Empirical Methods for Policy Evaluation II

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Motivation/Historical Background

- Long-standing debate about the extent to which economic theory should inform econometric modeling and estimation
  - Design-based vs. structural modeling approaches to policy evaluation
- Why not doing both?
  - Middle ground approach dates back to Marschak (1953)
  - McFadden (1977) validated ex-ante model predictions against actual data realized ex-post
  - Many others advocates since then...
- Why don't we see more of "the best of both worlds"?

Overview of this Part of the Course

- This part of the course covers models that span different sub-fields in empirical micro
- Showcase recent attempts of injecting research designs into those models
- Natural synergy for a better characterization of policy impacts
    - RCTs and natural experiments enhance the credibility of inference from structural estimation
    - Structural models can complement (quasi-)experimental analysis in a variety of ways

Outline for this Part of the Course

1. Ex-ante and ex-post policy evaluation
2. Dynamic discrete choice models
   - Policy/design: cash transfer program in Mexico/RCT
3. Matching models
   - Policy/design: public-sector teacher wage setting in Perú/RDD
4. Dynamic latent factor models
   - Policy/design: early childhood intervention in Colombia/RCT
5. Job search models
   - Policy/design: labor market reforms in the presence of informality/Diff-in-Diff

Course Requirements

1. Takehome (in pairs)
   - Model+identification+estimation
   - Data and questions posted on Moodle by Mid-dec
2. Referee report (individual)
   - Pick one paper in section 2.6 of the syllabus (pdfs also posted on Moodle)
3. Class participation
   - Please try to read in advance the papers to be discussed in class

Part 1: Ex-ante and Ex-post Evaluation Approaches

1. Ex-ante policy evaluation
   - **Chapter 2 in Wolpin (MIT press, 2013)**
2. The best of both worlds
   - Todd and Wolpin (JEL, 2021)
   - Galiani and Pantano (2021)

Two (Complementary?) Approaches

1. Ex-post evaluation (design-based approaches)
    - Effects of a given policy (treatment) on a set of individual outcomes
    - Isolate plausibly exogenous changes out of **realized** variations in a policy variable
2. Ex-ante evaluation (structural modeling approaches)
    - Policy and primitive parameters embedded in explicit economic models
    - Predict **hypothetical** variations in a policy variable

Hypothetical vs. Actual Programs

- Economic models allow predicting the effects of public policies before they are implemented and/or variants of existing policies
  - Improve program design to maximize impacts given costs
  - Inform program targeting by identifying sub-populations for which impacts are highest
  - Analyze program impacts over a time horizon that exceeds the length of time observed in the data
  - Analyze program impacts in the presence of spillover or general equilibrium effects

Empirical Approach

- Model-based estimation is an approach to empirical work that emphasizes, in this order:

1. The development of an economic model of the phenomenon being studied
2. The addition of a stochastic structure if the model itself does not possess one
3. The adaptation of an estimation technique given the nature of the model and the data at hand
4. A consideration of the identification of the "primitive" model parameters given the data, model, and estimator employed
5. Given estimates of primitive parameters, empirical comparative statics exercises and/or counterfactual policy experiments

Example of a Development Policy

- Many governments have adopted conditional cash transfer (CCT) programs as a way to alleviate poverty and stimulate human capital investments
  - Provide cash transfers to HHs conditional on school attendance of children
- Can we evaluate those programs before they are implemented?
  - Yes, with a model of schooling decisions in which the transfer decreases schooling costs

Data

- Household surveys
  - Child's age, gender, highest grade completed, current enrollment
  - Total labor earnings of the father and the mother
  - No school tuition costs, so in the data use variations in the opportunity cost
- Village-level data
  - Minimum wage paid to day laborers in each village (proxy for child market wage)
  - This can be thought of a measure of the potential earnings of a child laborer
  - Observed irrespectively of the working status of the children (no sample selection)

Economic Model

- Consider the following static optimization problem for the household

$$\max_{s\in\{0,1\}} U(c,s) \text{ s.t. } \begin{cases} c = y + w(1-s) \\ c = y + w(1-s) + \tau s \end{cases}$$

- Optimal schooling choices without and with the subsidy are

$$s^\star = g(y,w)$$
$$\tilde{s} = g(\tilde{y},\tilde{w})$$

  - $\tilde{y} = y + \tau$ and $\tilde{w} = w - \tau$

- The impact of the subsidy is equivalent to a (income-compensated) reduction in child wages

