XSMLE - A Command to Estimate Spatial Panel Models in Stata

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2013 German Stata Users Group Meeting

Outline

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A general specification for Spatial Panel models:

$$y_{it} = \alpha + \tau y_{it-1} + \rho \sum_{j=1}^{n} w_{ij} y_{jt} + \sum_{k=1}^{K} x_{itk} \beta_{k} + \sum_{k=1}^{K} \sum_{j=1}^{n} w_{ij} x_{jtk} \theta_{k} + \mu_{i} + \gamma_{t} + \nu_{it}$$
(1)

$$\nu_{it} = \lambda \sum_{j=1}^{n} m_{ij} \nu_{it} + \epsilon_{it} \qquad i = 1, ..., n \qquad t = 1, ..., T$$
 (2)

Static Models (au=0) and Dynamic Models ($au\neq 0$, Yu et al. (2008))

- ullet if heta=0 and o Spatial Autoregressive Model with Auto Regressive disturbances (SAC)
- if $\lambda = 0 \rightarrow \text{Spatial Durbin Model (SDM)}$
- if $\lambda = 0$ and $\theta = 0 \rightarrow \mathsf{Spatial}$ Autoregressive Model (SAR)
- if $\rho = 0$ and $\theta = 0 \rightarrow \mathsf{Spatial} \; \mathsf{Error} \; \mathsf{Model} \; (\mathsf{SEM})$
- if $\rho=0,\ \theta=0,$ and $\mu_i=\phi\sum_{j=1}^n w_{ij}\mu_i+\eta_i\to \text{Generalised Spatial Panel}$ Random Effects model (GSPRE)

A number of spatial-related routines have been written by users and available through SSC. A non-comprehensive list includes:

Data management and visualization

- shp2dta by K. Crow
- spmat by D.M. Drukker et al
- spwmatrix by P.W. Jeanty
- spmap by M. Pisati
- geocode3 by S. Bernhard

Cross sectional data

- spreg: SAR, SEM, SAC via ML or GS2SLS by D. M. Drukker et al
- spivreg: SAC via GS2SLS by D. M. Drukker et al
- spmlreg: SAR, SEM, SDM, SAC via ML by P.W. Jeanty
- spatreg: SAR, SEM via ML by M. Pisati
- spautoreg: SAR, SEM, SDM, SAC via ML or GS2SLS by E.A. Shehata

Panel data

spreg*xt suite SAR, SEM, SDM, SAC via LS, GLS, GMM or GS2SLS by E.A. Shehata (Lee, 2002)

DGP - 250 replications

$$y_{it} = \rho \sum_{i=1}^{n} w_{ij} y_{jt} + 0.3 x_{1it} + 0.7 x_{2it} + \mu_i + \gamma_t + \epsilon_{it}$$
 $n = 1, ..., 188$ $t = 1, ..., 5$

where the nuisance parameters μ_i ($i=1,\ldots,n$) are drawn from an iid standard Gaussian random variable. To allow for dependence between the unit-specific effects and the regressors, we generate the latter as follows

$$x_{kit} = 0.4\mu_i + (1 - 0.4^2)^{1/2} z_{kit}$$

where k = 1, 2 and the z_{kit} is an iid standard Gaussian random variable.

	$\rho = 0.3$		ho = 0.5		ho = 0.7	
	bias	MSE	bias	MSE	bias	MSE
xsmle	-0.0013	0.0020	-0.0016	0.0014	-0.0016	0.0007
spregfext	0.1473	0.0255	0.1972	0.0408	0.1859	0.0352
xtivreg2	0.0174	0.0091	0.0153	0.0063	0.0112	0.0033

Options common to all spatial models The weighting matrix Models' specific options Postestimation command after xsmle

xsmle fits (balanced) Spatial Panel data models via maximum likelihood (ML)

Requirements:

- (At least) Stata Version 10
- ullet The n imes n matrix of spatial weights. xsmle will deal with the longitudinal dimension automatically
- Data must be tsset or xtset.

