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# Spatial panel-data models using Stata

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**Abstract.** `xsmle` is a new user-written command for spatial analysis. We consider the quasi-maximum likelihood estimation of a wide set of both fixed- and random-effects spatial models for balanced panel data. `xsmle` allows users to handle unbalanced panels using its full compatibility with the `mi` suite of commands, use spatial weight matrices in the form of both Stata matrices and `spmat` objects, compute direct, indirect, and total marginal effects and related standard errors for linear (in variables) specifications, and exploit a wide range of postestimation features, including the panel-data case predictors of [Kelejian and Prucha \(2007, \*Regional Science and Urban Economics\* 37: 363–374\)](#). Moreover, `xsmle` allows the use of `margins` to compute total marginal effects in the presence of nonlinear specifications obtained using `factor variables`. In this article, we describe the command and all of its functionalities using simulated and real data.

**Keywords:** `st0470`, `xsmle`, spatial analysis, spatial autocorrelation model, spatial autoregressive model, spatial Durbin model, spatial error model, generalized spatial panel random-effects model, panel data, maximum likelihood estimation

## 1 Introduction

It is widely recognized that sample data collected from geographically close entities are not independent but spatially correlated, which means observations of closer units tend to be more similar than observations of further units ([Tobler 1970](#)).<sup>1</sup> Spatial clustering, or geographic-based correlation, is often observed for economic and sociodemographic variables such as unemployment, crime rates, house prices, per-capita health expenditures, and so on ([Ollé 2003, 2006](#); [Moscone and Knapp 2005](#); [Revelli 2005](#); [Kostov 2009](#); [Elhorst and Fréret 2009](#); [Elhorst, Piras, and Arbia 2010](#); [Moscone, Tosetti, and Vittadini 2012](#)). Theoretical models usually recognize the existence of spatial spillovers,

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1. Note that nonspatial structured dependence may also be observed. In these cases, measures of geographical proximity are replaced by measures of similarity, allowing one to investigate peer effects through social or industrial networks ([LeSage and Pace 2009](#); [Bramoullé, Djebbari, and Fortin 2009](#)).

which decline as distance between units increases; empirically, spatial panel-data models have become a popular tool for measuring such spillovers.

As far as we know, while both R and MATLAB offer a large suite of functions to estimate spatial panel-data models (Millo and Piras 2012; LeSage and Pace 2009)—with the notable exception represented by the accompanying code of Kapoor, Kelejian, and Prucha (2007)—Stata’s capabilities include a wide set of commands designed to deal only with cross-sectional data (Drukker et al. 2013; Drukker, Prucha, and Raciborski 2013a,b). We developed the `xsmle` command to estimate a wide range of spatial panel-data models using Stata. In particular, `xsmle` allows users to estimate both fixed-effects (FE) and random-effects (RE) spatial autoregressive (SAR) models, spatial Durbin models (SDMs), spatial error models (SEMs), FE spatial autocorrelation (SAC) models, and generalized spatial RE (GSPRE) models. For spatial autoregressive (SAR) and SDMs with FE, `xsmle` also allows a dynamic specification by implementing the bias-corrected maximum likelihood approach described in Yu, de Jong, and Lee (2008). Among other interesting features, `xsmle` allows users to i) use spatial weight matrices created through the `spmat` command of Drukker et al. (2013); ii) compute direct, indirect, and total marginal effects; iii) compute both clustered and Driscoll–Kraay standard errors; iv) test whether an FE or RE model is appropriate using a robust Hausman test; v) and exploit a wide range of predictors, extending to the panel-data case estimators of Kelejian and Prucha (2007).

The rest of this article is organized as follows. In section 2, we present a brief review of spatial panel-data models that can be estimated with `xsmle`. Section 3 documents `xsmle` syntax and its main options, while section 4 illustrates its main features using simulated and real datasets. The last section concludes.

