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Semiparametric estimation of social tariffs.

An illustration using the SF-6D value set.

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GRUPO DE TRABAJO EN ECONOMÍA DE LA SALUD

Semiparametric Estimation of Social Tariffs

An illustration using the SF-6D value sets

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- Standard model of health state valuations
  1. Data are skewed, truncated, non-continuous and hierachical (Brazier et al., 2003).
  2. How to control for individual characteristics?.
  3. Preferences of the whole population (NICE, 2003).
  4. Representative estimates and corrective weights.

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Alternative approach: semiparametric estimator.

The semiparametric estimator

- Eschews parametric assumptions on the relationship between the outcome and the regressors.
- No assumption on the distribution of health state values.
- Allows for an undetermined amount of heterogeneity.
- Accomodates covariates in a flexible way.

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- Eschews parametric assumptions on the relationship between the outcome and the regressors.
- No assumption on the distribution of health state values.
- Allows for an undetermined amount of heterogeneity.
- Accomodates covariates in a flexible way.
- Theoretical requirement: intercept equal to unity.
- Tests and corrects for sample selection.
- Easier to implement than the nonparametric estimator in Kharroubi et al. (2005).
- Provides the user with a table of estimated coefficients.

The standard approach

$$Y_{ij} = \alpha + \beta' Z_j + \varepsilon_{ij}, \text{ by OLS or RE.}$$

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$$\beta_{kw}\left(x, z_{k'w'}\right) = E\left[Y/Z_{kw} = 1, x, z_{k'w'}\right] - E\left[Y/Z_{kw} = 0, x, z_{k'w'}\right]$$

$$\beta_{kw} = E\left[\beta_{kw}(h)\right] = E\left[Y/Z_{kw} = 1\right] - E\left[Y/Z_{kw} = 0\right]$$

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- Inverse Probability Weighting (IPW) estimator:
  1. Easy to implement.
  2. Consistent and in some cases aymptotically efficient.
  3. Best overall finite sample perfomance (Busso et al., 2008).
  4. Allows to assess the effect of changes in the distribution of X on Y (DiNardo et al., 1996).

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- The propensity score: $p_{kw}(h) = P(Z_{kw} = 1/H = h)$.

The overlap assumption

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- No regressor predicts treatment status perfectly.
- Implications on the number and selection of health states being valued.
- The standard model is a regression model: extrapolation.
    1. EQ-5D tariffs for Holland (Lamers et al. (2006)) and Japan (Tsuchiya et al. (2002)): in one out of ten coefficients.
    2. EQ-5D tariff for the UK (Dolan (1997)): in six out of ten coefficients.

The *IPW1* estimator

- The quantity of interest:

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- Thus:

$$\widehat{\beta}_{kw,\, IPW1} = n^{-1} \sum_{i=1}^{n} \frac{Z_{kw} Y_j}{\widehat{p}_{kw}} - n^{-1} \sum_{i=1}^{n} \frac{(1 - Z_{kwi}) Y_{ij}}{1 - \widehat{p}_{kwi}} \qquad (1)$$

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$$\widehat{\beta}_{kw,\,IPW2} = n^{-1}\sum_{i=1}^{n}\frac{Z_{kwi}Y_{ij}}{\widehat{p}_{kwi}\widehat{p}_{si}} - n^{-1}\sum_{i=1}^{n}\frac{(1-Z_{kwi})\,Y_{ij}}{(1-\widehat{p}_{kwi})\,\widehat{p}_{si}} \qquad (2)$$

The *IPW2* estimator

- The *IPW2* estimator that we implement is:

$$\widehat{\beta}_{kw,\,IPW2} = \left(\sum_{i=1}^{n} \frac{Z_{kwi}}{\widehat{p}_{kwi}\widehat{p}_{si}}\right)^{-1} \sum_{i=1}^{n} \frac{Z_{kwi}Y_{ij}}{\widehat{p}_{kwi}\widehat{p}_{si}} - \left(\sum_{i=1}^{n} \frac{(1 - Z_{kwi})}{(1 - \widehat{p}_{kwi})\,\widehat{p}_{si}}\right)^{-1} \sum_{i=1}^{n} \frac{(1 - Z_{kwi})\,Y_{ij}}{(1 - \widehat{p}_{kwi})\,\widehat{p}_{si}} \tag{3}$$

- Weights for individuals of a given treatment status add up to one (Imbens, 2004).

The SF-6D

- Preference based measure of health. 18000 health states.
- Six dimensions of health each with between four to six levels of severity.
- Country-specific SF-6D value sets to date: UK (Brazier et al., 2002), Hong-Kong (Lam et al., 2008).
- Abellan et al. (2009) derive the Spanish SF-6D value set according to the standard model.