Options common to all spatial models The weighting matrix Models' specific options Postestimation command after xsmle

The basic xsmle syntax is the following

$$xsmle\ depvar\ [indepvars]\ [if]\ [in]\ [weight]\ [, options]$$

- The default model is the random-effects SAR model
- Only aweight are allowed but the declared weight variable must be constant within each panel unit
- The mi prefix is allowed
- Factor variables are allowed

Options common to all spatial models

- model(name) specifies the spatial model to be estimated. May be sar for the Spatial-AutoRegressive model, sdm for the Spatial Durbin Model, sem for the Spatial-Error Model, sac for the Spatial-Autoregressive with Spatially Autocorrelated Errors Model, gspre for the Generalised Spatial Random Effects Model.
- re use the random effects estimator; the default. This option cannot be specified when model(sac).
- fe use the fixed effects estimator. This option cannot be specified when model(gspre).
- type(type_options [, leeyu]) specifies fixed-effects type; only for fe estimators. May be ind for spatial fixed effects, time for time fixed effects or both for both spatial and time fixed effects. Suboption leeyu allows to transform the data according to Lee and Yu (2010) approach and can be used only when type(ind).

- <u>nocons</u>tant suppresses the constant term in the model. Only for re estimators.
- noeffects suppresses the computation of direct, indirect and total effects.
- nsim(#) sets the number of simulations for the LeSage and Pace (2009) procedure to compute the standard errors of the direct, indirect and total effects
- <u>constraints(constraints_list)</u> applies specified linear constraints.
- from(init_specs) specifies initial values for the coefficients.
- level(#) sets confidence level for confidence intervals; default is level(95).
- postscore save observation-by-observation scores in the estimation results list.
- posthessian save the Hessian corresponding to the full set of coefficients in the estimation results list.
- hausman performs the Hausman test.

Options common to all spatial models The weighting matrix Models' specific options Postestimation command after xsmle

Variance estimation

This section describes the arguments of the vce(vcetype) option.

- oim observed information matrix.
- opg outer product of the gradient vectors.
- robust clustered sandwich estimator where clustvar is the panelvar.
- cluster clustvar clustered sandwich estimator.
- dkraay(#) Driscoll-Kraay robust estimator. Where # is the maximum lag used in the calculation.

In xsmle the spatial weighting matrix can be

- a Stata matrix
- a spmat object

In both cases the matrix can be standardized or not.

e.g.

 a Stata matrix can be created using matrix define, imported from Mata using st_matrix("string scalar name", real matrix) or imported from GIS softwares like GeoDa using

spwmatrix gal using path_to_gal_file, wname(name_of_the_matrix)

spmat objects are created by spmat

spmat import name_of_the_object using path_to_file

SAR model

- <u>wmatrix(name)</u> specifies the weight matrix for the spatial-autoregressive term.
- dlag includes (time) lagged dependent variable in the model.

SDM model

- <u>wmatrix(name)</u> specifies the weight matrix for the spatial-autoregressive term.
- <u>dmatrix(name)</u> specifies the weight matrix for the spatially lagged regressors; default is to use the matrix specified in wmat(name).
- durbin(dvarlist) specifies the regressors that have to be spatially lagged; default is to lag all independent variables specified in varlist.
- dlag includes (time) lagged dependent variable in the model.

SEM model

 <u>ematrix</u>(name) specifies the weight matrix for the spatial-autocorrelated error term.

SAC model

- <u>wmatrix(name)</u> specifies the weight matrix for the spatial-autoregressive term.
- <u>ematrix</u>(name) specifies the weight matrix for the spatial-autocorrelated error term.

