Beyond Mean Impacts in Empirical Research

Taught by:

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http://www.ssb.no/english/research/people/mmo/index.html

Time:

Day 1: 05.05.2011, 15:00-18:30

Day 2: 06.05.2011, 09:00-13:30

Venue:

DIW Berlin, Gustav Schmoller Room (1.2.026), Mohrenstr. 58, 10117 Berlin

Course prerequisite:

Understand the main techniques of quantitative economics and econometrics at a level appropriate for an economics graduate.

Course Description:

This course discusses workhorse models in empirical economics in a framework with heterogeneous potential outcomes, in which case causal effects will also be heterogeneous. The main focus is on estimation and interpretation of regression models in situations where the underlying relationship is heterogeneous and/or nonlinear. This should be a key issue for empirical research, because economic theory often makes strong predictions concerning heterogeneity and/or nonlinearity in the relationship of interest. In order to test theory or assess policy, it is therefore useful to move beyond mean impacts. For example, economic theory often predicts systematic heterogeneity in the impact of recent welfare reforms on earnings, transfers, and income. Yet most studies of welfare reform focus on mean impacts. As a consequence, they risk to average together labor supply responses of different magnitude and even sign, obscuring the extent of welfare reform's effects.

<u>Day 1:</u>

The first day focuses on the issue of nonlinearity when the regressor of interest takes on multiple values, so-called variable treatment intensity. There are numerous applications with variable treatment intensity, including the economic return to schooling, class size and child development, family size and child quality, fertility and maternal labor supply, family income and child development, and maternal smoking and children's birth weight. In most applications with variable treatment intensity, the researcher uses a linear regression model, which restricts the marginal effects to be constant across all margins. Although the linear specification is convenient and could be preferable on grounds of efficiency, it often runs counter to economic theory predicting a nonlinear (and sometimes non-monotonic) relationship.

We will first show how OLS, fixed effect and IV generate a weighted average of marginal effects when the underlying relationship is non-linear, with a weighting function we can estimate and study, so to learn where the action is coming from. Next, we examine the biases due to nonlinearity in the commonly used tests for non-zero treatment effects, selection bias, and instrument validity. We conclude this section with a discussion of possible remedies to the problems caused by the linearity restriction.

<u>Reading list:</u>

1. *Angrist, J. D. & G. Imbens (1995): “Two-Stage Least Squares Estimation of Average Causal Effects in Models with Variable Treatment Intensity," Journal of the American Statistical Association, 90(430), 431-442.
2. Angrist, J. D. & A. B. Krueger (1999): “Empirical Strategies in Labor Economics," in Handbook of Labor Economics, ed. by O. Ashenfelter, and D. Card.
3. Heckman, J., S. Urzua & E. Vytlacil (2006): “Understanding Instrumental Variables in Models with Essential Heterogeneity," Review of Economics and Statistics, 88(3), 389-432.
4. Løken, K, M. Mogstad & M. Wiswall (2011): “What Linear Estimators Miss: The Effects on Family Income of Child Outcomes”, NYU Working Paper. Available at: http://homepages.nyu.edu/~mw109/loken_mogstad_wiswall_family_income.pdf
5. *Mogstad, M. & M. Wiswall (2011): “Linearity in Instrumental Variables Estimation: Problems and Solutions”, NYU Working Paper. Available at: http://homepages.nyu.edu/~mw109/mogstad_wiswall_iv_linearity.pdf

<u>Day 2:</u>

The second day focuses on the issue of (treatment effect) heterogeneity when the regressor of interest is binary. One important reason for the popularity of OLS regressions in empirical research is that they provide consistent estimates of the impact of an explanatory variable, *X*, on the *population unconditional mean* of an outcome variable, *Y*. However, when the question of interest concerns other aspects of the distribution of Y, we must turn to estimation methods that “go beyond the mean”. To this end, conditional quantile regressions have become a popular tool. Unfortunately, conditional quantiles *do not* average up to their unconditional population counterparts. As a result, the estimates obtained by running a (series of) quantile regression(s) cannot be used to estimate the impact of *X* on the corresponding unconditional quantile(s). That is, it cannot answer a question as simple as “what is the impact on median earnings of increasing everybody’s education by one year, holding everything else constant?”. Instead, Bitler et al. (2005) and Firpo (2007) propose estimating bivariate quantile regressions, where controls are factored out by propensity score weighting. As an alternative, Firpo et al. (2009) propose an alternative *RIF*-estimator, based on the recentered influence function. Both methods allow identification of effects on the unconditional quantiles, and thus the counterfactual outcome distribution in the absence of treatment.

This part of the course aims at discussing the estimation of quantile treatment effects in empirical methods that assumes selection on observables (OLS) and/or selection on unobservables (Differences-in-differences, IV).

<u>Reading list:</u>

1. Alberto Abadie & Joshua Angrist & Guido Imbens, 2002. "Instrumental Variables Estimates of the Effect of Subsidized Training on the Quantiles of Trainee Earnings," Econometrica, Econometric Society, vol. 70(1), pages 91-117, January.
2. *Susan Athey & Guido W. Imbens, 2006. "Identification and Inference in Nonlinear Difference-in-Differences Models," Econometrica, Econometric Society, vol. 74(2), pages 431-497, 03.
3. *Marianne P. Bitler & Jonah B. Gelbach & Hilary W. Hoynes, 2006. "What Mean Impacts Miss: Distributional Effects of Welfare Reform Experiments," American

Economic Review, American Economic Association, vol. 96(4), pages 988-1012, September.

4. Bitler, Marianne P. & Gelbach, Jonah B. & Hoynes, Hilary W., 2008. "Distributional impacts of the Self-Sufficiency Project," Journal of Public Economics, Elsevier, vol. 92(3-4), pages 748-765, April.
5. Sergio Firpo, 2007. "Efficient Semiparametric Estimation of Quantile Treatment Effects," Econometrica, Econometric Society, vol. 75(1), pages 259-276, 01.
6. *Sergio Firpo & Nicole M. Fortin & Thomas Lemieux, 2009. "Unconditional Quantile Regressions," Econometrica, Econometric Society, vol. 77(3), pages 953-973, 05.
7. *Frölich, Markus & Melly, Blaise, 2008. "Unconditional Quantile Treatment Effects under Endogeneity," IZA Discussion Papers 3288, Institute for the Study of Labor (IZA).
8. Havnes, Tarjei & Mogstad, Magne, 2010. "Is Universal Child Care Leveling the Playing Field? Evidence from Non-Linear Difference-in-Differences," IZA Discussion Papers 4978, Institute for the Study of Labor (IZA).
9. Roger Koenker & Kevin F. Hallock, 2001. "Quantile Regression," Journal of Economic Perspectives, American Economic Association, vol. 15(4), pages 143-156, Fall.