## 2 Spatial panel-data models

Here we summarize spatial panel-data models, focusing on those that can be estimated with `xsmle`. Note that `xsmle` is primarily designed to deal with balanced panel data in which  $n$  units are observed for exactly  $T$  periods. We will turn to unbalanced panels in section 4.1, where we show how to handle these by exploiting the official Stata `mi` suite of commands.

In what follows, we denote the  $n \times 1$  column vector of the dependent variable with  $\mathbf{y}_t$  and the  $n \times k$  matrix of regressors with  $\mathbf{X}_t$ , where  $t = 1, \dots, T$  indicating time periods. For each cross-section,  $\mathbf{W}$  is the  $n \times n$  matrix describing the spatial arrangement of the  $n$  units, and each entry  $w_{ij} \in \mathbf{W}$  represents the spatial weight associated to units  $i$

and  $j$ .<sup>2</sup> To exclude self-neighbors, the diagonal elements  $w_{ii}$  are conventionally set equal to zero. Note that `xsmle` allows the use of two different formats for the weight matrix; that is,  $\mathbf{W}$  can be a Stata matrix or an `spmat` object. This allows the user to leverage the capabilities of other Stata commands that allow the creation and management of weight matrices, such as `spmat`, `spatwmat` (Pisati 2001), or `spwmatrix` (Jeanty 2010). Furthermore, `xsmle` automatically takes care of the longitudinal nature of the data. Hence, users need to provide only the cross-sectional  $n \times n$  weight matrix to fit a specific model.

`xsmle` allows users to fit the following models:

SAR model. The basic equation for the SAR model is

$$\mathbf{y}_t = \rho \mathbf{W} \mathbf{y}_t + \mathbf{X}_t \boldsymbol{\beta} + \boldsymbol{\mu} + \boldsymbol{\epsilon}_t \quad t = 1 \dots, T$$

It is assumed that  $\boldsymbol{\mu} \sim N(0, \sigma_\mu^2)$  in the RE case, while  $\boldsymbol{\mu}$  is a vector of parameters to be estimated in the FE variant. The standard assumptions—that  $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$  and  $E(\epsilon_{it}\epsilon_{js}) = 0$  for  $i \neq j$  or  $t \neq s$ —apply in this case.

SDM. This model is a generalization of the SAR model, which also includes spatially weighted independent variables as explanatory variables,

$$\mathbf{y}_t = \rho \mathbf{W} \mathbf{y}_t + \mathbf{X}_t \boldsymbol{\beta} + \mathbf{W} \mathbf{Z}_t \boldsymbol{\theta} + \boldsymbol{\mu} + \boldsymbol{\epsilon}_t$$

where  $\mathbf{M}$  is a matrix of spatial weights that may or may not be equal to  $\mathbf{W}$ . This model can be further generalized by using  $\mathbf{Z}_t \neq \mathbf{X}_t$ .

SAC model. This model (alternatively referred to as the SAR with spatially autocorrelated errors, SAC) extends the SAR model by allowing for a spatially autocorrelated error,

$$\begin{aligned} \mathbf{y}_t &= \rho \mathbf{W} \mathbf{y}_t + \mathbf{X}_t \boldsymbol{\beta} + \boldsymbol{\mu} + \boldsymbol{\nu}_t \\ \boldsymbol{\nu}_t &= \lambda \mathbf{M} \boldsymbol{\nu}_t + \boldsymbol{\epsilon}_t \end{aligned}$$

where  $\mathbf{M}$  is a matrix of spatial weights that may or may not be equal to  $\mathbf{W}$ . The literature focuses on the FE variant of this specification because the RE variant can be written as a special case of the SAR specification.