GSPRE model

- <u>wmatrix(name)</u> specifies the weight matrix for the spatial-autocorrelated random-effects.
- ematrix(name) specifies the weight matrix for the spatial-autocorrelated error term.
- <u>err</u>or(#) defines the structure of the model. # is equal to 1 when $\lambda \neq \phi \neq 0$, # is equal to 2 when $\lambda = 0$, # is equal to 3 when $\phi = 0$, # is equal to 4 when $\lambda = \phi$.

Postestimation command allows to post-estimate spatial fixed or random effects. The methods implemented in this command are the panel data extensions of those available in Drukker, Prucha, and Raciborski (2011)

$$\texttt{predict} \ \left[\ \textit{type} \ \right] \ \textit{newvar} \ \left[\ \textit{if} \ \right] \ \left[\ \textit{in} \ \right] \ \left[\ \textit{,} \ \ \text{statistic} \ \right]$$

where statistic includes:

- rform the default, calculates predicted values from the reduced-form equation: $y_{it} = (I_n \rho W)^{-1}(x_{it}\beta + \alpha_i)$
- limited predicted values based on the limited information set. This
 option is available only when model(sac).
- naive predicted values based on the observed values of $y_{it} = \rho W y_{it} + x_{it} \beta + \alpha_i$
- xb calculates the linear prediction including the fixed or random effect $x_{it}\beta + \alpha_i$.
- a estimates α_i , the fixed or random-effect. In the case of fixed-effects models, this statistic is allowed only when type (ind)

DGP - Fixed effects SDM

$$y_{it} = 0.3 \sum_{j=1}^{n} w_{ij} y_{jt} + 0.5 x_{1it} - 0.3 x_{2it} - 0.2 x_{3it} + 0.3 \sum_{j=1}^{n} w_{ij} x_{1it} + 0.6 \sum_{j=1}^{n} w_{ij} x_{2it} + 0.9 \sum_{j=1}^{n} w_{ij} x_{3it} + \mu_{i} + \gamma_{t} + \epsilon_{it} \quad n = 1, ..., 188 \ t = 1, ..., 5$$

where the nuisance parameters μ_i ($i=1,\ldots,n$) are drawn from an iid standard Gaussian random variable. To allow for dependence between the unit-specific effects and the regressors, we generate the latter as follows

$$x_{kit} = 0.4\mu_i + (1 - 0.4^2)^{1/2} z_{kit},$$

where k = 1, 2, 3, z_{1it} is standard Gaussian, z_{2it} is $N(0, 1.5^2)$ and z_{3it} is $N(0, 2^2)$.

No missing data Postestimation Testing Missing data Testing with missing data

- .. *** load a dta dataset containing the spatial contiguity matrix
- . use ASL_contiguity_mat_ns.dta, clear
- . *** get an spmat objects from dta
- . spmat dta W W*, replace
- . *** Summarize the spmat obj
- . spmat summarize W, links

Summary of spatial-weighting object ${\tt W}$

Matrix	l	Description
Dimensions Stored as Links	•	188 x 188 188 x 188
total	1	906
min	1	1
mean	1	4.819149
max	1	13

940

. ** Fixed-effects Durbin model (correctly specified, row normalized W) . xsmle y x1 x2 x3, wmat(W) model(sdm) fe type(ind) nsim(500) nolog Warning: All regressors will be spatially lagged

SDM with spatial fixed-effects Number of obs =

Group variable: id Number of groups = 188 Time variable: t Panel length =

R-sq: within = 0.5727between = 0.3663overall = 0.4554

Mean of fixed-effects = -0.0137

Log-likelihood = -1230.7734

	уl	Coef.	Std. Err.	z	P> z	[95\% Con:	f. Interval]
Main	+						
	x1	.5186041	.0364303	14.24	0.000	.4472019	.5900062
	x2	2946314	.0236541	-12.46	0.000	3409925	2482702
	x3	1923373	.0192912	-9.97	0.000	2301474	1545272
Wx	·+·						
	x1	.3772047	.075502	5.00	0.000	. 2292235	.5251859
	x2	.5765484	.0449332	12.83	0.000	.4884809	.6646159
	x3	.8692021	.0372769	23.32	0.000	.7961408	.9422634
Spatial	+-						
r	ho	. 2519025	.0374278	6.73	0.000	.1785454	.3252596
Variance	i						
sigma2	2_e	.7915998	.0366863	21.58	0.000	.7196959	.8635037
	+-						

