

Combining Experimental Information with Structural Programmes: Evaluating PROGRESA

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March 2009

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- There are two ways these two approaches can interact.
 - ① We can use experimental information to validate a model (Todd and Wolpin)
 - ② We can use the same information to help identify a possibly richer structural model (Attanasio, Meghir, Santiago)

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 - 1 The structural model will help us interpret the data and understand the mechanisms through which an intervention works.
 - 2 The model may allow simulation of alternative policies thereby offering a mechanism for improving effectiveness.
 - 3 Finally, validation offers the possibility of understanding better the shortcomings of models

Modelling the impact of PROGRESA using a randomised experiment

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- This is a very simple structural model of education choice
- The key idea is to exploit the randomised nature of the grant to identify the impact of monetary incentives on educational participation

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$$Y_{it}^s = \mu_i^s + a^{s'} z_{it} + b^s ed_{it} + 1(p_{it} = 1)\beta^p x_{it}^p + 1(s_{it} = 1)\beta^s x_{it}^s + \varepsilon_{it}^s$$

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- The utility from school also depends on accumulated schooling, the idea being that going to school may actually strengthen attachment.

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- The wage is thus the opportunity cost of schooling.

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 - 1 Education has benefits in the future
 - 2 Past education can change attitudes towards attendance
 - 3 The grant itself creates dynamics because not going to school one year reduces the total number of years the child can be subsidised: the grant is only available until 17.

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- Decisions are taken from age 9 to 18. Before that nearly all attend.

Modelling the impact of PROGRESA using a randomised experiment

Terminal Value Function

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Terminal Value Function

- At 18 adult life starts with a value of $V(ed_{i,18})$.
- This defines in a reduced form way what the accumulated education is worth and needs to be estimated
- In a model where we follow people up later in life, the terminal value would be pinned down by labour market outcomes.
- We specify

$$V(ed_{i,18}) = \frac{\alpha_1}{1 + \exp(-\alpha_2 * ed_{i,18})}$$

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 - ② The possibility that the child will not pass the grade p_t^S . This depends on grade and age and is known to all concerned.
- With richer data this probability could be made to depend on effort, thus making it endogenous.

Modelling the impact of PROGRESA using a randomised experiment

Laws of motion

- The law of motion for the state variable ed_{it} is

$$ed_{it+1} = ed_{it} + 1 \text{ if attend and pass grade}$$

$$ed_{it+1} = ed_{it} \text{ otherwise}$$

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- The variables z_{it} have a deterministic path known to everybody (simplifying assumption)

Modelling the impact of PROGRESA using a randomised experiment

Value functions

- The value function for attending school is $V_{it}^s(ed_{it}|z_{it})$ and the value for work is denoted $V_{it+1}^w(ed_{it}|z_{it})$

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- Thus the value of school at age t can be written as

$$V_{it}^s(ed_{it}|z_{it}) = E \max \left[V_{it+1}^s(ed_{it} + 1|z_{it+1}), V_{it+1}^w(ed_{it} + 1|z_{it+1}) \right] \times \\ \left. \begin{aligned} & u_{it}^s + \beta \{ p_t^s(ed_{it} + 1) \times \\ & + (1 - p_t^s(ed_{it} + 1)) \times \\ & E \max [V_{it+1}^s(ed_{it}|z_{it+1}), V_{it+1}^w(ed_{it}|z_{it+1})] \} \end{aligned} \right\}$$

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- And the value of working is

$$V_{it}^w(ed_{it}|z_{it}) = u_{it}^w + \beta E \max \{ V_{it+1}^s(ed_{it}), V_{it+1}^w(ed_{it}) \}$$

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- Denote $u_{it}^s = \tilde{u}_{it}^s + \varepsilon$
- Then we have that at any point in the lifecycle

$$\begin{aligned} E \max \{ V_{it}^s (ed_{it}), V_{it}^w (ed_{it}) \} = \\ E \max \{ \tilde{u}_{it}^s + \varepsilon + \beta V_{it+1}^s (ed_{it}), u_{it}^w + \beta V_{it}^w (ed_{it}) \} = \\ \tilde{u}_{it}^s + \beta V_{it+1}^s (ed_{it}) + E(\varepsilon | \varepsilon > u_{it}^w - \tilde{u}_{it}^s - \beta [V_{it}^w (ed_{it}) - V_{it+1}^s (ed_{it})]) \\ + [u_{it}^w + \beta V_{it}^w (ed_{it})] \times (1 - P^S) \end{aligned}$$

