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PhD Programme
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Microeconometrics for PhDs

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Course Description

We explore in-depth additional themes of econometrics that are at the frontier of research – not of theoretical econometrics but at the frontier of applied research. The course proceeds as a workshop where students are encouraged to develop their own estimation alongside the sessions.

In particular, we start with quantile regressions, which has been developed by Roger Koenker and introduced to economics by Buchinsky. Quantile regression is particularly interesting if one is interested in not predicting the mean but predicting the tails of the distribution of the outcome variables. Quantile regression is for instance used for Value-At-Risk estimation.

We then turn to matching, an estimation technique developed by Donald Rubin and that enjoys widespread use. The theory of matching is still not fully understood, and we will see the latest developments on the consistency and the standard errors of matching estimators from Guido Imbens' work.

The next topic is heterogeneity in instrumental variable estimation: definition of the Local Average Treatment Effect (LATE).

Structural models of differentiated products are widely used in Marketing, Economics, and Technology and Operations Management. We read the seminal Berry, Levinsohn and Pakes model and develop an estimation procedure.

The last topic for microeconometrics is Bayesian Econometrics. We show that Bayesian techniques, far from being detached from frequentist econometrics, provide fast algorithms for the estimation of parameters with complex likelihood functions.

Materials

The following textbooks will be used.

- William H. Greene's *Econometric Analysis*.
- A. Colin Cameron, Pravin K. Trivedi, *Microeconometrics Using Stata*, Stata Press, 2009.
- J. Angrist and S. Pischke, *Mostly Harmless Econometrics: An Empiricist's Companion,* Princeton University Press, 2009.
- A. Colin Cameron and P.K. Trivedi's Microeconometrics, Methods and Applications, at Cambridge University Press.
- Yudi Pawitan, In All Likelihood, Oxford University Press, 2013.

Everything else you need is either handed out in class or posted on the course website at http://www.ouazad.com/PhD-Econometrics/.

Assessment

Students are assessed based on their presentation of a paper in one of the fields of the course.

Software

Each session specifies the recommended software. Quantile estimation can be performed in Stata. Matching can be done using psmatch2 in Stata. BLP models are best estimated in R or Matlab.

Frequently Asked Questions

What are the course's prerequisites?

- The course will assume that econometrics A and B have been undertaken and that good grades have been obtained. Knowledge of a flexible programming language is typically needed (Matlab or R), as well as an excellent knowledge of Stata or SAS.

How do I work for this course ?

- You will present a paper of your choice on one of these topics. Also, for each session you should try to implement the estimation techniques using either sample data or your research data.

Session 1: Quantile Regression

- **Key concepts:**
  - The quantile function.
  - The quantile GMM estimator.
  - Standard errors in the GMM framework.
  - Interpreting quantile regression output.

- **Readings:**
  - Koenker, Roger, and Gilbert Bassett Jr. "Regression quantiles."*Econometrica: journal of the Econometric Society* (1978): 33-50.
  - Buchinsky, Moshe. "Recent advances in quantile regression models: a practical guideline for empirical research." *Journal of human resources*(1998): 88-126.

- Woo-Jin Chang, Steve Monahan, Amine Ouazad, "The Higher Moments of Future Return on Equity", (2015).

- **Software**:
  - qreg in Stata.

The quantile regression framework allows the estimation of the impact of covariate on outcomes. We show under which conditions such impact can be interpreted as causal. The quantile regression estimator is shown to be a GMM estimator, which can be estimated using a linear programming technique.

Session 2: Matching

- **Key concepts:**
  - The ignorability assumption.
  - Mahalanobis matching.
  - Propensity score matching.
  - Consistency of the matching estimator.

- **Chapters**
  - *Microeconometrics,* Cameron and Trivedi, Chapter 25.