[CONTINUES]

In a spatial setting, the effect of an explanatory variable change in a particular unit affects not only that unit but also its neighbors (LeSage and Pace, 2009).

$$\begin{bmatrix} \frac{\partial Y}{\partial x_{nk}} \end{bmatrix} = (I - \rho W)^{-1} \begin{bmatrix} \beta_k & w_{12}\theta_k & \cdot & w_{1n}\theta_k \\ w_{21}\theta_k & \beta_k & \cdot & w_{2n}\theta_k \\ \cdot & \cdot & \cdot & \cdot \\ w_{n1}\theta_k & w_{n2}\theta_k & \cdot & \beta_k \end{bmatrix}$$

If we have only 2 units and 1 regressor:

• SAR and SAC
$$o (I - \rho W)^{-1} \left[egin{array}{cc} eta_1 & 0 \\ 0 & eta_1 \end{array}
ight]$$

• SEM
$$\rightarrow \left[\begin{array}{cc} \beta_1 & \mathbf{0} \\ \mathbf{0} & \beta_1 \end{array} \right]$$

• SDM
$$\rightarrow (I - \rho W)^{-1} \begin{bmatrix} \beta_1 & w_{12}\theta_1 \\ w_{21}\theta_1 & \beta_1 \end{bmatrix}$$

[CONTINUES]

Direct							
	x1	.5481382	.0362326	15.13	0.000	.4771237	.6191527
	x2	2642811	.0231199	-11.43	0.000	3095953	2189669
	x3	1422518	.0176968	-8.04	0.000	1769369	1075668
Indirect	۱						
	x1	.6480929	.090572	7.16	0.000	.470575	.8256108
	x2	.6450951	.0599307	10.76	0.000	.5276331	.7625571
	x3	1.050599	.058257	18.03	0.000	.9364176	1.164781
Total	+ا ا						
	x1	1.196231	.1038425	11.52	0.000	.9927034	1.399759
	x2	.380814	.0677252	5.62	0.000	.2480751	.513553
	x3	.9083474	.0660288	13.76	0.000	.7789334	1.037761

[.] estimates store sdm_fe

No missing data Postestimation Testing Missing data Testing with missing data

** Fixed-effects Durbin model (correctly specified, row normalized W)
. xsmle y X1 x2 x3, wmat(W) model(sdm) re type(ind) nsim(500) nolog noeff
Warning: Option type(ind) will be ignored
Warning: All regressors will be spatially lagged

SDM with random-effects

Number of obs = 940

Group variable: id

Number of groups = 188

Time variable: t

Panel length = 5

R-sq: within = 0.5666 between = 0.4543 overall = 0.4936

Log-likelihood = -1513.7006

y I	Coef.	Std. Err.	z	P> z	[95\% Con:	f. Interval]
Main						
x1	.6230976	.0408605	15.25	0.000	.5430126	.7031826
x2	2439834	.0264129	-9.24	0.000	2957518	192215
x3	1688081	.0211584	-7.98	0.000	2102778	1273385
_cons	0169191	.0811545	-0.21	0.835	1759791	.1421409
Wx I						
x1	.3706183	.0824133	4.50	0.000	.2090911	.5321454
x2	.557779	.0493092	11.31	0.000	.4611347	.6544234
x3	.8845199	.0411496	21.50	0.000	.8038681	.9651717
Spatial						
rho	. 2472432	.0376366	6.57	0.000	.1734769	.3210096
Variance						
lgt_theta	3920581	.1040247	-3.77	0.000	5959428	1881735
sigma_e	1.005536	.0528831	19.01	0.000	.9018867	1.109185

hausman sdm_fe sdm_re, eq(1:1 2:2 3:3)

