

Spatial Regression Models: Identification strategy using STATA

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Intruduction

- Spatial regression models are usually intended to estimate parameters related to the interaction of agents across space
 - Social interactions, agglomeration externalities, technological spillovers, strategic interactions between governments etc.
- In this class we will explore estimation of Social interactions models using STATA
- Methods of estimation
- Identification strategy
- As an example we will use some data on pupils' marks and look at the peer effect.

Data Set

- The paper evaluates the friendship peer effects on student academic performance. The identification comes from the unique student friendship dataset from a Brazilian public institution (FUNDAJ), the strategy considers the architecture of these social networks within classrooms, in addition to group and individual fixed effects
- The file fundaj.dta is a random sample of 1,431 students from 120 schools in Recife city.

General set up: Peer effect at school

$$y_i = x'_i \gamma + m(y, s) \beta + m(x, s)'_i \theta + m(k, s)'_i \delta + m(v, s)'_i \lambda + \varepsilon_i$$

- y is child's math marks
- x is gender, age, parents' education, etc
- $m(y, s)$ is average child marks peer
- $m(x, s)$ is average gender, age, parent's education at school s_i
- $m(z, s)$ is other stuff at school e.g. principal wage
- $m(v, s)$ are unobserved child characteristics (e.g. intelligence)

General set up

- See e.g. Le Sage and Pace Introduction to Spatial Econometrics

$$y_i = x'_i\gamma + m(y, s)\beta + m(x, s)'_i\theta + m(k, s)'_i\delta + m(v, s)'_i\lambda + \varepsilon_i$$

- **SAR (spatial autoregressive)** effects: captured by β
 - Spillovers from neighbouring region outcome on regional outcome e.g. patents
- **SLX (spatially lagged X)** effects, captured by θ
 - Influence of neighbouring regions' observable characteristics on regional outcome e.g. R&D expenditure
- **SE (spatial error)** represents unobserved similarity between neighbours or spillovers between unobservables
 - e.g. the innovative culture

General form of spatial regression

- Spatial econometrics:

$$y = X\gamma + Wy\beta + WX\theta + WZ\delta + Wv\lambda + \varepsilon$$

- Social interaction:

- Outcome for i depends on the expected (average) outcome for the spatial group, average characteristics of the group and average unobservables of the group
- Or some other sort of dependence (spillover) between group members and the individual

$$y = x\gamma + E[y_i|W_i]\beta + E[x_i|W_i]\theta + E[z_i|W_i]\delta + E[v_i|W_i]\lambda + \varepsilon$$

Endogenous effect/SAR specifications

- These are specifications with a spatially lagged dependent variable

$$y_i = x'_i \gamma + m(y, s) \beta + u_i$$
$$y = x \gamma + E[y_i | W_i] \beta + \varepsilon$$

- Theory is that children mark depends on peer effect
 - **Outcome** is dependent on the observable **outcome** for peers (neighbours)
 - ρ supposed to represent reaction functions, direct spillovers from peers (neighbours) occurring through observed behaviour.

Mechanical feedback endogeneity

- Unbiased and consistent estimation by OLS requires that error term and regressors are uncorrelated. Does this assumption hold for this model?
- Consider simple i-j case

$$y_i = \rho y_j + x_i \beta + u_i$$

$$y_j = \rho y_i + x_j \beta + u_j$$

\Rightarrow

$$y_i = \rho \{ \rho y_i + x_j \beta + u_j \} + x_i \beta + u_i$$

$$= \rho \{ \rho (\rho y_j + x_i \beta + u_i) + x_j \beta + u_j \} + x_i \beta + u_i$$

- The ‘spatially lagged’ or ‘average neighbouring’ dep. var. y_j is correlated with the unobserved error term:

Instrumental variables

- Good Instrument
 - **1. Correlated with endogenous variable z , conditional on x : ‘powerful first stage’**
 - **2. Uncorrelated with v : ‘satisfies the exclusion restriction’**
- Instrument is variable that predicts the endogenous variable y_j but does not affect outcome y_i directly

Instrumental variables

- Gibbons, Stephen and Overman, Henry G. (2012) Mostly pointless spatial econometrics. Journal of regional science, 52 (2). pp. 172-191
- So a possible set of ‘instruments’ (predictors) for $\mathbf{W}y$ are

$$[\mathbf{WX}, \mathbf{W}^2\mathbf{X}, \mathbf{W}^3\mathbf{X}, \dots]$$

- Correlated with peers marks but not with pupils marks

Computer exercise

Data set

- Classes room best friends of each student marques V2-V1432
- The students math marks - marks
- Student characteristics – popular and boy=1
- School characteristics – principal_wage

```
. tab idpupil v5 if idpupil<=25
```

idpupil	v5		Total
	0	1	
10	1	0	1
14	1	0	1
16	0	1	1
18	1	0	1
21	1	0	1
22	0	1	1
23	1	0	1
25	1	0	1
Total	6	2	8