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2. Two sources of locational information are generally exploited. First, the location in Cartesian space (for example, latitude and longitude) is used to compute distances among units. Second, the knowledge of the size and shape of observational units allows the definition of contiguity measures. For example, one can determine which units are neighbors in the sense that they share common borders. Thus the former source points toward the construction of spatial distance matrices, while the latter is used to build spatial contiguity matrices. Note that the aforementioned sources of locational information are not necessarily different. For instance, a spatial contiguity matrix can be constructed by defining units as contiguous when they lie within a certain distance; on the other hand, by computing the coordinates of the centroid of each observational unit, one can obtain approximated spatial distance matrices using the distances between centroids. More details are available in LeSage and Pace (2009).

SEM. The SEM focuses on SAC in the error term, as in

$$\begin{aligned} \mathbf{y}_t &= \mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\mu} + \boldsymbol{\nu}_t \\ \boldsymbol{\nu}_t &= \lambda\mathbf{M}\boldsymbol{\nu}_t + \boldsymbol{\epsilon}_t \end{aligned}$$

This is a special case of the SAC model, but it is also a special case of the SDM.

GSPRE. This model can be represented as

$$\begin{aligned} \mathbf{y}_t &= \mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\mu} + \boldsymbol{\nu}_t \\ \boldsymbol{\nu}_t &= \lambda\mathbf{M}\boldsymbol{\nu}_t + \boldsymbol{\epsilon}_t \\ \boldsymbol{\mu} &= \phi\mathbf{W}\boldsymbol{\mu} + \boldsymbol{\eta} \end{aligned}$$

This is a generalization of the SEM, in which the panel effects, represented by the vector  $\boldsymbol{\mu}$ , are spatially correlated. The vectors  $\boldsymbol{\mu}$  and  $\boldsymbol{\epsilon}_t$  are assumed to be independently normally distributed errors, so the model is necessarily an RE specification with  $\boldsymbol{\mu} = (\mathbf{I} - \phi\mathbf{W})^{-1}\boldsymbol{\eta}$  and  $\boldsymbol{\nu}_t = (\mathbf{I} - \lambda\mathbf{W})^{-1}\boldsymbol{\epsilon}_t$ . There are various special cases of the general specification, with (a)  $\lambda \neq \phi \neq 0$ , (b)  $\lambda = 0$ , (c)  $\phi = 0$ , (d)  $\lambda = \phi$ .

In addition to the distinction between the FE and RE, there is a separate distinction between static and dynamic specifications. The aforementioned models are all static in that they involve contemporaneous values of the dependent and independent variables. `xsmle` also allows the estimation of SAR and SDM models, such as

$$\mathbf{y}_t = \tau\mathbf{y}_{t-1} + \psi\mathbf{W}\mathbf{y}_{t-1} + \rho\mathbf{W}\mathbf{y}_t + \mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\mu} + \boldsymbol{\epsilon}_t$$

where the lagged (in time) dependent variable or the lagged (in both time and space) dependent variable can be included in the specification.

## 2.1 Estimation

Various methods of fitting spatial panel models have been proposed. Broadly, they fall into two categories: i) generalized method of moments and ii) quasi-maximum likelihood (QML) estimators. All models that can be fit using `xsmle` fall into the second category. A synopsis guide with all estimable models and their features is reported in table 1.<sup>3</sup> The gain from programming gradients is large, so `v1` evaluators are used for all but one of the specifications. The exception is the RE SEM, whose likelihood function involves a transformation using the Cholesky factors of a rather complicated matrix containing the parameters to be estimated, so the matrix differentiation is extremely messy.

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3. Elhorst (2010a) suggests that the computation time required to carry out full maximum likelihood estimation can be reduced by transforming variables in a way that permits the likelihood function to be concentrated so the estimation can be carried out in two steps. In translating his routines to Mata, we found that using a concentrated likelihood tended to increase both the number of iterations and the time required to fit the models.

