Distributive Conflicts and Willingness to Pay for the Environment

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October 10, 2013

Spanish Stata Users Group Meeting
University Carlos III of Madrid

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Introduction

- There are two separate strands of literature dealing with willingness to pay for the environment and with preferences for redistributive policies. Both approaches are not connected in the previous literature
- One well established result in the literature on redistribution is that income is negatively correlated with demand of redistribution
- However, previous results suggest that income is positively correlated with willingness to pay taxes to protect the environment
- One possible explanation is that there exist a distributive conflict between redistributive and environmental taxes. The poor and the rich do not differ in their preferences for the overall level of taxation but on their preferences for specific taxes

Redistributive and environmental taxes

- Redistributive taxes produce a zero-sum game in which the poor are net beneficiaries and the rich are net contributors
- Environmental taxes produce public goods (non-rival and non-excludable consumption)
- Those who have high incomes would oppose redistributive taxes but they might support environmental taxes, since they could benefit from a better quality of the environment
- Those who have low incomes would prefer to spend public money in redistribution, since the effect on their welfare will be greater than the effect of a better quality of the environment

Our strategy

- We think of preferences for redistributive and environmental taxes as two related preferences for taxation, which are connected to the socio-economic status in opposite ways
- From a methodological perspective that would require estimating simultaneously the effect of the socio-economic status on the two dependent variables. However, this is a tough job when we have a multilevel structure, such as comparative data from different countries
- We estimate a bivariate probit model including random effects at country level
- Since there was no command available in Stata previous to version 13, we use `gllamm`. The command `gsem` was recently added to Stata in version 13.

Variables

- Dependent variables:
  - Willingness to pay taxes to protect the environment
  - Government should take measures to reduce income inequalities
- Explanatory variables:
  - Income (standardized using PPP)
  - Education: years of schooling
  - Gender
  - Age
  - Unemployed
  - Union membership
  - Environmental awareness
- Data: ISSP, Environment (2010)
- Sample: 8,539 individuals within 10 countries

Bivariate probit

There are two latent (non-observable) variables:

$$\begin{aligned} y_{i1}^* &= x_i\beta + \epsilon_{i1} \\ y_{i2}^* &= z_i\lambda + \epsilon_{i2} \end{aligned}$$

Instead we observe $y_{ik} = 1$ if $y_{ik}^* > 0$ and $y_{ik} = 0$ otherwise (for $k = 1, 2$). It is assumed that:

$$\begin{aligned} E(\epsilon_1) &= E(\epsilon_2) = 0 \\ Var(\epsilon_1) &= Var(\epsilon_2) = 1 \\ Cov(\epsilon_1, \epsilon_2) &= \rho \end{aligned}$$

ϵ_1 and ϵ_2 follow a cumulative bivariate normal distribution with mean $[0, 0]'$

Two-level model

Now, let consider the two-level model for the latent variables:

$$\begin{aligned} y^*_{ij1} &= x_{ij}\beta + u_{j1} + \epsilon_{i1} \\ y^*_{ij2} &= z_{ij}\lambda + u_{j2} + \epsilon_{i2} \end{aligned}$$

Errors are distributed as $(\epsilon_{ij1}, \epsilon_{ij2})' \sim N(0, \Sigma)$ and $(u_{j1}, u_{j2})' \sim N(0, \Omega)$:

$$\Sigma = \begin{pmatrix} \sigma^2_{\epsilon_1} & \\ \sigma_{\epsilon_1\epsilon_2} & \sigma^2_{\epsilon_2} \end{pmatrix}, \; \Omega = \begin{pmatrix} \tau^2_1 & \\ \tau_{12} & \tau^2_2 \end{pmatrix}$$

and they are assumed to be independent across levels:

$$Cov_{ij}\left(\epsilon_{ijk}, u_{jk}\right) = 0, \forall\, i, j, k$$

Correlations

Intra-class correlation (ICC):

$$\rho\left(y_{ijk}, y_{i'jk}\right) = \frac{\tau_k^2}{\sigma_{\epsilon_k}^2 + \tau_k^2}$$

Correlation between two variables for the same individual:

$$\rho\left(y_{ij1}, y_{ij2}\right) = \frac{\left(\sigma_{\epsilon_1\epsilon_2} + \tau_{12}\right)}{\sqrt{\left(\sigma_{\epsilon_1}^2 + \tau_1^2\right)\left(\sigma_{\epsilon_2}^2 + \tau_2^2\right)}}$$

Correlation between two variables for two different individuals within the same cluster:

$$\rho\left(y_{ij1}, y_{i'j2}\right) = \frac{\tau_{12}}{\sqrt{\left(\sigma_{\epsilon_1}^2 + \tau_1^2\right)\left(\sigma_{\epsilon_2}^2 + \tau_2^2\right)}}$$

