0.232)
Income (nature logarithm)	–0.013 (0.037)	–0.061 (0.067)
Illness last month	0.629 (0.073)**	
Chronic disease	0.125 (0.075)	
Distance	–0.053 (0.021)*	
Inverse mills ratio		–0.154 (0.155)
LR χ^2	223.84	
Wald χ^2		51.32
p	<0.001	<0.001

Poll 1 on sample section:

a. Sample selection models are used to eliminate bias due to unobservable characteristics.

b. Sample selection models are used to eliminate bias only due to observable characteristics.

c. Sample selection models do not assume joint normality of the selection and outcome equations.

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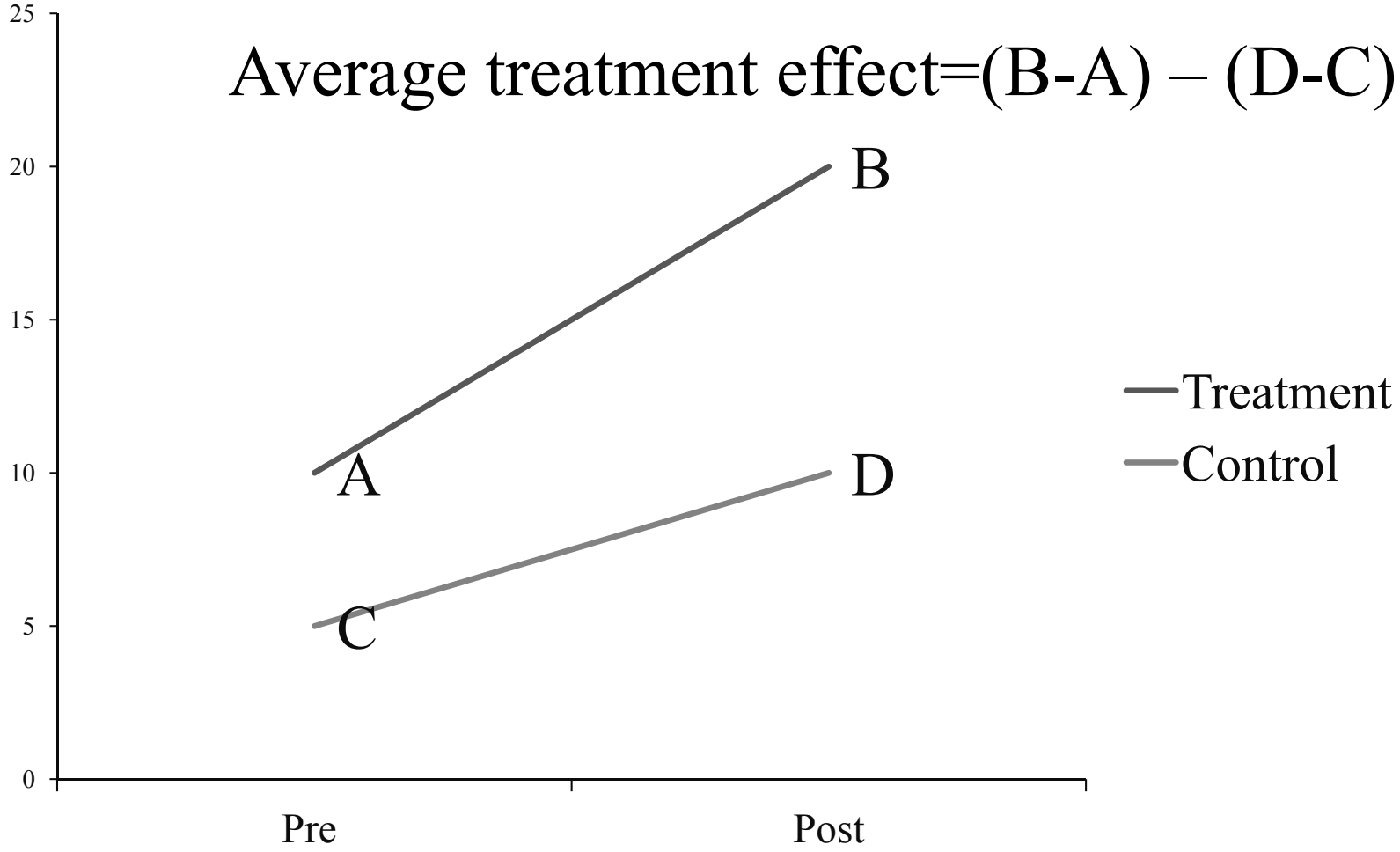
  - Differences-in-differences
  - Regression discontinuity

