Large-N statistical (econometric) analyses in environmental economics

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What is econometrics?

• Application of statistical methods to economic questions.

• Links to methods of empirical analysis in many other social sciences (political science, sociology, ...) some medical sciences (epidemiology), some natural/physical sciences (ecology).

• Fields that value and sometimes perform experiments, but are often stuck with using observational data to evaluate hypotheses of interest.
“Taking the ‘con’ out of econometrics”

• “Credibility revolution” in empirical economics since ~1990s – strong focus on causality and identification.

• The modern econometrics (”program evaluation”) toolkit:
  • Randomized experiments
  • Regression models with flexible controls for potential confounders – those variables that might mask causal effects of interest
  • Instrumental variables models for the analysis of real and natural experiments
  • Differences-in-differences type strategies that use repeated observations to control for unobserved omitted factors

Angrist, JD, and J-S Pischke. The credibility revolution in empirical economics: how better research design is taking the con out of econometrics. *J. Econ. Perspect.* 24(2): 3-30.
Angrist & Pischke’s four questions

• (1) What is the causal relationship of interest?
  • How does an ESA listing affect the survival probability of a species?
  • How does information disclosure affect drinking water violations?
  • Do protected areas reduce tropical deforestation?
  • What is the effect of air pollution regulations on mortality?
  • Does “spring protection” reduce the incidence of waterborne disease?

• (2) What is the (real or hypothetical) experiment that could ideally be used to capture the causal effect of interest?

Angrist & Pischke’s four questions, cont.

• (3) What is your identification strategy?
  • How do you use your observational data to approximate a real experiment?
  • Often hinges on the ability to construct a “reasonable” counterfactual.

• (4) What is your mode of statistical inference?
  • What is the population to be studied, the sample to be used, and what are the assumptions to be made when constructing standard errors for your coefficient estimates?

Selection bias: the need for a good counterfactual

• What if we simply compare outcomes (say, whether a species survives, or not) for ESA-listed species and non-listed species?

• Observed difference in outcomes = average effect of listing on listed species + selection bias

• Selection bias
  • Treatment and control groups differ due to factors that also affect a policy/program’s outcomes.
  • In this example: pre-listing difference in survival probability between unlisted and listed species.
  • If listed species were less likely to survive ex ante, then selection bias would be negative.
  • If listed species were more likely to survive, then selection bias would be positive.
Experiments in environmental economics

• Random assignment to control/treatment groups solves the selection problem (randomized experiments are the “gold standard” in empirical analysis).

• Until recently, not much experimental work (in the field) by economists, including environmental economists – this has changed dramatically.

• Two recent examples:
  • Kremer et al. (2011). Spring Cleaning
  • Jessoe and Rapson (2014). Knowledge is (less) power
When experiments aren’t possible/desirable, what next?

• Design an empirical approach that tests your hypothesis in a manner that replicates, as closely as possible, the conditions of a controlled experiment.

• Keep the methods as straightforward/simple as possible.
  • Interpretation of estimates should not be heavily “model dependent”
  • Hence the emphasis on linear regression, even where earlier analysts might have worried more about the downsides to this class of approaches.

• Be willing to trade fancy models for robustness of simpler ones.
Natural experiments in environmental economics

• A natural experiment takes advantage of treatment and control groups created by nature, chance, or exogenous policy shifts, and exploits the variation between these groups to estimate the effect of interest.

• Examples:
  
  • Libecap and Lueck (2011) analyze the effect of land demarcation systems on property values, exploiting variation in Ohio related to post-Civil-War land grants.
  
  • Kotchen and Grant (2011) analyze the effect of daylight savings time on electricity consumption, exploiting variation in Indiana counties’ adoption of DST.
Regression models

• Regression models with flexible controls for potential confounders – those variables that might mask causal effects of interest.

• Typical models of this type include sets of “fixed effects” for both the spatial and intertemporal units of interest, rather than (or in addition to) a rich set of descriptive covariates.

• Controlling for observables isn’t enough – must also control for potentially confounding \textit{unobservable} heterogeneity.
Examples of regression models

• Olmstead et al. (2013) – estimate the impact of shale gas development in PA on water quality.
  • Include fixed effects for each water quality monitor, and each month (Jan. 2000 - Dec. 2011). Controls for average pollutant levels observed at each monitor over the period, and average levels observed at all monitors in each time period.

• Olmstead and Sigman (ongoing) – estimate the impact of drought on economic activity, and the mediating influence of dams.
  • Include fixed effects for each 10km x 10km grid cell (whole world, less areas with no lights for the whole period), and for each year.
Instrumental variables (IV) models

• Identify a variable, or set of variables, that is correlated with your treatment of interest, but otherwise independent of potential outcomes (technically, uncorrelated with the unexplained variation in outcomes).

• Use these variables as “instruments” to first obtain an estimate of the treatment variable (which no longer contains the confounding variation), and then in a second stage, estimate the effect of interest.
Some examples of IV models

• Pitt et al. (2005)
  • Estimate the impact of indoor air pollution (PM from cooking) on women’s health in Bangladesh.
  • But households may allocate cooking to women in poorer health (e.g., older), which could bias estimates.

• Olmstead and Sigman (2015)
  • Estimate the effect of being upstream of an international border on the intensity with which countries dam rivers.
  • Treaties could mitigate any observed “common property” problems.
  • But some of the same things that drive damming of rivers may also drive treaty formation.
Difference-in-difference type models

• Difference-in-differences
  • Data on treated vs. control observations, pre vs. post treatment.
  • Calculate the change in outcomes among treated group between the two periods, and subtract from that the change in outcomes among the control group.

• Matching
  • Match the treatment group observations to otherwise “very similar” observations that did not receive the treatment.
  • Use these matches to statistically construct a counterfactual control group.

• Regression Discontinuity
  • Assignment to the treatment is based on the value of an observed covariate, and whether that value lies on one side or the other of a fixed threshold.
Some examples of DID-type models

- **DID**: Bennear (2007) examines whether “management-based regulation” affects firms’ releases of toxic chemicals. She compares pre/post regulation differences in releases among plants covered by these regs, with pre/post differences among plants not covered.

- **Matching**: Ferraro et al. (2007) examine whether ESA listing affects species’ endangerment status, using matching. The matches are made using taxonomy and size, pre-treatment endangerment status, number of scientific pubs on a species, League of Conservation Voters scores of state delegations.

- **RD**: Chay and Greenstone (2005) examine the effects of air pollution (PM) on housing values, exploiting the discontinuity in regulation that occurs between attainment/nonattainment counties under the CAA.
Concluding thoughts

• Empirical economists who study environmental amenities and environmental policy use “large-N” statistical methods – we call this practice “econometrics,” but the tools resemble those in other fields.

• One important difference may be the emphasis on causal inference using observational data.
  • Experiments are still the “gold standard”
  • But many interesting/important questions can’t be explored through field experiments.
  • Economists have had to adopt (from other disciplines) and create methods to bring some of the qualities of controlled experiments to observational studies.