Bringing the Model to the Data

- Add observables (X) and unobservables (ϵ) preference shifters
- Unobserved heterogeneity is not systematically related to wages and income

$$f(\epsilon|y, w, X) = f(\epsilon, X) \tag{1}$$

- Given (1), variations in wages and income identify the impact of the program

Non-Parametric Estimation

- Ex-ante average treatment effect is:

$$\hat{\Delta}_{np} = \frac{1}{N}\sum_{j=1}^{N}\left[\underbrace{\hat{\mathbb{E}}(s_i|w_i = w_j - \tau_j, y_i = y_j + \tau_j, X_i)}_{\text{Predicted schooling under the program}} - \underbrace{s_j(w_j, y_j, X_i)}_{\text{Observed schooling}}\right]$$

  - $\mathbb{E}(s_i|w_i = w_j - \tau_j, y_i = y_j + \tau_j, X_i)$ can be estimated by nonparametric regression (kernel, local linear regression or series estimation)
  - Need common support in the data: i.e. set of families with X_i for which the values $w_j - \tau$ and $y_j + \tau$ lie within the observed support of w_i and y_i

Counterfactual Subsidy Levels

	Boys		
Ages	2* Original	Original	0.75*Original
12-13	0.04 (59%)	0.01 (87%)	0.003 (98%)
14-15	0.24 (45%)	0.01 (83%)	0.05 (98%)
12-15	0.12 (53%)	0.06 (86%)	0.02 (98%)
	Girls		
	2* Original	Original	0.75*Original
12-13	0.06 (48%)	0.06 (91%)	0.05 (98%)
14-15	0.23 (51%)	0.07 (89%)	0.03 (98%)
12-15	0.14 (50%)	0.06 (90%)	0.05 (98%)
	Boys and Girls		
	2* Original	Original	0.75*Original
12-13	0.05 (54%)	0.04* (89%)	0.03 (98%)
14-15	0.23 (48%)	0.09 (86%)	0.04 (98%)
12-15	0.13 (52%)	0.06 (88%)	0.03 (98%)

† Bandwidth equals 200 pesos. Trimming implemented using the 2% quantile of positive density values as the cut-off point.

Unconditional Income Grant

	Boys		
Ages	Predicted	Sample-Sizes‡	% overlapping support
12-13	-0.02 (0.03)	374, 610	89%
14-15	-0.06 (0.05)	309, 569	90%
12-15	-0.04 (0.03)	683, 1179	89%
	Girls		
	Predicted	Sample-Sizes‡	% overlapping support
12-13	-0.03 (0.04)	361, 589	88%
14-15	0.00 (0.05)	316, 591	88%
12-15	-0.02 (0.03)	677, 1180	88%
	Boys and Girls		
	Predicted	Sample-Sizes‡	% overlapping support
12-13	-0.03 (0.03)	735, 1199	88%
14-15	-0.03 (0.03)	625, 1160	89%
12-15	-0.03 (0.02)	1360, 2359	89%

†Standard errors based on 500 bootstrap replications. Bandwidth equals 200 pesos. Trimming implemented using the 2% quantile of positive density values as the cut-off point.
‡The first number refers to the total control sample and the second to the subset of controls that satisfy the PROGRESA eligibility criteria.

Adding Home Production

- Suppose that now we modify the model to allow for an alternative use of children's time, home production $l \in \{0, 1\}$

$$\max_{(s,l)} U(c, l, s) \text{ s.t. } \begin{cases} c = y + w(1 - s - l) \\ c = y + w(1 - s - l) + \tau s \end{cases}$$

- Optimal schooling choices without and with the subsidy are different

$$s^{\star\star} = g(y, w)$$
$$\tilde{\tilde{s}} = h(\tilde{y}, \tilde{w}, \tau)$$

- Non-parametric ex-ante approach is not feasible
- Which policy restores the equivalence between the schooling demand functions?

