EMPIRICAL STRATEGIES IN LABOUR ECONOMICS

University of Minho **J. Angrist**
NIPE Summer School **June 2009**

This course covers core econometric ideas and widely used empirical modeling strategies. The main theoretical ideas are illustrated with examples. Our text is *Mostly Harmless Econometrics* by Angrist and Pischke. The outline below is keyed to the *MHE* table of contents. In a short course, we have to pick and choose our topics, even more than usual. I plan to lecture on Chapters 3, 4, and 8 from MHE, emphasizing advanced regression topics, instrumental variables with heterogeneous potential outcomes, and clustering and related standard errors problems.

This 3-day course consists of three 90 minute lectures per day. We'll break briefly in the morning for coffee and in the early afternoon for lunch (well, lunch for me, anyway). In between lectures, I'd be happy to talk with you about *your* empirical projects. Feel free to interrupt me with questions in class – I'll be asking you questions too!

OUTLINE

Chapters 1 and 2: Questions About Questions and The Experimental Ideal.

This easy-to-read background material sets the stage for the more technical material to come. Please look at this on your own.

Chapter 3: Making Regression Make Sense

Lecture Note I: Regression and the CEF

Regression approximates the Conditional Expectation Function (CEF)
Review of large sample theory for OLS estimates
Why regression is called regression and what regression-to-the-mean means

Lecture Note II: Causal Regression (our main occupation); Regression vs. Matching

Linking a regression model to a causal model; Conditional independence assumptions
Omitted variables bias
Bad control
Matching to estimate the effect of treatment on the treated
Theoretical comparison of regression and matching

Extras (time-permitting)

Bad control
Even more on regression and matching
Limited dependent variables and marginal effects

Lecture Note III: Training Programs and the Propensity Score

The propensity score theorem
The Lalonde/Dehejia-Wahba/Smith-Todd controversy
Why I think the propensity score is useful but not special

Chapter 4: Instrumental Variables in Action

Lecture Note IVa: Constant-effects models

IV and omitted variables bias: using 2SLS to estimate a “long regression” without controls
The Wald estimator and grouped data
Two-sample IV and related methods

IV details (part 1)

The bias of 2SLS

Lecture Note IVb: Instrumental variables with heterogeneous potential outcomes

Local average treatment effects; internal vs. external validity
The *compliers* concept; identification of effects on the treated and ATE
IV in randomized trials
Counting and characterizing compliers

Generalizing LATE

Models with variable treatment intensity

IV details (part 2; time-permitting)

2SLS mistakes
Limited dependent variables reprise

Chapter 8: Nonstandard standard errors issues

The bias of robust standard errors

Why robust s.e.s are biased
A simple example

Clustering and serial correlation in panels

Clustering and the Moulton problem
Serial correlation in panels and differences-in-differences models
Fewer than 42 clusters.

EMPIRICAL STRATEGIES IN LABOUR ECONOMICS

University of Minho **J. Angrist**
NIPE Summer School **June 2009**

READINGS

J.D. Angrist and J.S. Pischke, *Mostly Harmless Econometrics: An Empiricists Companion*, Princeton University Press, 2008.

The reading list is keyed to the *MHE* table of contents. An asterisk denotes material in the reading packet distributed to students. Published journal articles should be available via JSTOR.

1-2. INTRODUCTION AND BACKGROUND

MHE, Chapters 1-2.

3. REGRESSION

3.1 Regression and the CEF; Review of large-sample theory

MHE, Section 3.1

*G. Chamberlain, "Panel Data," Chapter 22 in *The Handbook of Econometrics*, Volume II, Amsterdam: North-Holland, 1983.

3.2 Regression and Causality

MHE Section 3.2

*J. Angrist and A. Krueger, "Empirical Strategies in Labor Economics," Chapter 23 in O. Ashenfelter and D. Card, eds., *The Handbook of Labor Economics*, Volume III, North Holland, 1999 (esp. Sections 2.1-2.2).

3.3 Regression and matching

MHE Chapter 3.3.1

J. Angrist, "Estimating the Labor Market Impact of Voluntary Military Service Using Social Security Data on Military Applicants," *Econometrica*, March 1998.
A. Abadie and G. Imbens, "Large Sample Properties of Matching Estimators for Average Treatment Effects," *Econometrica* 74(1), 2006, 235-267.
G. Imbens, "Nonparametric Estimation of Average Treatment Effects under Exogeneity: A Review," *The Review of Economics and Statistics*, 86(1), 2004.