		Coeffi			
	1	(b)	(B)	(b-B)	$sqrt(diag(V_b-V_B))$
		sdm_fe	sdm_re	Difference	S.E.
comp1	i				
	x1	.5186041	.6230976	1044935	•
	x2	2946314	2439834	050648	
	x3	1923373	1688081	0235292	
comp2					
	x1	.3772047	.3706183	.0065864	•
	x2	.5765484	.557779	.0187694	
	х3	.8692021	.8845199	0153178	
comp3		,			
	rho	.2519025	. 2472432	.0046593	

 $\label{eq:beta} b = \text{consistent under Ho} \ \ \text{and Ha}; \ \ \text{obtained from xsmle} \\ B = \text{inconsistent under Ha}, \ \ \text{efficient under Ho}; \ \ \text{obtained from xsmle}$

```
Test: Ho: difference in coefficients not systematic  \begin{array}{ll} \text{chi2(7) = (b-B)'[(V_b-V_B)^{-}(-1)](b-B)} \\ & = & -47.08 & \text{chi2<0 => model fitted on these} \\ & & \text{data fails to meet the asymptotic} \\ & & \text{assumptions of the Hausman test;} \\ & & \text{see suest for a generalized test} \\ \end{array}
```

. ** Fixed-effects Durbin model (correctly specified, row normalized W) . xsmle y x1 x2 x3, wmat(W) model(sdm) fe type(ind) hausman noeff nolog Warning: All regressors will be spatially lagged ... estimating random-effects model to perform Hausman test

SDM with spatial fixed-effects Number of obs = 940

Group variable: id Number of groups = 188 Time variable: t Panel length =

R-sq: within = 0.5727between = 0.3663overall = 0.4554

Mean of fixed-effects = -0.0137

I.og-likelihood = -1230 7734

DOP TIMOTIMOOG	120011101					
уl		Std. Err.			[95\% Conf.	Interval]
Main						
x1	.5186041	.0364303	14.24	0.000	.4472019	.5900062
x2	2946314	.0236541	-12.46	0.000	3409925	2482702
x3	1923373	.0192912	-9.97	0.000	.2301474	1545272
Wx						
x1	.3772047	.075502	5.00	0.000	.2292235	.5251859
x2	.5765484	.0449332	12.83	0.000	.4884809	.6646159
x3	.8692021	.0372769	23.32	0.000	.7961408	.9422634
Spatial						
rho	. 2519025	.0374278	6.73	0.000	.1785454	.3252596
Variance						
sigma2_e	.7915998	.0366863	21.58	0.000	.7196959	.8635037
Ho: difference	in coeffs not	systematic	chi2(7)	= 89.58	Prob>=chi2	= 0.0000

No missing data Postestimation Testing Missing data Testing with missing data

. estat ic

	, , ,	11(model)		BIC
l 940			2477.547	2516.314

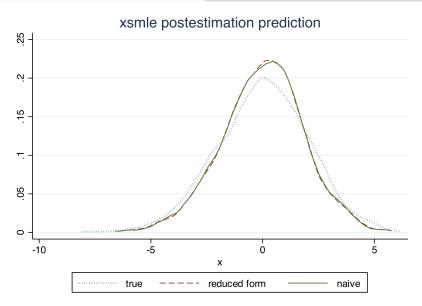
Note: N=Obs used in calculating BIC; see [R] BIC note

. estimates store sdm

No missing data Postestimation Testing Missing data Testing with missing data

- . ******* Postestimation
- . predict yhat, rform
- . predict yhat1, naive
- . predict alphahat, a
- . sum alpha alphahat