Table 1. A summary of `xsmle` estimation capabilities

Model	Estimation method	Time FE	Individual FE	Random effects	<code>wmatrix()</code>	<code>ematrix()</code>	<code>dmatrix()</code>	Dynamic
SAR	QML	x	x	x	x			x
SEM	QML	x	x	x		x		
SAC	QML	x	x		x	x		
SDM	QML	x	x	x	x		x	x
GSPRE	QML			x	x	x		

For dynamic models, that is, those including a time-lagged dependent variable, a time and space-lagged dependent variable, or both, `xsmle` implements only the FE variant of the SAR and SDM models using the bias-corrected QML approach described by Yu, de Jong, and Lee (2008), which is consistent when both  $n \rightarrow \infty$  and  $T \rightarrow \infty$ . The command starts by constructing maximum likelihood estimates, treating the aforementioned lagged variables as exogenous regressors. Bias corrections are then computed for each of the coefficients and used to adjust the initial maximum likelihood estimates.

For each model, the default asymptotic variance–covariance (VC) matrix of the coefficients is obtained from the observed information matrix.<sup>4</sup> Angrist and Pischke (2009) emphasize the potential dangers of this approach for datasets for which there may be unknown serial correlation in the errors within each panel unit. To our knowledge, there are no established methods of computing robust standard errors for spatial panel-data models. Mimicking the derivation of robust standard errors for nonspatial panel models, `xsmle` implements two different approaches: i) one-way clustered standard errors and ii) Driscoll and Kraay (1998) standard errors. As in other panel-data official Stata commands, specifying `vce(robust)` is equivalent here to specifying `vce(cluster panelvar)`, where `panelvar` is the variable that identifies the panels.

As for the Driscoll–Kraay standard errors, the `xsmle` implementation is based on Hoechle’s (2007) `xtscc` command. The Driscoll–Kraay approach provides a specific variant of the Newey–West robust covariance estimator computed using the Bartlett kernel and a time series of scores’ cross-sectional averages.<sup>5</sup>

In our test runs, the differences between the asymptotic and robust standard errors are usually small, but we have not focused on cases with small values of  $n$  and  $T$ . In principle, it would be useful to include a bootstrap estimator for the VC matrix. Unfortunately, there is a major barrier to applying standard bootstrap methods in this case. The crucial assumption for resampling is that the errors for the observations or units from which each sample is drawn should be independent. For panel or clustered data, this means the resampling is based on panel units or clusters. For spatial panels, our base model assumes the observations for different panel units are correlated over space for any given period  $t$ . It follows that resampling based on panel units cannot be reconciled with the hypothesis of spatial interactions in the relationships of interest. As an alternative, we could use time periods as the resampling unit, but this will be valid only if there is no serial correlation within panels. Further, for many applications of spatial panel estimation, the value of  $T$  is considerably smaller than  $n$ , so large sample assumptions of bootstrap statistics do not apply. Statisticians have developed bootstrap methods for spatial data but at the cost of imposing substantial restrictions on the extent of spatial interactions that can be examined. The methods have tended to focus on regular lattices, but they can be applied to spatial data for fairly small economic units such as counties and labor market areas.

4. A variant obtained from the outer product of the gradients is also available by specifying `vce(opg)`.

5. The bandwidth for the kernel is specified with a default value of `floor{4(T/100)2/9}` if no value is specified.

**Direct, indirect, and total marginal effects**

Because spatial regression models exploit the complicated dependence structure between units, the effect of an explanatory variable's change for a specific unit will affect the unit itself and, potentially, all other units indirectly. This implies the existence of direct, indirect, and total marginal effects. With the exception of the SEM and the GSPRE models, and only if the `effects` option is specified, these effects are computed using the formulas reported in table 2. The command automatically distinguishes between short- and long-run marginal effects when a dynamic spatial model is fit.