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

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

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

  $Y_{i1} - Y_{i0} = \beta_1 + (P_{i1} - P_{i0}) * \beta_2 + \varepsilon_{i1} - \varepsilon_{i0}$
- 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
- Stata command xtreg will run FE

D-D Example

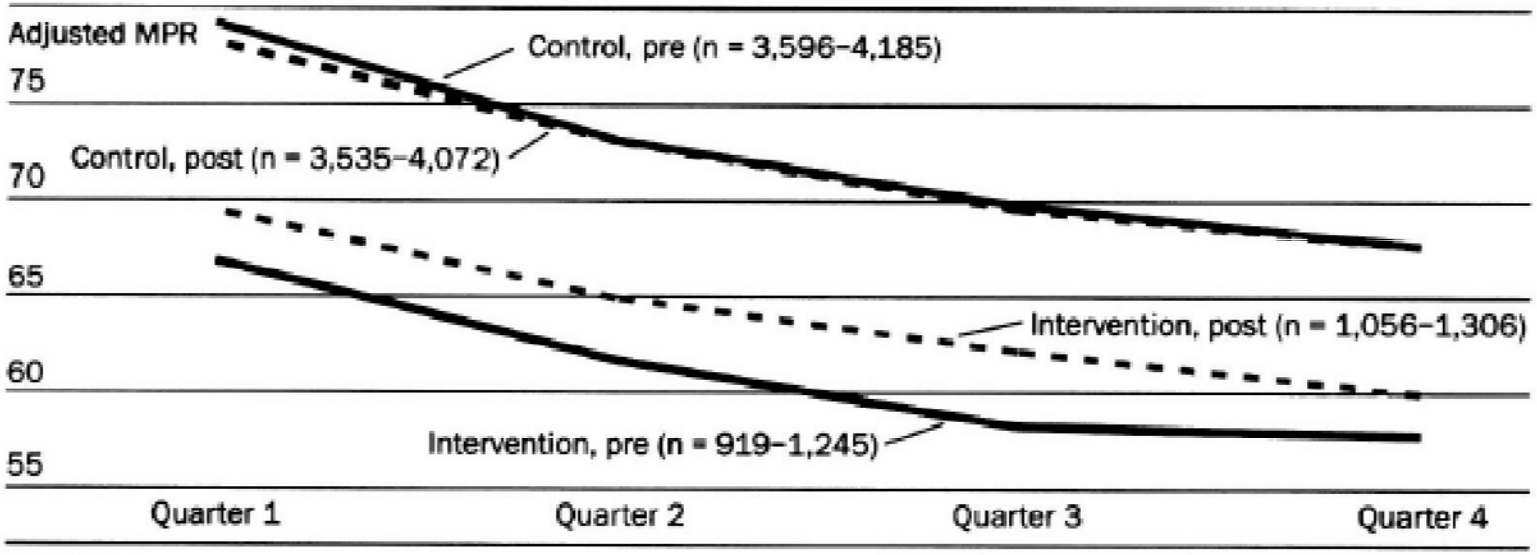
- Chernew ME et al. Impact Of Decreasing Copayments On Medication Adherence Within A Disease Management Environment. *Health Affairs; Jan/Feb 2008; 27, 1;103-112.*
- Two health plans implemented disease management programs, but only one reduced drug copayments
- Drug adherence for two groups of patients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

Poll 2 on differences-in-differences

a. Differences-in-differences eliminates confounding due to time trends.

b. Differences-in-differences can eliminate omitted variables bias from time invariant factors.

c. Both a and b

d. None of the above

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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