Variable	1 Оъ	s Mean	Std. Dev	. Min	Max
alpha alphahat				-2.261747 -2.688471	



Postestimation
Testing
Missing data
Testing with missing data

Using matrix notation the SDM ($\lambda=0$) may be derived from a SEM model

$$\begin{cases}
\mathbf{y} = X\beta + \mathbf{u} \\
\mathbf{u} = \lambda W\mathbf{u} + \epsilon
\end{cases}$$

hence

$$\mathbf{u}(1 - \lambda W) = \epsilon$$

$$\mathbf{y}(1 - \lambda W) = X\beta(1 - \lambda W) + \epsilon$$

$$\mathbf{y} = \lambda W\mathbf{y} + X\beta - \lambda WX\beta + \epsilon$$

$$\mathbf{y} = \lambda W\mathbf{y} + X\beta + \theta WX + \epsilon$$

and test the following constraints

$$\theta = -\beta\lambda \Rightarrow \text{the model is a SDM}.$$

```
** Test for SAR
. test \lceil Wx \rceil x1 = \lceil Wx \rceil x2 = \lceil Wx \rceil x3 = 0
 (1) [Wx]x1 - [Wx]x2 = 0
 (2) \lceil Wx \rceil x1 - \lceil Wx \rceil x3 = 0
 (3) [Wx]x1 = 0
            chi2(3) = 740.80
          Prob > chi2 = 0.0000
. ** Test for SEM
. testnl ([Wx]x1 = -[Spatial]rho*[Main]x1) ([Wx]x2 = -[Spatial]rho*[Main]x2) ([
> Wx]x3 = -[Spatial]rho*[Main]x3)
  (1) [Wx]x1 = -[Spatial]rho*[Main]x1
  (2) [Wx]x2 = -[Spatial]rho*[Main]x2
  (3)
        [Wx]x3 = -[Spatial]rho*[Main]x3
                 chi2(3) =
                                  545.31
            Prob > chi2 =
                                    0.0000
```

```
** Test for SAC
. xsmle v x1 x2 x3. wmat(W) emat(W) model(sac) fe type(ind) noeff nolog
SAC with spatial fixed-effects
                                           Number of obs =
                                                              940
Group variable: id
                                         Number of groups =
                                                              188
Time variable: t
                                            Panel length =
                                                              - 5
R-sq:
       within = 0.2652
       between = 0.0011
       overall = 0.0912
Mean of fixed-effects = -0.0117
Log-likelihood = -1386.0860
        y | Coef. Std. Err. z P>|z| [95\% Conf. Interval]
-----
Main
       x1 | .3212791 .0341734 9.40 0.000 .2543005 .3882577
       x2 | -.3135993 .0232111 -13.51 0.000 -.3590923 -.2681064
        x3 | -.2997975 .0178884 -16.76 0.000
                                             -.334858 -.2647369
Spatial
       rho | -.6676721 .0542468 -12.31 0.000 -.7739939 -.5613504
    lambda |
             .8426981 .0209346
                                 40.25 0.000
                                                 .801667
                                                          .8837293
Variance
   sigma2 e | 1.001782 .0440957
                                 22.72 0.000
                                                .9153562
```

No missing data Postestimation **Testing** Missing data Testing with missing data

. estat ic

 Model	 Obs	ll(null)	11(model)	 df	AIC	BIC
. 1	940				2784.172	

Note: N=Obs used in calculating BIC; see [R] BIC note

.