Table 2. Direct, indirect, and total effects

Type of model	Short-term direct effect	Short-term indirect effect	Long-term direct effect	Long-term indirect effect
Static				
SDM	none	none	$\{(\mathbf{I} - \rho \mathbf{W})^{-1} \times (\beta_k \mathbf{I} + \theta_k \mathbf{W})\}^{\bar{d}}$	$\{(\mathbf{I} - \rho \mathbf{W})^{-1} \times (\beta_k \mathbf{I} + \theta_k \mathbf{W})\}^{\text{rsum}}$
SEM	none	none	$\beta_k$	none
SAR	none	none	$\{(\mathbf{I} - \rho \mathbf{W})^{-1} \times (\beta_k \mathbf{I})\}^{\bar{d}}$	$\{(\mathbf{I} - \rho \mathbf{W})^{-1} \times (\beta_k \mathbf{I})\}^{\text{rsum}}$
SAC	none	none	$\{(\mathbf{I} - \rho \mathbf{W})^{-1} \times (\beta_k \mathbf{I})\}^{\bar{d}}$	$\{(\mathbf{I} - \rho \mathbf{W})^{-1} \times (\beta_k \mathbf{I})\}^{\text{rsum}}$
Dynamic				
SDM	$\{(\mathbf{I} - \rho \mathbf{W})^{-1} \times (\beta_k \mathbf{I} + \theta_k \mathbf{W})\}^{\bar{d}}$	$\{(\mathbf{I} - \rho \mathbf{W})^{-1} \times (\beta_k \mathbf{I} + \theta_k \mathbf{W})\}^{\text{rsum}}$	$\{(\mathbf{I} - \tau) \mathbf{I} - (\rho + \psi) \mathbf{W}\}^{-1} \times (\beta_k \mathbf{I} + \theta_k \mathbf{W})\}^{\bar{d}}$	$\{(\mathbf{I} - \tau) \mathbf{I} - (\rho + \psi) \mathbf{W}\}^{-1} \times (\beta_k \mathbf{I} + \theta_k \mathbf{W})\}^{\text{rsum}}$
SAR	$\{(\mathbf{I} - \rho \mathbf{W})^{-1} \times (\beta_k \mathbf{I})\}^{\bar{d}}$	$\{(\mathbf{I} - \rho \mathbf{W})^{-1} \times (\beta_k \mathbf{I})\}^{\text{rsum}}$	$\{(\mathbf{I} - \tau) \mathbf{I} - (\rho + \psi) \mathbf{W}\}^{-1} \times (\beta_k \mathbf{I})\}^{\bar{d}}$	$\{(\mathbf{I} - \tau) \mathbf{I} - (\rho + \psi) \mathbf{W}\}^{-1} \times (\beta_k \mathbf{I})\}^{\text{rsum}}$

Source: Adapted from Elhorst (2014). Note: The superscript  $\bar{d}$  denotes the operator that calculates the mean diagonal element of a matrix, and the superscript rsum denotes the operator that calculates the mean row sum of the nondiagonal elements.

Note that the analytical results reported in table 2 are valid only for linear (in variables) specifications. Thus, by default, a “factor variables” specification will block the computation of these effects.<sup>6</sup> Nonetheless, in these cases, `xsmle` allows for the use of `margins` to at least compute total marginal effects. As described in section 4.1, `xsmle` also computes the standard errors of marginal effects using Monte Carlo simulation (the default) or the Delta method.

### Robust Hausman test

A classical question in panel-data empirical analyses refers to the choice between FE and RE variants (when both can be estimated). An answer to this question can be given using the Hausman (1978) statistic,