- First we describe situation in which we have the spatial-weighting matrix precomputed and simply want to put it in an `spmat object`

```
spmat dta peer v2-v1432, id(idchild) replace
```

```
. spmat summarize peer, links
```

```
Summary of spatial-weighting object peer
```

Matrix	Description
-----+-----	
Dimensions	1431 x 1431
Stored as	1431 x 1431
Links	
total	3558
min	1
mean	2.486373
max	10

- Estimate a regression to look at effect of popular, boy and principal wage on child marks using classical special econometrics model: SAR

$$\mathbf{y} = \rho \mathbf{W} \mathbf{y} + \mathbf{X} \boldsymbol{\beta} + \mathbf{u}$$

```
spreg ml mark popular boy principal_wage, id(idpupil) dlmat(peer) nolog
```

```
Spatial autoregressive model          Number of obs   =    1431
(Maximum likelihood estimates)        Wald chi2(3)    =   19.8763
                                       Prob > chi2     =    0.0002
```

	mark	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----							
mark							
	popular	1.809878	.5849103	3.09	0.002	.6634747	2.95628
	boy	.249489	.7963501	0.31	0.754	-1.311329	1.81030
principal_wage							
	_cons	-.00121	.0003863	-3.13	0.002	-.0019671	-.000452
	_cons	39.17803	1.745047	22.45	0.000	35.7578	42.5982
-----+-----							
lambda							
	_cons	.0315783	.0055472	5.69	0.000	.020706	.042450
-----+-----							
sigma2							
	_cons	214.8521	8.03456	26.74	0.000	199.1047	230.599
-----+-----							

- The estimated ρ coefficient is positive and significant, indicating SAR dependence. In other words, an exogenous shock to one pupil will cause changes in the marks in the class peers.
- The estimated θ and δ vector does not have the same interpretation as in a simple linear model, because including a spatial lag of the dependent variable implies that the outcomes are determined simultaneously.

```
. spreg gs2sls mark popular boy principal_wage, id(idpupil) dmat(peer)
```

```
Spatial autoregressive model  
(GS2SLS estimates)
```

```
Number of obs = 1431
```

mark	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
mark					
popular	1.783077	.5856426	3.04	0.002	.6352389 2.93091
boy	.1485575	.8012924	0.19	0.853	-1.421947 1.71906
principal_wage	-.0012348	.000387	-3.19	0.001	-.0019934 -.000476
_cons	39.76611	1.815093	21.91	0.000	36.20859 43.3236
lambda					
_cons	.0274628	.0065471	4.19	0.000	.0146307 .040294

There are no apparent differences between the two sets of parameter estimates.

- classical special econometrics model: SARAR

$$\mathbf{y} = \rho \mathbf{W} \mathbf{y} + \mathbf{X} \boldsymbol{\beta} + \mathbf{u}$$

$$\mathbf{u} = \rho \mathbf{W} \mathbf{u} + \mathbf{e}$$

```
. spreg ml mark popular boy principal_wage,id(idpupil) dlmat(peer) elmat(peer) nolog
```

Spatial autoregressive model
(Maximum likelihood estimates)

Number of obs = 1431
Wald chi2(3) = 18.3844
Prob > chi2 = 0.0004

mark2		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----							
mark							
	popular	1.725857	.5877355	2.94	0.003	.573917	2.87779
	boy	.204751	.8264258	0.25	0.804	-1.415014	1.82451
principal_wage		-.0012425	.0004083	-3.04	0.002	-.0020429	-.000442
	_cons	39.97857	1.864488	21.44	0.000	36.32424	43.632
-----+-----							
lambda							
	_cons	.0261876	.0066554	3.93	0.000	.0131433	.03923
-----+-----							
rho							
	_cons	.0234643	.0129945	1.81	0.071	-.0020045	.04893
-----+-----							
sigma2							
	_cons	214.2306	8.014287	26.73	0.000	198.5229	229.938
-----+-----							