The propensity score

MHE Section 3.3.2-3.3.3

O. Ashenfelter, "Estimating the Effect of Training Programs on Earnings," *The Review of Economics and Statistics* 60 (1978), 47-57.
O. Ashenfelter and D. Card, "Using the Longitudinal Structure of Earnings to Estimate the Effect of Training Programs on Earnings," *The Review of Economics and Statistics* 67 (1985):648-66.
R. LaLonde, "Evaluating the Econometric Evaluations of Training Programs with Experimental Data," *American Economic Review* 76 (September 1986): 604-620.
J. Heckman and J. Hotz, "Choosing Among Alternative Nonexperimental Methods for Estimating the Impact of Social programs: The Case of Manpower Training," *JASA* 84 (1989): 862-8.
J. Heckman, H. Ichimura, and P. Todd, "Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme," *The Review of Economic Studies* 64, October 1997.
P. Rosenbaum and R. Rubin, "Reducing Bias in Observational Studies Using Subclassification on the Propensity Score," *JASA* 79[387], September 1984, 516-524.
Rosenbaum, P. R. And D. B. Rubin, 1983, "The Central Role of the Propensity Score in Observational Studies for Causal Effects," *Biometrika* 70[1], April 1983, 41-55.
R. Dehejia and S. Wahba, "Causal Effects in Nonexperimental Studies: Re-evaluating the Evaluation of Training Programs," *JASA* 94 (Sept. 1999).
J. Smith and P. Todd, "Does Matching Overcome LaLonde's Critique of Nonexperimental Estimators?" *Journal of Econometrics*, 2005(1-2).
J. Hahn, "On the Role of the Propensity Score in Efficient Estimation of Average Treatment Effects," *Econometrica* 66, March 1998.
J. Angrist and J. Hahn, "When to Control for Covariates? Panel-Asymptotic Results for Estimates of Treatment Effects," *Review of Economics and Statistics*, February 2004.
K. Hirano, G. Imbens, and G. Ridder, "Efficient Estimation of Average Treatment Effects Using the Estimated Propensity Score," *Econometrica* 71(4), 2003.

4. INSTRUMENTAL VARIABLES

4.1 2SLS with constant effects; the Wald estimator, grouped data

MHE Section 4.1

J. Angrist and A. Krueger, "Instrumental Variables and the Search for Identification," *Journal of Economic Perspectives*, Fall 2001.
J. Angrist, "Grouped Data Estimation and Testing in Simple Labor Supply Models," *Journal of Econometrics*, February/March 1991.
J. Angrist, "Lifetime Earnings and the Vietnam Era Draft Lottery: Evidence from Social Security Administrative Records," *American Economic Review*, June 1990.
*J. Angrist and S. Chen, "Long-Term Economic Consequences of Vietnam-Era Conscription: Schooling, Experience and Earnings," IZA Discussion Paper, August 2008.

4.3 Two-Sample IV and related estimators

MHE Section 4.3

J. Angrist and A. Krueger, "The Effect of Age at School Entry on Educational Attainment: An Application of Instrumental Variables with Moments from Two Samples," *JASA 87* (June 1992).
J. Angrist and A. Krueger, "Split-Sample Instrumental Variables Estimates of the Returns to Schooling," *JBES*, April 1995.
[*]Inoue, Atsushi and G. Solon, "Two-Sample Instrumental Variables Estimators," manuscript, forthcoming in *The Review of Economics and Statistics.*

4.6.4 The bias of 2SLS

MHE Section 4.6.4

J. Angrist, G. Imbens, and A. Krueger, "Jackknife Instrumental Variables Estimation," *Journal of Applied Econometrics* 14(1), 57-67.
Flores-Lagunes, Alfonso, "Finite-Sample Evidence on IV Estimators with Weak Instruments," *Journal of Applied Econometrics* 22, 2007, 677-694

4.4 Instrumental variables with heterogeneous potential outcomes

MHE Section 4.4

G. Imbens and J. Angrist, "Identification and Estimation of Local Average Treatment Effects," *Econometrica*, March 1994.
J. Angrist, G. Imbens, and D. Rubin, "Identification of Causal Effects Using Instrumental Variables," with comments and rejoinder, *JASA*, 1996.
J. Angrist and A. Krueger, "Does Compulsory Schooling Attendance Affect Schooling and Earnings?," *Quarterly Journal of Economics* 106, November 1991, 979-1014.
J. Angrist, "Treatment Effect Heterogeneity in Theory and Practice," *The Economic Journal* 114, March 2004, C52-C83.

4.5 Generalizing LATE

MHE Section 4.5.3 – variable treatment intensity

J. Angrist and G. Imbens, "Two-Stage Least Squares Estimation of Average Causal Effects in Models with Variable Treatment Intensity," *JASA*, June 1995.
[*]J. Angrist, V. Lavy, and Analia Schlosser, "Multiple Experiments for the Causal Link Between the Quantity and Quality of Children," MIT Working Paper 06-26, September 2006.

4.6 IV details

Limited dependent variables reprise

MHE Section 4.6.3

J. Angrist, "Estimation of Limited Dependent Variable Models with Dummy Endogenous Variables: Simple Strategies for Empirical Practice," *JBES* 19(1), January 2001.

8. NON-STANDARD STANDARD ERRORS ISSUES

MHE, Chapter 8

A. Chesher and I. Jewitt, "The Bias of a Heteroskedasticity-Consistent Covariance Matrix Estimator," *Econometrica* 55, September 1987.