Estimation using GLLAMM

- For continuous outcomes `xtmixed` can be used to estimate such models. However, for categorical outcomes the only option was to use `gllamm`. In Stata 13 `gsem` allows to model categorical outcomes
- We stack both the dependent and the explanatory variables and define a three-level model in which k denotes the response variable, i is the individual and j is the country
- First we define equations for random effects at individual and country levels for intercepts `econs` and `rcons`:

```
eq fac: econs rcons
constraint def 1 [id1_1]rcons=1
eq econs: econs
eq rcons: rcons
```

Estimation using GLLAMM

- We constrain the loading of the second factor, because the first one is already fixed by `gllamm`
- The following model is estimated with `gllamm`:

```
gllamm resp2 elninc eeducyrs efemale eage eunemp eunion eenvaw ///
econs rlninc reducyrs rfemale rage runemp runion rcons, ///
i(id v4) eqs(fac econs rcons) nrf(1 2) nocons ///
family(binomial) link(probit) constr(1) adapt ip(g) nip(21)
```

- Explanataroy variables are denoted by *e* for environmental taxes and by *r* for redistributive taxes. The model does not include intercept, since we have defined intercepts for each equation
- Individuals are identified by `id` and countries by `v4`
- We use adaptive Gaussian quadrature with 21 integration points. It takes one week!!

Estimated variances

- `gllamm` estimates the following variance structure:

```
Variances and covariances of random effects
------------------------------------------------------------------------------


***level 2 (id)

    var(1): .15537817 (.02648068)

    loadings for random effect 1
    econs: 1 (fixed)
    rcons: 1 (0)


***level 3 (v4)

    var(1): .05597373 (.01981084)
    cov(2,1): -.00734886 (.02031006) cor(2,1): -.11561144

    var(2): .07218617 (.02400351)
------------------------------------------------------------------------------
```

Coefficients and variances

- Since the variance of `econs` is not constrained to 1 (as it should be in a probit model), we need to rescale the coefficients reported by `gllamm`:

```
nlcom (elninc: [resp2]elninc/sqrt(1+[id1_1]econs^2))
```

- Variances, covariances and correlations are obtained using `nlcom`:

```
nlcom (cov: 1-([id1_1]rcons/sqrt(([id1_1]rcons^2+[id1_1]econs^2)*(1+[id1_1]econs^2))))
nlcom (rho: (1-([id1_1]rcons/sqrt(([id1_1]rcons^2+[id1_1]econs^2)*(1+[id1_1]econs^2)))) ///
/sqrt([id1_1]econs^2*[id1_1]rcons^2))
nlcom (var21: [v42_1]econs^2)
nlcom (var22: [v42_2]rcons^2+[v42_2_1]_cons^2)
nlcom (cov2: [v42_2_1]_cons*[v42_1]econs)
nlcom (rho2: ([v42_2_1]_cons*[v42_1]econs)/([v42_1]econs*sqrt([v42_2]rcons^2 ///
+[v42_2_1]_cons^2)))
nlcom (icc_e: [v42_1]econs^2/([id1_1]econs^2+[v42_1]econs^2))
nlcom (icc_r: ([v42_2]rcons^2+[v42_2_1]_cons^2)/([id1_1]rcons^2 ///
+([v42_2]rcons^2+[v42_2_1]_cons^2)))
nlcom (corr_i: ((1-[id1_1]rcons/sqrt(([id1_1]rcons^2+[id1_1]econs^2)*(1+[id1_1]econs^2))) ///
+([v42_2_1]_cons*[v42_1]econs))/sqrt(([id1_1]econs^2+[v42_1]econs^2)*([id1_1]rcons^2 ///
+([v42_2]rcons^2+[v42_2_1]_cons^2))))
nlcom (corr_j: ([v42_2_1]_cons*[v42_1]econs)/sqrt(([id1_1]econs^2+[v42_1]econs^2)*([id1_1]rcons^2 ///
+([v42_2]rcons^2+[v42_2_1]_cons^2))))
```