Estimation using IV/2SLS

- Use `spmat` to creat spatial lag of *mark*, *boy* and *popular*

`spmat lag double wmark peer mark`

`spmat lag double wpopular peer popular`

`spmat lag double wboy peer boy`

```
. sum wmark wpop wboy mark2 pop boy
```

Variable	Obs	Mean	Std. Dev.	Min	Max
wmark	1,431	104.5283	67.11725	0	465
wpopular	1,431	3.259958	2.151483	1	14
wboy	1,431	.9357093	1.225055	0	8
mark	1,431	41.16352	14.95653	0	85
popular	1,431	1.341719	.6647463	1	3
boy	1,431	.4255765	.494603	0	1

- Including the spatial lag of *mark*, *sex* and *popular* in the regressions

```
. regress mark wmark popular wpopular boy wboy principal_wage, cluster(idesc)
```

```
Linear regression                               Number of obs   =       1,431
                                                F(6, 110)       =         8.87
                                                Prob > F        =       0.0000
                                                R-squared       =       0.0437
                                                Root MSE      =       14.657
```

(Std. Err. adjusted for 111 clusters in idesc)

	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
mark						
wmark	.0527915	.0141398	3.73	0.000	.0247697	.080813
popular	1.828549	.5648417	3.24	0.002	.7091654	2.94793
wpopular	-.3729638	.3839338	-0.97	0.333	-1.13383	.387902
sex	1.877473	1.0537	1.78	0.078	-.2107139	3.9656
wsex	-.9674357	.4718134	-2.05	0.043	-1.902459	-.032412
principal_wage	-.0010861	.0003935	-2.76	0.007	-.0018659	-.000306
_cons	37.96964	1.968381	19.29	0.000	34.06877	41.8705

- Estimate the 2SLS/IV regression using wpopular and wboy as instruments for wmark – FIRST STAGE

```
. reg wmark wpopular wboy boy popular principal_wage ,cluster(idesc)
```

```
Linear regression                               Number of obs   =       1,431
                                                F(5, 110)       =       156.68
                                                Prob > F        =       0.0000
                                                R-squared      =       0.7154
                                                Root MSE       =       35.868
```

(Std. Err. adjusted for 111 clusters in idesc)

```
-----+-----
```

	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
wmark						
wpopular	24.10899	1.15788	20.82	0.000	21.81434	26.4036
wboy	7.565048	2.166797	3.49	0.001	3.270965	11.8591
boy	-16.92019	2.544356	-6.65	0.000	-21.9625	-11.8778
popular	-2.92456	1.723615	-1.70	0.093	-6.340361	.491240
principal_wage	-.003971	.0015175	-2.62	0.010	-.0069785	-.000963
_cons	42.61488	7.048311	6.05	0.000	28.64678	56.5829

```
-----+-----
```

```
. testparm wpopular wboy
```

```
( 1) wpopular = 0
```

```
( 2) wboy = 0
```

```
      F( 2, 110) = 254.35
```

```
          Prob > F = 0.0000
```

- Estimate the 2SLS/IV regression using wpopular and wboy as instruments for wmark – IV

```
. ivreg mark (wmark= wpopular wboy) popular boy principal_wage ,cluster (idesc)
```

```
Instrumental variables (2SLS) regression      Number of obs      =      1,431
                                             F(4, 1430)         =          9.31
                                             Prob > F           =      0.0000
                                             R-squared          =      0.0382
                                             Root MSE          =      14.689
```

(Std. Err. adjusted for 1,431 clusters in idesc)

```
-----+-----
                Robust
            mark      Coef.   Std. Err.   t      P>|t|   [95% Conf. Interval]
-----+-----
            wmark      .0283833   .0077867   3.65   0.000     .0129518   .04381
            popular    1.789071   .587324   3.05   0.003     .6251313   2.95301
              boy      .1711308   .8216546   0.21   0.835    -1.457196   1.79945
principal_wage    -.0012293   .00041   -2.96   0.004    -.0020536   -.00040
      _cons        39.63459   2.199265  18.02   0.000    35.27616   43.99301
-----+-----
```

```
Instrumented:  wmark
Instruments:   popular boy principal_wage
                wpopular wboy
-----+-----
```

Limitations of this approach

- Following Gibbons et. al. (2012):
 - IV/2SLS relies on instruments WX , W^2X etc. having no direct effect on y
 - In principle you can use W^2X ... W^3X as instruments, for Wy in the equation assuming W^2X ... W^3X don't belong in this equation:

$$y = \rho Wy + X\beta_1 + WX\beta_2 + e$$

- Difficult to justify if W chosen arbitrarily
- Also WX , W^2X ... W^3X are all likely to be very highly correlated (remember these are all averages) so W^2X ... W^3X not likely to be a good predictor of Wy , conditional on WX