DGP - Fixed effects SDM with missing values

$$y_{it} = 0.5 \sum_{j=1}^{n} w_{ij} y_{jt} - 1.5 x_{1it} - 0.7 x_{2it} - 0.3 x_{3it} - 0.9 x_{4it} +$$

$$+ 0.75 \sum_{j=1}^{n} w_{ij} x_{1it} + 0.35 \sum_{j=1}^{n} w_{ij} x_{2it} + .15 \sum_{j=1}^{n} w_{ij} x_{3it} +$$

$$+ .45 \sum_{j=1}^{n} w_{ij} x_{4it} + \mu_{i} + \gamma_{t} + \epsilon_{it} \quad n = 1, \dots, 188 \quad t = 1, \dots, 5$$

where the nuisance parameters μ_i ($i=1,\ldots,n$) are drawn from an iid standard Gaussian random variable. To allow for dependence between the unit-specific effects and the regressors, we generate the latter as follows

$$x_{kit} = 0.4\mu_i + (1 - 0.4^2)^{1/2} z_{kit},$$

where k = 1, 2, 3, 4, z_{1it} and z_{3it} are $N(0, 1.5^2)$ and z_{2it} and z_{4it} are standard Gaussian. 5% missing values are randomly assigned to x_{1it} and x_{3it} to generate xm_{1it} and xm_{3it} .

. sum y x1 x1m x2 x3 x3m x4

Variable	Obs.	Mean	Std. Dev.	Min	Max
y	940	.0392334	2.649594	-7.947968	7.694182
x1	940	.0447793	1.456754	-5.412737	4.76092
x1m	901	.039974	1.452938	-5.412737	4.76092
x2	940	.0209358	1.03554	-3.141913	3.0158
x3	940	0236917	1.426842	-4.23553	4.351037
x3m	884	0292849	1.433476	-4.23553	4.351037
x4	940	0297022	1.020829	-3.721222	3.210468

. xsmle y x1 x2 x3 x4, wmat(W) model(sdm) fe type(ind) nolog noeff Warning: All regressors will be spatially lagged

[OUTPUT OMITTED]

. estimates store sdm_nomissing

^{. **} Fixed-effects SDM model (correctly specified)

Postestimation
Testing
Missing data
Testing with missing data

mi set wide

- . mi register imputed x1m x3m
- . mi impute mvn x1m x3m = x2 x4, add(50) rseed(12345)

Performing EM optimization:

note: 7 observations omitted from EM estimation because of all imputation variables missing

observed log likelihood = -1518.1423 at iteration 5

Performing MCMC data augmentation ...

Multivariate imputation	<pre>Imputations =</pre>	50
Multivariate normal regression	added =	50
Imputed: m=1 through m=50	updated =	0

5000	Iterations =	unifor	Prior:
100	burn-in =		
100	between =		

	 	0bs	servations		
Variable	comp	lete ind	complete	imputed	total
x1m x3m	 	901 884	39 56	39 56	940 940

(complete + incomplete = total; imputed is the minimum across m
 of the number of filled in observations.)

No missing data

```
. ***** SDM estimates using multiple imputed data
 mi estimate (coeff1: [Wx]x1m + [Spatial]rho*[Main]x1m) ///
                        (coeff2: [Wx]x2 + [Spatial]rho*[Main]x2) ///
                        (coeff3: [Wx]x3m + [Spatial]rho*[Main]x3m) ///
>
                        (coeff4: [Wx]x4 + [Spatial]rho*[Main]x4), ///
>
                        dots post saving(sdm_imputed, replace):
>
                        xsmle v x1m x2 x3m x4, wmat(W) model(sdm) ///
>
                        fe type(ind) nolog noeff
Imputations (50):
  ......10......20......30.......40.......50 done
Multiple-imputation estimates
                                              Imputations
                                                                      50
SDM with spatial fixed-effects
                                              Number of obs
                                                                     940
                                              Average RVI
                                                                  0.3120
DF adjustment: Large sample
                                              DF:
                                                     min
                                                                  168.38
                                                                 1679.48
                                                     avg
                                                     max
                                                                 4655.10
Model F test:
                  Equal FMI
                                              F(10.8545.3) =
                                                                  332.30
Within VCE type:
                        OIM
                                              Prob > F
                                                                  0.0000
                         Std. Err.
                                            P>|t|
                                                     [95\% Conf. Interval]
Main
        x1m |
             -1.430412
                         .0337574
                                  -42.37
                                            0.000
                                                    -1.496734
                                                                -1.36409
             -.7335296
                         .0466659
                                   -15.72
                                            0.000
                                                   -.825132
                                                               -.6419272
        v3m I
              -.274662
                         .0313065
                                   -8.77 0.000
                                                    -.3361047 -.2132194
         x4 | -.9359276
                          .044795
                                    -20.89
                                            0.000
                                                    -1.023766
                                                               -.8480894
Wx
        x1m |
               .5188195
                         .0864699
                                     6.00
                                            0.000
                                                     .3491775
                                                                .6884615
         x2 |
               .1321088
                         .0904967
                                     1.46
                                            0.144
                                                    -.0453216
                                                                .3095391
        x3m I
               .0546988
                         .0643793
                                     0.85
                                           0.396
                                                    -.0716161
                                                                .1810137
         x4 |
               .3360411
                         .1018539
                                     3.30
                                            0.001
                                                     .1363592
                                                                 .535723
```