$$\hat{\xi} = \hat{\delta}' \hat{\mathbf{V}}_0^{-1} \hat{\delta} \quad (1)$$

where  $\hat{\delta} = (\hat{\beta}_{\text{FE}} - \hat{\beta}_{\text{RE}})$  is the difference between the FE and RE estimates and  $\hat{\mathbf{V}}_0$  is an estimate of the VC matrix of  $\hat{\delta}$ . The asymptotic distribution of (1) under the null hypothesis of no systematic difference between the two sets of estimates is  $\chi^2$  with  $c$  degrees of freedom, with  $c$  being usually the size of the estimated parameter vector. This test can be easily implemented in Stata using the official `hausman` command. However, one of the common issues with spatial panel-data models is that the Hausman specification test often fails to meet its asymptotic assumptions, especially in small samples. This is because, under the alternative hypothesis,  $\hat{\mathbf{V}}_0 = \hat{\mathbf{V}}_{\text{FE}} - \hat{\mathbf{V}}_{\text{RE}}$  is not ensured to be positive definite. `xsmle` allows users to overcome this issue because it directly accounts for  $\widehat{\text{Cov}}(\hat{\beta}_{\text{FE}}, \hat{\beta}_{\text{RE}})$ ; that is,  $\hat{\mathbf{V}}_0 = \hat{\mathbf{V}}_{\text{FE}} + \hat{\mathbf{V}}_{\text{RE}} - 2\widehat{\text{Cov}}(\hat{\beta}_{\text{FE}}, \hat{\beta}_{\text{RE}})$ . In particular, `xsmle` estimates  $\hat{\mathbf{V}}_0$  through  $\mathbf{D}\widehat{\mathbf{W}}_0\mathbf{D}'$ , where  $\mathbf{D} = (\mathbf{I}_c, -\mathbf{I}_c)$  and  $\mathbf{I}_c$  denotes the identity matrix of size  $c$ . The joint VC matrix,  $\widehat{\mathbf{W}}_0$ , is consistently estimated using the following sandwich formula,

$$\widehat{\mathbf{W}}_0 = \begin{pmatrix} \mathbf{H}_{\text{FE}} & \mathbf{O} \\ \mathbf{O} & \mathbf{H}_{\text{RE}} \end{pmatrix}^{-1} \begin{pmatrix} \mathbf{S}_{\text{FE,FE}} & \mathbf{S}_{\text{FE,RE}} \\ \mathbf{S}_{\text{RE,FE}} & \mathbf{S}_{\text{RE,RE}} \end{pmatrix} \begin{pmatrix} \mathbf{H}_{\text{FE}} & \mathbf{O} \\ \mathbf{O} & \mathbf{H}_{\text{RE}} \end{pmatrix}^{-1}$$

with

$$\begin{aligned} \hat{\mathbf{H}}_p &= -\frac{1}{n} \sum_{i=1}^n \frac{\partial^2 L_{pi}(\hat{\beta}_p)}{\partial \beta \partial \beta'}, \quad p = \text{FE, RE} \\ \hat{\mathbf{S}}_{pq} &= \frac{1}{n} \sum_{i=1}^n \frac{\partial L_{pi}(\hat{\beta}_p)}{\partial \delta} \frac{\partial L_{qi}(\hat{\beta}_q)}{\partial \beta'}, \quad p, q = \text{FE, RE} \end{aligned}$$

where  $\hat{\mathbf{H}}_{\text{FE}}^{-1}(\hat{\mathbf{S}}_{\text{FE,FE}})\hat{\mathbf{H}}_{\text{FE}}^{-1}$  and  $\hat{\mathbf{H}}_{\text{RE}}^{-1}(\hat{\mathbf{S}}_{\text{RE,RE}})\hat{\mathbf{H}}_{\text{RE}}^{-1}$  are the cluster-robust VC matrices of  $\hat{\beta}_{\text{FE}}$  and  $\hat{\beta}_{\text{RE}}$ , where the cluster is represented by the panel unit. Note that the `hausman` option is allowed only for static models.

6. We thank an anonymous referee for bringing this point to our attention. Like other Stata estimation commands, `xsmle` cannot recognize nonlinear specifications not based on factor variables, for example, user-defined second-order terms or interactions.

### 3 The xsmle command

The `xsmle` command is written using the `optimize()` suite of functions and the optimization engine used by `ml`. It shares the same features of all Stata estimation commands. Stata 10.1 is the earliest version that can run `xsmle`. Only analytic weights (`aweight`) are allowed, but the declared *weights* variable must be constant within each unit of the panel. `xsmle` supports the `mi` prefix but does not support the `svy` prefix. Factor variables are allowed if Stata 11 (or later) is used to run the command.