- **Papers**
  - Heckman, Ichimura, Todd (1998), "*Matching as an econometric evaluation estimator*," Review of Economic Studies.
  - Dehejia and Wahba (1999), "*Causal Effects in Nonexperimental Studies: Reevaluating the Evaluation of Training Programs*," Review of Economics and Statistics.
  - Rosenbaum and Rubin (1983), "*The Central Role of the Propensity Score in Observational Studies for Causal Effects*," Biometrika, Vol. 70, Issue 1, 1983.
  - Caliendo & Kopeinig, "Some Practical Guidance for the Implementation of Propensity Score Matching," IZA Discussion Paper, 2005.

The matching estimator requires the ignorability assumption, i.e. the randomization of the assignment of the treatment to the subjects. Thus in that sense matching's assumptions are as stringent as OLS. We show that matching allows a flexible estimation of the Average Treatment on the Treated and of the Average Treatment Effect. Matching relaxes the linearity assumption of OLS. Matching can also be more efficient than OLS. The important Dehejia and Wahba (1999) paper shows how matching can recover estimates that are very close to the effects obtained using a randomized controlled experiment.

Session 3: Heterogeneity in Instrumental variable estimation

- **Key concepts**:
  - The Local Average Treatment Effect.

- **Readings**

    - Imbens, Guido W., and Joshua D. Angrist. "Identification and Estimation of Local Average Treatment Effects." *Econometrica* 62.2 (1994): 467-475.
    - Angrist, Joshua D. "Treatment effect heterogeneity in theory and practice*." *The Economic Journal* 114.494 (2004): C52-C83.

In general treatments have heterogeneous causal impacts on subjects' outcomes. With such heterogeneity, what does an IV estimator estimate? Imbens and Angrist (1994) shows that the IV estimator estimates the Local Average Treatment Effect. We apply this insight to the estimators we developed in Econometrics A, and in particular to the regression discontinuity design.

Session 4: Structural Models of Differentiated Product Choice

- **Key concepts**
    - Multinomial logit.
    - Random coefficients models.
    - Instrument variable estimation of Random Coefficients Models.
    - Two-step GMM.
    - Contraction mapping.

- **Readings**
    - Berry, Steven, James Levinsohn, and Ariel Pakes. "Automobile prices in market equilibrium." *Econometrica: Journal of the Econometric Society*(1995): 841-890.
    - Petrin, Amil. "Quantifying the Benefits of New Products: The Case of the Minivan." *Journal of Political Economy* 110.4 (2002).
    - Dubé, Jean-Pierre, Jeremy T. Fox, and Che-Lin Su. "Improving the numerical performance of static and dynamic aggregate discrete choice random coefficients demand estimation." *Econometrica* 80.5 (2012): 2231-2267.

The Berry, Levinsohn, and Pakes paper introduced the world to the so-called BLP model. This model has become the workhorse of marketing, industrial organization, and operations research. It can be daunting but we will see that it boils down to a simple two-stage least squares estimation in its simplest form. We will implement the paper in R.

Session 5: Bayesian Econometrics

- **Key concepts**
    - Priors. Improper priors.
    - The likelihood function.
    - The Bayesian estimator.
    - Confidence intervals, hypothesis testing in the Bayesian framework.
    - Gibbs sampling.
    - Monte Carlo Markov Chain estimator.

- **Reading**

- Lancaster, Tony. *An introduction to modern Bayesian econometrics*. Oxford: Blackwell, 2004.

Bayesian statistics is formally a different branch of statistics, and therefore Bayesian econometrics (as opposed to frequentist econometrics) is a different branch of econometrics. While in frequentist econometrics, true parameters exist and are yet to be discovered, in Bayesian econometrics parameters are random variables. We hold probability judgments on such parameters. We show how to build the posterior distribution of a parameter. We show how to choose a prior. We then present Bayesian estimators of parameters.

Although the foundations of Bayesian econometrics are different than the foundations of frequentist econometrics, the two yield identical results if one assume a flat improper prior. Alternatively, with an infinite number of observations, the choice of the prior becomes irrelevant and the maximum likelihood estimator and the Bayesian estimator converge to the same value.

This course therefore introduces Bayesian econometrics as providing two useful estimation techniques: the Gibbs sampling, and the Monte Carlo Markov Chain (MCMC) methods.