Parametric Approach

- Consider the following functional form for the utility function under the original problem (for simplicity, no child leisure and no X)

$$U(C, s; \epsilon) = C + \alpha s + \beta C s + \epsilon s, \ \epsilon \sim N(0, \sigma_\epsilon^2)$$

- The probability of school attendance under the subsidy is

$$P(s = 1) = 1 - \Phi\left(\frac{(w - \tau) - \alpha - \beta(y + \tau)}{\sigma_\epsilon}\right)$$

- Model parameters can be estimated by ML from data with no subsidy ($\tau = 0$) given the same sources of variation mentioned in the non-parametric case

Parametric Approach

- Given parameter estimates, the effect of introducing a subsidy of τ on the attendance rate can be calculated from

$$\hat{\Delta}_p = \Phi\left(\frac{(w-\tau)-\hat{\alpha}-\hat{\beta}(y+\tau)}{\hat{\sigma}_\epsilon}\right) - \Phi\left(\frac{w-\hat{\alpha}-\hat{\beta}y}{\hat{\sigma}_\epsilon}\right)$$

- Unlike the non-parametric case, there is no condition on the support of $y+\tau$ and $w-\tau$
- Functional forms and distributional assumptions substantially decrease the computational burden (curse of dimensionality) in solving/estimating structural models

Adding Dynamics

- Assume two schooling periods and no borrowing or saving
- Household utility is

$$U(C_1, C_2, s_1, s_2)$$

- Budget constraint under the subsidy is

$$C_t = (y_t + \tau) + (w_t - \tau)(1 - s_t),\ t = 1, 2$$

- Schooling decision in period 1 is based on the following comparison

$$\begin{aligned} V(s_1 = 1) =& U(y_1 + \tau, 1, \epsilon_1) + \delta \mathbb{E} \max[U(y_2 + \tau, 1, 1; \epsilon_2), U((y_2 + \tau) + (w_2 - \tau), 1, 0; \epsilon_2)] \\ V(s_1 = 0) =& U((y_1 + \tau) + (w_1 - \tau), 0; \epsilon_1) + \\ & \delta \mathbb{E} \max[U(y_2 + \tau, 0, 1; \epsilon_2), U((y_2 + \tau) + (w_2 - \tau), 0, 0; \epsilon_2))] \end{aligned}$$

Adding Dynamics

- The school attendance decision in period 2 is

$$\begin{aligned} s_2^\diamond &= 1 \text{ iff } U(y_2+\tau, s_1, 1; \epsilon_2) - U((y_2+\tau)+(w_2-\tau), s_1, 0; \epsilon_2) \geq 0 \\ &= 0 \text{ otherwise} \end{aligned}$$

- The school attendance decision in period 1 is

$$\begin{aligned} s_1^\diamond &= 1 \text{ iff } V(s_1 = 1) \geq V(s_1 = 0) \\ &= 0 \text{ otherwise} \end{aligned}$$

- The feasibility of ex-ante evaluation depends on what elements are in the household's information set

Perfect Foresight

- If households have perfect foresight about w_2 and y_2 but not about ϵ_2, then

$$s_1^\diamond = g\left[y_1 + \tau, y_2 + \tau, w_1 - \tau, w_2 - \tau; \epsilon_1, f(\epsilon_2 \mid \epsilon_1)\right]$$

  - Same school demand function for the no subsidy case and hence non-parametric ex-ante approach is feasible
  - If ϵ_t is iid, then $f(\epsilon_2 \mid \epsilon_1) = f(\epsilon_2)$, and hence conditional on $s_1^\diamond$ the matching procedure as in the static model can be used to estimate the impact of the subsidy on period 2 school attendance

Imperfect Foresight

- If households are uncertain about y_2 (assume y_t is iid), then

$$s_1^{\diamond\diamond} = m\left[y_1 + \tau, y_2 + \tau, w_1 - \tau, w_2 - \tau, \tau; \epsilon_1, \epsilon_2, f(y_2)\right]$$

  - Integrating over $f(y_2)$ in $V(s_1 = 0)$ and $V(s_1 = 1)$ changes the form of the school attendance demand function
  - Subsidy τ will now enter parametrically into the value functions and hence non-parametric ex-ante approach is not feasible
  - Same result under uncertainty about w_2

Economic models for policy analysis

- Estimating the effect of a new policy does not necessarily require specifying the complete structure of the model governing decisions
- Nonparametric ex ante policy evaluation may be feasible even when there is no variation in the data in the policy instrument (here, the price of schooling)
- If not feasible, one needs to impose extra-assumptions on the distribution of observed and unobserved heterogeneity