One major prerequisite for using the command concerns the construction of the  $n \times n$  matrix of spatial weights. This matrix can be a Stata matrix or `spmat` object, and it may follow any spatial weighting scheme, though it is usual to normalize spatial weights so either the row or column sums are equal to one.<sup>7</sup> `xsmle` does not allow the use of time-varying weight matrices. This means that the weights matrix is forced to be the same for each cross-section, and `xsmle` will automatically replicate it for all time periods. This could be a limitation, especially in long panels, so a possible extension to `xsmle` may provide the option to read multiple (time-varying) weight matrices. Note that the maximum dimension of a single Stata matrix depends on Stata's flavor:  $40 \times 40$  (Small),  $800 \times 800$  (IC), and  $11000 \times 11000$  (SE or MP). To overcome this limitation, one must specify bigger matrices as `spmat` objects. A second requirement for `xsmle` is that the data must be `tsset` or `xtset` by the *panel* and *time* variables before the command is executed.<sup>8</sup>

The basic `xsmle` syntax is the following:

```
xsmle depvar [indepvars] [if] [in] [weight] [, options]
```

The default is the RE SAR model. A description of the main estimation and postestimation options is provided below. A full description of all available options is provided in the `xsmle` help file.

#### 3.1 Main options for xsmle

##### Options common to all models

`model(name)` specifies the spatial model to be fit. *name* may be `sar` for the SAR model, `sdm` for the SDM, `sac` for the SAR with spatially autocorrelated errors model, `sem` for the SEM, or `gspre` for the GSPRE model. The default is `model(sar)`.

7. It is not assumed that  $\mathbf{W}$  is symmetric, but  $(\mathbf{I} - \rho\mathbf{W})$  must be nonsingular. This implies conditions on the eigenvalues of  $\mathbf{W}$  discussed extensively in the literature (for example, see [LeSage and Pace \[2009, chap. 3\]](#)).

8. This avoids the necessity of adding syntax to specify the panel and time variables. However, there is a corollary that should be noted. The natural way of organizing spatial panel data for estimation purposes is to stack each panel unit for period  $t = 1$  followed by panel units for  $t = 2$ , and so on. Thus `xsmle` internally sorts the dataset by time and panel unit but restores the original sorting on exit.

`vce(vcetype)` specifies how to estimate the VC matrix corresponding to the parameter estimates. The standard errors reported in the estimation results table are the square root of the variances (diagonal elements) of the VC estimator. *vcetype* may be one of the following:

`oim` uses the observed information matrix.

`opg` uses the sum of the outer product of the gradients.

`robust` is the synonym for clustered sandwich estimator, where *clustvar* is the *panelvar*.

`cluster clustvar` specifies the clustered sandwich estimator.

`dkraay #` specifies the Driscoll–Kraay robust estimator. *#* is the maximum lag used in the calculation.

`robust` is the synonym for `vce(cluster panelvar)`.

`cluster(clustvar)` is the synonym for `vce(cluster clustvar)`.

`constraints(constraints)`; see [R] **estimation options**.

`level(#)` sets the confidence level for confidence intervals; the default is `level(95)`.

`postscore` saves observation-by-observation scores in the estimation results list.

`posthessian` saves the Hessian corresponding to the full set of coefficients in the estimation results list.

*display\_options*: `vsquish`, `baselevels`, `allbaselevels`; see [R] **estimation options**.

*maximize\_options*: `difficult`, `technique(algorithm_spec)`, `iterate(#)`, `[no]log`, `from(init_specs)`, `tolerance(#)`, `ltolerance(#)`, `nrtolerance(#)`, `nonrtolerance`; see [R] **maximize**. These options are seldom used.