No missing data Postestimation Testing Missing data Testing with missing data

	. 3869484	.0429191	9.02	0.000		166	.4711502
Variance					.92254	124	1.213542
Transformation DF adjustment: Within VCE typ	: Large samp	ole DIM		Average DF:	min	=	0.1161 1606.62 7184.40 12514.96
<pre>coeff1: [Wx]x1m + [Spatial]rho*[Main]x1m coeff2: [Wx]x2 + [Spatial]rho*[Main]x2 coeff3: [Wx]x3m + [Spatial]rho*[Main]x3m coeff4: [Wx]x4 + [Spatial]rho*[Main]x4</pre>							
	Coef.						
coeff1 coeff2 coeff3	0347924 1516852 0516019 0261852	.0575259 .0829808 .0636324	-0.60 -1.83 -0.81	0.545 0.068 0.418	1475 3143 17641	552 351 .31	.0779673 .0109806 .0732093

[.] estimates store ${\tt sdm_imputed}$

```
. ** Test for SAR
. mi test [Wx]x1m [Wx]x2 [Wx]x3m [Wx]x4
note: assuming equal fractions of missing information
 (1) \lceil Wx \rceil x 1m = 0
 (2) [Wx]x2 = 0
 (3) \lceil Wx \rceil x 3m = 0
 (4) [Wx]x4 = 0
       F(4.8383.2) = 10.09
           Prob > F = 0.0000
. ** Test for SEM
. mi testtr coeff1 coeff2 coeff3 coeff4
note: assuming equal fractions of missing information
       coeff1: [Wx]x1m + [Spatial]rho*[Main]x1m
       coeff2: [Wx]x2 + [Spatial]rho*[Main]x2
       coeff3: [Wx]x3m + [Spatial]rho*[Main]x3m
       coeff4: [Wx]x4 + [Spatial]rho*[Main]x4
 (1) coeff1 = 0
 (2) coeff2 = 0
 (3) coeff3 = 0
 (4) coeff4 = 0
       F(4,17424.6) =
                          1.13
            Prob > F =
                         0.3395
```

. estout sdm_nomissing sdm_imputed, c(b se) ren(x1m x1 x3m x3)

	sdm_nomiss~g b/se	
Main		
x1	-1.49692	-1.430412
	.023471	.0337574
x2	7440764	7335296
	.0340518	.0466659
x3	297554	274662
	.0233121	.0313065
x4	9451319	9359276
	.0349799	.044795
Wx		
x1	. 6416344	
	.070266	
x2	. 1982546	
	.0729333	
ж3	.057889	
	.0494267	.0643793
x4	.4091564	
	. 0829535	.1018539
2		
Spatial rho	4500000	0000404
rno		.3869484
	.0356911	.0429191
Variance		
sigma2 e	.7564478	1.068042
0 1	.0355401	.0737025

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