Computing the Emax functions

- In the above $P^S = \Pr(\text{Attend}) = \Pr(\varepsilon > u_{it}^w - \tilde{u}_{it}^s + \beta [V_{it}^w(ed_{it}) - V_{it+1}^s(ed_{it})])$

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- For the Normal this becomes $E(\varepsilon | \varepsilon > u_{it}^w - \tilde{u}_{it}^s - +\beta [V_{it}^w(ed_{it}) - V_{it+1}^s(ed_{it})]) = \phi(a) / [P^S]$

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- In this case the DP becomes computationally as easy as any nonlinear static regression.

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- We do this for two reasons:
 - 1 Child wages are likely to be measured with error. We use the village adult wage, observed everywhere as an instrument
 - 2 Wages are not observed for non-working kids. We thus correct for selection the estimated wage equations and predict wages for non-working children.

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Wages

- Strictly speaking we should be integrating out wages — not predicting them. In a linear model the two are identical. This is however a nonlinear model (because of the future value functions) so what we do is just a simplifying approximation.

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- The wage equation we obtain is

$$\ln w_{ij} = -1.38 + 0.893 \ln w_j^{ag} + 0.084 \text{ age}_i + 0.120 \text{ Mills}_i + \omega_{ijt}$$

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- Note that the wage equation does not depend on education for the children. This is because we found that education has no returns in the village economy (perhaps 1% a year)

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- Returns to education are enjoyed by those who obtain it by migrating and working in urban centres in adult life.

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- This is the initial conditions problem

Modelling the impact of PROGRESA using a randomised experiment

Initial Conditions

- To understand the problem consider the probability of attendance as implied by the model above and denote as $P(Attend_{it} = 1 | z_{it}, x_{it}^p, x_{it}^s, wage_{it}, ed_{it}, \mu_i)$

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- Since we do not observe μ we need to integrate it out.
- The joint distribution of attendance and μ is

$$\begin{aligned} & G(Attend_{it} = 1, \mu | z_{it}, x_{it}^P, x_{it}^S, wage_{it}, ed_{it}) \\ &= P(Attend_{it} = 1 | z_{it}, x_{it}^P, x_{it}^S, wage_{it}, ed_{it}, \mu_i) \times \\ & \quad g(\mu | z_{it}, x_{it}^P, x_{it}^S, wage_{it}, ed_{it}) \end{aligned}$$

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 - ① Their causal effect on attendance
 - ② Their correlation with the unobservable and hence with the ability composition of each education level
- While we may be willing to assume that the characteristics and unobserved heterogeneity are independent this is impossible for education, whose entire path depends on ability: Higher and higher levels of education are associated with higher levels of ability. Thus as we move from one education level to the next the ability composition changes.

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- Current attendance depends on distance to school
- We make past stock of schooling depend on the distance to school as it was in the past, relying for identification on new schools being built.

Modelling the impact of PROGRESA using a randomised experiment

The likelihood contribution

- So the likelihood contribution becomes

$$L_i = \int_{\mu} \left[\begin{array}{l} P(\text{Attend}_{it} = 1 | z_{it}, x_{it}^p, x_{it}^s, \text{wage}_{it}, \text{ed}_{it}, \mu_i) \times \\ P(\text{ed}_{it} = e | z_{it}, x_{it}^p, x_{it}^s, \text{dist}_{it-1}, h_i, \text{wage}, \mu_i) dg(\mu) \end{array} \right]$$

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- where $P(\text{ed}_{it} = e | z_{it}, x_{it}^p, x_{it}^s, h_i, \text{wage}, \mu_i)$ is a reduced form equation of the stock of education and it includes as an explanatory instrument distance from school in the past (dist_{it-1}).

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- As in the earlier lectures we approximate $g(m)$ with a discrete distribution, in this case just three points of support suffice.