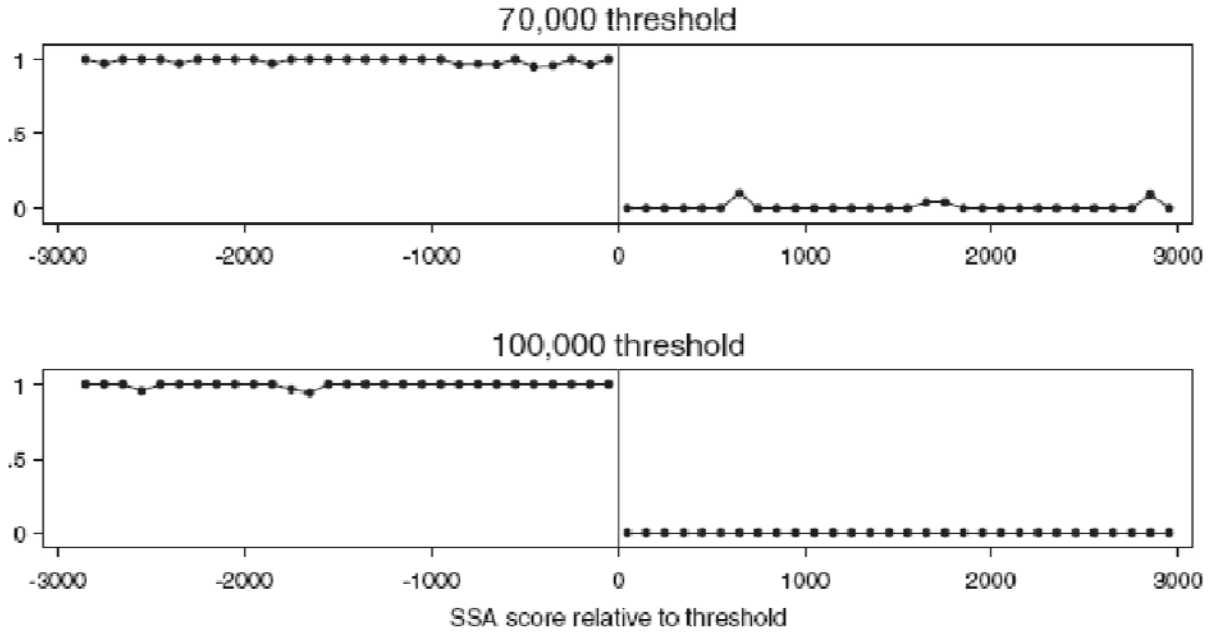
- Strengths
  - Z can have direct impact on outcome (unlike instrumental variables)
- Weaknesses
  - Need to test functional form for effect of treatment (e.g. linear, interaction, quadratic terms) or can get biased treatment effects if model is misspecified.

RD Example

- Bauhoff, S., Hotchkiss, D. R. and Smith, O. (2011), The impact of medical insurance for the poor in Georgia: a regression discontinuity approach. Health Econ., 20: 1362–1378.
- 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



Intervals of 100 points
Excludes non-responses.

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)

Poll 3 on Regression discontinuity

a. Regression discontinuity can be used when treatment is assigned based on some unknown factor.

b. Regression discontinuity can't be used when treatment assignment is directly related to the outcome.

c. Regression discontinuity can be used when treatment is assigned based on cutoff of a continuous eligibility score

Poll 4 on final review

a. Quasi-experimental methods can help address common sources of bias of treatment effects in observational studies.

b. Quasi-experimental methods attempt to reduce any systematic differences between treatment and control groups.

c. Quasi-experimental methods provide stronger study designs in order to make inferences about causality.

d. All of the above

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.
- Heckman, J. (1979). "Sample selection bias as a specification error". *Econometrica* **47** (1): 153–61.
- 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

- Zhoua A, Gaob J, Xueb Q, Yangb X, Yan J. Effects of rural mutual health care on outpatient service utilization in Chinese village medical institutions: evidence from panel data. Health Econ. 18: S129–S136 (2009)
- 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 Econ. 2011*; 20: 1362–1378.

Next Lectures

July 25, 2012
Propensity Scores
Todd Wagner

August 8, 2012
Instrumental Variables Models
Patsi Sinnott