Moulton, Brent. 1986. "Random Group Effects and the Precision of Regression Estimates", *Journal of Econometrics*, 32, pp. 385-397.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan, "How Much Should We Trust Differences-in-Differences Estimates?," *QJE* 119 (February 2004), 249-275.

EMPIRICAL STRATEGIES IN LABOUR ECONOMICS

University of Minho **J. Angrist**
NIPE Summer School **June 2009**

PROBLEMS

1. Discuss the relationship between regression and matching, as described below:

a. Suppose all covariates are discrete and you are trying to estimate a treatment effect conditional on covariates. Prove that if the regression model for covariates is saturated, then matching and regression estimates will estimate the same parameter (i.e., have the same *plim*) in either of the following two cases: (i) treatment effects are independent of covariates; (ii) treatment assignment is independent of covariates.

b. Propose a weighted matching estimator that estimates the same thing as regression.

c. Why might you prefer regression estimates over matching estimates, even if you are primarily interested in the effect of treatment on the treated?

d. (extra credit) Calculate matching and regression estimates in the empirical application of your choice. Discuss the difference between the two estimates with the aid of a figure like the one used in Angrist (1998) for this purpose.

2. You are interested in estimating a regression of log wages, y_i, on years of schooling, s_i, while controlling for another variable related to schooling and earnings that we will call a_i. Consider the following regression:

$$y_i = \beta + \rho s_i + a_i\gamma + \epsilon_i \tag{1}$$

Assume that the regression coefficients β, ρ and γ are defined such that ϵ_i is uncorrelated with s_i and a_i.

a. Suppose you estimate a bivariate regression of y_i on s_i instead. What is the plim of the coefficient on s_i in terms of the parameters in equation (1)? When does the "short regression" estimate of ρ equal the "long regression" estimate?

b. Why is the long regression more likely to have a causal interpretation? Or is it?

3. Consider using information on quarter of birth, Q_i (= 1, 2, 3, 4), as an instrument for equation (1) when a_i is unobserved. You are trying to use an instrument to get the long-regression ρ in a sample of men born (say) in 1930-39.

a. What is the rationale for using Q_i as an instrument?

b. Show that using $z_i = 1[Q_i=1]$ plus a constant as an instrument for a bivariate regression of y_i on s_i produces a "Wald estimate" of ρ based on comparisons by quarter of birth. Given the rationale in (a), is this estimator consistent for ρ in equation (1)?

c. Suppose that the omitted variable of interest, a_i, is still unobserved but we know that it is the age of i measured in quarters. What is the plim of the Wald estimator in this case? Can you sign the bias of the Wald estimator?

d. Suppose that instead of using z_i, you use Q_i itself as an instrument. Show that the resulting estimator is not consistent either (continuing to assume a_i is omitted and equal to age in quarters). Can you use the two inconsistent estimators (Wald and IV using Q_i) to produce a consistent estimate of ρ?

e. Now suppose that a_i is observed and included in your model. Explain when and how you can consistently estimate ρ by 2SLS using 3 quarter of birth dummies, $z_{1i} = 1[Q_i=1]$, $z_{2i} = 1[Q_i=2]$, and $z_{3i} = 1[Q_i=3]$, plus a constant as the excluded instruments.

f. As an alternative to 2SLS, consider using a dummy for "middle quarters,:
$z_{im} = I[Q_i=2 \text{ or } Q_i=3]$, plus a constant as instruments for a <u>bivariate</u> regression of y_i on s_i. Show that this also produces a consistent estimate of ρ when Q_i is uniformly distributed (still assuming that a_i is age in quarters). Explain why this strategy works. On what basis might you choose between these alternative estimators?

g. Suppose the equation of interest includes a quadratic function of age in quarters:

$$y_i = \beta + \rho s_i + a_i\gamma_0 + a_i^2\gamma_1 + \epsilon_i \qquad (2)$$

Explain why the "middle-quarters" estimator no longer works. Can you think of an estimator that does?

4. Construct an extract from the 1980 Census similar to the one used by Angrist and Krueger (1991). use this extract to compute and compare the estimates discussed in questions 2 and 3.

5. Discuss the link between causal effects and structural parameters in a Bivariate Probit model of the relationship between divorce and female labor force participation. The purpose of the model is to determine whether female employment strengthens a marriage or increases divorce. Organize your discussion as outlined below:

a. Explain in words why the causal effect of employment on divorce is difficult to determine. Is the problem here primarily one of identification or estimation? Can you design an experiment to answer the question of interest?

b. Write the potential outcomes and potential treatment assignments in your causal model in terms of latent indices with unobserved random errors in a structural model.

c. What should the population be for this study? What does it mean for employment to be "endogenous" in the structural model? How about in the causal model?

d. Show how to use the Probit structural parameters and distributional assumptions to calculate the population average treatment effect (ATE), the effect on the treated (ETT), and LATE. Which parameters are identified without distributional assumptions?

e. Discuss the relationship between the three average causal effects, LATE, ATE, and ETT. Can you say which is likely to be largest and which is likely to be smallest?

f. Compare OLS with Probit and IV with Bivariate Probit in the application of your choice (as in Angrist, 2001).