Modelling the impact of PROGRESA using a randomised experiment

Unobserved Heterogeneity

	A	B	C
Point of Support 1	-27.023 <i>1.779</i>	-26.480 <i>1.773</i>	-26.563 <i>1.765</i>
Point of Support 2	-31.203 <i>2.074</i>	-30.485 <i>2.067</i>	-30.683 <i>2.056</i>
Point of Support 3	-21.765 <i>1.401</i>	-21.257 <i>1.390</i>	-21.313 <i>1.387</i>
probability of 1	0.309 <i>0.029</i>	0.313 <i>0.031</i>	0.307 <i>0.029</i>
probability of 2	0.590 <i>0.030</i>	0.584 <i>0.032</i>	0.592 <i>0.031</i>
probability of 3	0.101	0.103	0.1017
load factor for Initial condition	- 0.016 <i>0.009</i>	- 0.016 <i>0.009</i>	- 0.016 <i>0.009</i>

Notes: Column A: Dummies for Poor (i.e. programme eligible)
B: Dummies for Poor and for Treatment village
C: Dummies for Poor and for ineligible in treatment village
Asymptotic standard errors in italics

Modelling the impact of PROGRESA using a randomised experiment

Initial conditions Equation (subset of parameters)

Selected Parameters from the Initial Conditions Equation

Other controls and instruments

poor	-0.259	-0.259	-0.259
	<i>0.026</i>	<i>0.026</i>	<i>0.026</i>
indigenous	0.002	0.002	0.002
	<i>0.023</i>	<i>0.023</i>	<i>0.023</i>
primary 1997 (pre-experiment)	0.257	0.257	0.257
	<i>0.054</i>	<i>0.054</i>	<i>0.054</i>
secondary 1997 (pre-experiment)	0.077	0.077	0.077
	<i>0.024</i>	<i>0.024</i>	<i>0.024</i>
Km from secondary School	-0.01057	-0.011	-0.01057
	<i>0.00177</i>	<i>0.002</i>	<i>0.00177</i>
cost of attending secondary	0.00014	0.000	0.00014
	<i>0.00022</i>	<i>0.000</i>	<i>0.00022</i>

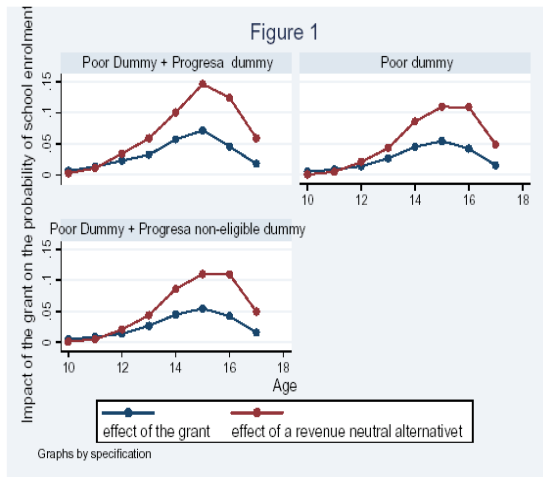
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Main results (subset of parameters)

	A	B	C
wage	0.144 <i>0.048</i>	0.145 <i>0.047</i>	0.144 <i>0.048</i>
PROGRESA Grant	2.664 <i>0.984</i>	1.940 <i>0.812</i>	2.667 <i>0.988</i>
<i>Mother's Education - Default is less than primary</i>			
Primary	-0.176 <i>0.117</i>	-0.182 <i>0.115</i>	-0.173 <i>0.116</i>
Secondary	-0.428 <i>0.138</i>	-0.426 <i>0.141</i>	-0.430 <i>0.142</i>
Preparatoria	-1.517 <i>0.366</i>	-1.483 <i>0.432</i>	-1.483 <i>0.437</i>
age	3.017 <i>0.227</i>	2.976 <i>0.226</i>	3.001 <i>0.226</i>
Prior Years of education	-1.812 <i>0.139</i>	-1.792 <i>0.196</i>	-1.798 <i>0.197</i>
log-Likelihood	-26801.35	-26798.745	-26797.546
Discount rate $\beta = 0.85$ State dummies included			

Modelling the impact of PROGRESA using a randomised experiment

Simulations - Restructuring the grant



Modelling the impact of PROGRESA using a randomised experiment

Simulations - Alternative Policies