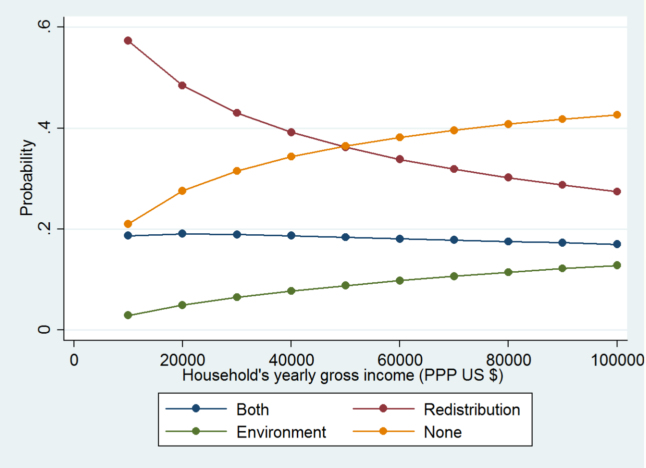
Preferences for taxes. Linear model

	$(u=0,\rho\neq0)$		$(u\neq0,\rho=0)$		$(u\neq0,\rho\neq0)$	
	e	r	e	r	e	r
Income	0.134***	-0.412***	0.109***	-0.343***	0.108***	-0.345***
	(0.021)	(0.021)	(0.023)	(0.023)	(0.023)	(0.023)
Years of education	0.032***	-0.015***	0.033***	-0.017***	0.033***	-0.017***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Female	-0.028	0.161***	-0.024	0.170***	-0.023	0.17***
	(0.024)	(0.024)	(0.023)	(0.024)	(0.023)	(0.024)
Age	0.005***	-0.001	0.004***	0.000	0.004***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Unemployed	-0.041	-0.024	-0.039	0.001	-0.039	-0.001
	(0.031)	(0.032)	(0.031)	(0.031)	(0.031)	(0.032)
Union member	-0.051**	0.214***	-0.015	0.211***	-0.013	0.208***
	(0.025)	(0.025)	(0.027)	(0.027)	(0.027)	(0.027)
Environmental awareness	0.324***		0.322***		0.316***	
	(0.013)		(0.013)		(0.013)	
Constant	-0.525**	8.037***	-0.267	7.279***	-0.229	7.421***
	(0.215)	(0.218)	(0.247)	(0.251)	(0.247)	(0.243)
Corr $\left(\hat{Y}^{(e)},\hat{Y}^{(r)}\right)$	0.073***				0.084***	
	(0.011)				(0.011)	
Corr $\left(\hat{Y}^{(e)},\hat{Y}^{(r)}\vert u\right)$					0.063***	
					(0.024)	
Corr $\left(u^{(e)},u^{(r)}\right)$					-0.268	
					(0.331)	
ICC$^{(e)}$					0.061***	
					(0.015)	
ICC$^{(r)}$					0.058***	
					(0.022)	

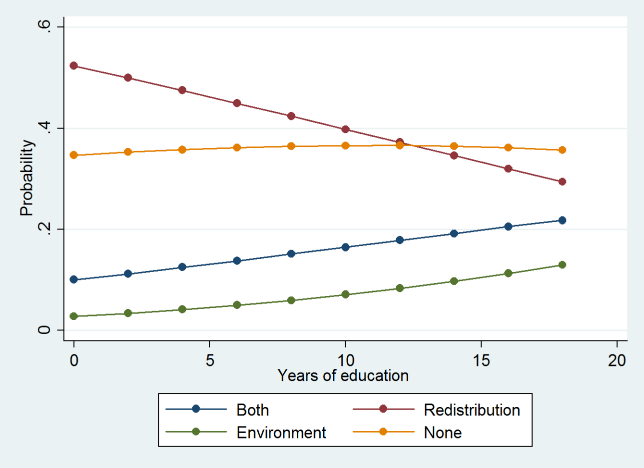
Preferences for taxes. Bivariate probit

	$(u=0, \rho \neq 0)$		$(u \neq 0, \rho = 0)$		$(u \neq 0, \rho \neq 0)$	
	e	r	e	r	e	r
Income	0.146***	-0.438***	0.110***	-0.367***	0.111***	-0.367***
	(0.027)	(0.025)	(0.030)	(0.028)	(0.03)	(0.028)
Years of education	0.040***	-0.013***	0.041***	-0.016***	0.041***	-0.016***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Female	-0.092***	0.172***	-0.088***	0.189***	-0.084***	0.189***
	(0.031)	(0.028)	(0.031)	(0.029)	(0.031)	(0.029)
Age	0.005***	0.001	0.004***	0.001	0.004***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Unemployed	-0.077*	-0.048	-0.080*	-0.021	-0.079*	-0.021
	(0.041)	(0.038)	(0.042)	(0.039)	(0.042)	(0.039)
Union member	-0.077**	0.189***	-0.019	0.204***	-0.019	0.201***
	(0.032)	(0.030)	(0.036)	(0.033)	(0.036)	(0.033)
Environmental awareness	0.327***		0.332***		0.325***	
	(0.018)		(0.018)		(0.018)	
Constant	-3.970***	4.996***	-3.658***	4.217***	-3.619***	4.242***
	(0.284)	(0.265)	(0.326)	(0.308)	(0.331)	(0.302)
Corr $\left(\hat{Y}^{(e)}, \hat{Y}^{(r)}\right)$	0.332***				0.341***	
	(0.022)				(0.021)	
Corr $\left(\hat{Y}^{(e)}, \hat{Y}^{(r)} \| u\right)$					0.267***	
					(0.054)	
Corr $\left(u^{(e)}, u^{(r)}\right)$					-0.116	
					(0.3206)	
ICC$^{(e)}$					0.265***	
					(0.075)	
ICC$^{(r)}$					0.067***	
					(0.021)	

Income and preferences for taxes



Education and preferences for taxes



Conclusions

Main findings

- Preferences for environmental and redistributive taxes are linked, but there is variability between countries
- Income and education increase support for environmental taxes while they reduce support for redistributive taxes

Methodological issues

- Multilevel models for correlated categorical outcomes are relevant in many situations in social research, but they are difficult to estimate
- `gllamm` performs well for our research problem, although it is slow.

Thank you. Comments are welcomed!!