The data

- 78 health states: orthogonal design in Brazier et al. (2002) augmented to ensure common support condition.
- A lottery equivalence method was used for the valuation.
  1. Biases caused by the overweighting of the certainty are minimized.
  2. State the probability p that makes you indifferent between prospects (FH, p, Death) and (FH, 0.5, h).
  3. Multiple sequence of choices to search for indifference.
  4. Theoretical and empirical arguments that support this lottery method in Abellan et al. (2009).
- 17 subsamples (n=60 each) valuing a different subset of 5 health states.
- Computer assisted personal interviews.

Main findings

- Values are correlated with some individual characteristics: age, household income, marital status and number of children at home.

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- Values are correlated with some individual characteristics: age, household income, marital status and number of children at home.
- Substantial differences between the parametric and semiparametric estimates.
  1. Semiparametric estimates are always significant.
  2. Semiparametric estimates are higher in absolute value.
  3. The magnitude of the discrepancy is negatively related to the severity of the departure.
  4. The effect of a departure from full health is heterogeneous in the respondent's characteristics.

	OLS	RE	IPW1	IPW2
c	1.000	1.000	1.000	1.000
PF2	-0.016*	-0.025	-0.069	-0.045
PF3	-0.031	-0.054	-0.091	-0.085
PF4	-0.088	-0.118	-0.134	-0.142
PF5	-0.103	-0.106	-0.171	-0.156
PF6	-0.332	-0.333	-0.300	-0.336
RL2	-0.014*	0.005*	-0.062	-0.078
RL3	-0.041	-0.046	-0.102	-0.133
RL4	-0.078	-0.091	-0.156	-0.182
SF2	-0.036	-0.070	-0.055	-0.066
SF3	-0.063	-0.079	-0.079	-0.071
SF4	-0.203	-0.194	-0.222	-0.249
SF5	-0.210	-0.240	-0.236	-0.249

	OLS	RE	IPW1	IPW2
PAIN2	-0.016*	-0.043	-0.109	-0.137
PAIN3	-0.033	-0.048	-0.074	-0.039
PAIN4	-0.202	-0.174	-0.206	-0.241
PAIN5	-0.208	-0.232	-0.284	-0.327
PAIN6	-0.318	-0.342	-0.361	-0.403
MH2	-0.064	-0.025	-0.100	-0.063
MH3	-0.080	-0.050	-0.164	-0.184
MH4	-0.096	-0.073	-0.141	-0.071
MH5	-0.226	-0.197	-0.315	-0.350
VIT2	-0.055	-0.042	-0.097	-0.121
VIT3	-0.120	-0.094	-0.188	-0.207
VIT4	-0.154	-0.155	-0.268	-0.285
VIT5	-0.197	-0.180	-0.239	-0.281

Main findings (II)

- Differences between the *IPW1* and the *IPW2* estimators.
  1. The distribution of X is imbalanced in the population and the estimation sample.
  2. No evidence of sample selection bias when X is restricted to sex and age intervals.
  3. Standard model + corrective weights = population valid estimates?.
- The estimated tariffs.

	Estimated tariffs			
	OLS	RE	IPW1	IPW2
Mean	0.445	0.444	0.293	0.168
St. Dev.	0.215	0.214	0.223	0.252
Percentiles				
10	0.158	0.158	-0.002	-0.162
25	0.302	0.302	0.140	-0.006
50	0.456	0.461	0.297	0.171
75	0.601	0.604	0.449	0.345
90	0.716	0.717	0.582	0.495
Negative values (%)	2.63	2.53	10.19	25.76
MAE	0.174	0.176	0.238	0.299
$\|pred.error\| < 0{,}01$	4.48	3.86	3.76	1.83
$\|pred.error\| < 0{,}05$	20.56	20.16	13.86	10.60
$\|pred.error\| < 0{,}10$	39.82	38.10	26.91	18.39

Conclusions

1. A new approach to model health state values.
2. No assumption on the distribution of health states values, accomodates covariates, heterogeneous returns, tests and corrects for sample selection.
3. Highlights the importance of the number and selection of health states valued in the sample.
4. Its technical complexity is only slightly higher than that of the standard regression model.
5. Easier to implement and interpret than the nonparametric method in Kharroubi et al. (2005). We provide a table of estimated coefficients.

Future/current research

1. Cross-country differences in preference-based tariffs.

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2. Tariffs for population subgroups.

Thanks!!!