Combining Ex-ante and Ex-post Approaches

1. Out of Sample Validation

- Concerns about the plausibility of the model assumptions undermine the credibility of its predictions
  - Within-sample goodness-of-fit tests provide useful but not necessarily compelling evidence of the validity of the model
- The reliability of the model's predictions is better assessed in terms of **out-of-sample fit**
  - Estimate a model by holding out the treatment/control group, and then validate its predictions about program impacts

Out of Sample Validation – Example

	Boys			
Ages	Experimental	Predicted	Sample-Sizes‡	% overlapping support
12-13	0.05** (0.02)	0.01 (0.03)	374, 10	87%
14-15	0.02 (0.03)	0.01* (0.04)	309. 569	83%
12-15	0.03 (0.02)	0.06 (0.03)**	683, 1179	86%
	Girls			
	Experimental	Predicted	Sample-Sizes‡	% overlapping support
12-13	0.07 (0.07)	0.06* (0.03)	361, 589	91%
14-15	0.11** (0.04)	0.07 (0.05)	316, 589	89%
12-15	0.09 ** (0.02)	0.06** (0.03)	677, 1180	90%
	Boys and Girls			
	Experimental	Predicted	Sample-Sizes‡	% overlapping support
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†Standard errors based on 500 bootstrap replications. Bandwidth equals 200 pesos. Trimming implemented using the 2% quantile of positive density values as the cut-off point.

‡The first number refers to the total control sample and the second to the subset of controls that satisfy the

Combining Ex-ante and Ex-post Approaches

2. Identification

- One can directly use the exogenous source of variation for **identification** of the model parameters
  - Estimate a model on both treatment and control groups that relaxes some behavioral/distributional assumptions
- In the previous model, the impact of the subsidy on schooling is assumed equivalent to a decrease in child wages
  - Transfers are actually handed out to the mother, while we do not know who receives the child's wage
  - Who receives the money likely matters (e.g., collective models)

Sources of Variation for Identification – Example

- Consider the alternative model:

$$U^s - U^w = \alpha + (\beta^s - \beta^w)Y + \theta^s \tau - \theta^w w$$

- Previous model assumes income pooling conditional on schooling ($\theta^s = \beta^s$ and $\theta^w = \beta^w$)
- By estimating on the control group only, $\tau = 0$ and so we have to impose that the transfer and the wage have the same effect on schooling decision ($\theta^s = \theta^w$)
- Estimating the model on both treated and control villages enables to identify both θ^s (through variations in transfer) and θ^w (through variation in child wages)

Combining Ex-ante and Ex-post Evaluation

3. Interpretation of policy impacts

- The role of economic theory is to elucidate the assumptions that underlie the **interpretation of the policy effect**
- Many ways through which model-based approach complements (quasi-)experimental evidence
  1. Equilibrium/scaling-up effects
  2. Decompose the different channels behind the policy effect
  3. Benchmark current policy Vs. counterfactual policy scenarios

Interpretation of Policy Impacts – Example

- In the previous model, an increase in child wages will reduce schooling
- Since such wages are determined within the local labor market, they may also be affected by the program because the latter reduces the labor supply of children
  - The importance of this equilibrium effect depends on the elasticity of substitution between child labor and adult labor in the local labor market
- Attanasio et al (2012) use the cross-village randomization to identify this GE effect and document an increase in the wage rate by 6%
- Incorporating this channel is important as it attenuates the program's impact on schooling

Toward Model-based Field Experiments?

These considerations have key implications for the design of randomized experiments

1. Pre-Analysis Plans (PAP) to enhance out-of-sample validation and avoid data-mining issues in structural models
    - If a researcher commits to holding out either the treatment or the control group, all data mining in terms of model development must be based only on the subsample used for estimation. If all the data are used for estimation, then out-of-sample validation is eschewed
2. Design experiments so as to enable the estimation of richer models
    - No need to develop/estimate the full model ex-ante

Next Week: Dynamic Discrete Choice Models & RCTs

1. Methods
   - Keane, Todd and Wolpin (Ch4 in HLE, 2011)
2. Evaluation of the *Progresa* cash transfer program in Mexico
   - **Todd and Wolpin (AER, 2006)**
   - Attanasio, Meghir and Santiago (ReStud, 2012)