### Options for the SAR model

`wmatrix(name)` specifies the weight matrix for the SAR term. *name* can be a Stata matrix or an `spmat` object. This matrix can be standardized or not. `wmatrix()` is required.

`re` uses the random-effects estimator; `re` is the default.

`fe` uses the fixed-effects estimator.

`type(type_option[, leeyu])` specifies fixed-effects type. *type\_option* may be `ind` for individual-fixed effects, `time` for time-fixed effects, or `both` for time- and individual-fixed effects. The `leeyu` suboption transforms the data according to [Lee and Yu \(2010\)](#).

`dlag(dlag)` defines the structure of the spatiotemporal model. When *dlag* is equal to 1, only the time-lagged dependent variable is included; when *dlag* is equal to 2, only

the space-time-lagged dependent variable is included; when *dlag* is equal to 3, both the time-lagged and space-time-lagged dependent variables are included.

**noconstant** suppresses the constant term in the model. It is used only for the **re** estimator.

**effects** computes direct, indirect, and total effects and adds them to **e(b)**.

**vceeffects**(*vcee\_type* [, **nsim**(#)]) sets how the standard errors for the direct, indirect, and total effects are computed. *vcee\_type* may be **dm** for delta method standard errors, **sim** [, **nsim**(#)] for Monte Carlo standard errors, where **nsim**(#) sets the number of simulations for the LeSage and Pace (2009) procedure, or **none** for no standard errors.

**hausman** performs the robust Hausman test, automatically detecting the alternative estimator. The test is computed estimating the VC matrix of the difference between **fe** and **re** estimators as in White (1982). It is allowed only for static models.

### Options for the SDM model

**wmatrix**(*name*) specifies the weight matrix for the SAR term. *name* can be a Stata matrix or an **spmat** object. This matrix can be standardized or not. **wmatrix**() is required.

**dmatrix**(*name*) specifies the weight matrix for the spatially lagged regressors; the default is to use the matrix specified in **wmat**(*name*). *name* can be a Stata matrix or an **spmat** object. This matrix can be standardized or not.

**durbin**(*varlist*) specifies the regressors that have to be spatially lagged; the default is to lag all independent variables in *varlist*.

**re** uses the random-effects estimator; **re** is the default.

**fe** uses the fixed-effects estimator.

**type**(*type\_option* [, **leeyu**]) specifies fixed-effects type. *type\_option* may be **ind** for individual-fixed effects, **time** for time-fixed effects, or **both** for time- and individual-fixed effects. The **leeyu** suboption transforms the data according to Lee and Yu (2010).

**dlag**(*dlag*) defines the structure of the spatiotemporal model. When *dlag* is equal to 1, only the time-lagged dependent variable is included; when *dlag* is equal to 2, only the space-time-lagged dependent variable is included; when *dlag* is equal to 3, both time-lagged and space-time-lagged dependent variables are included.

**noconstant** suppresses the constant term in the model. It is used only for the **re** estimator.

**effects** computes direct, indirect, and total effects and adds them to **e(b)**.

`vceeffects(vcee.type[, nsim(#)])` sets how the standard errors for the direct, indirect, and total effects are computed. *vcee.type* may be `dm` for delta method standard errors, `sim[, nsim(#)]` for Monte Carlo standard errors, where `nsim(#)` sets the number of simulations for the LeSage and Pace (2009) procedure, or `none` for no standard errors.

`hausman` performs the robust Hausman test, automatically detecting the alternative estimator. The test is computed estimating the VC matrix of the difference between `fe` and `re` estimators as in White (1982). It is allowed only for static models.

### Options for the SAC model

`wmatrix(name)` specifies the weight matrix for the SAR term. *name* can be a Stata matrix or an `spmat` object. This matrix can be standardized or not. `wmatrix()` is required.

`ematrix(name)` specifies the weight matrix for the SAC error term. *name* can be a Stata matrix or an `spmat` object. This matrix can be standardized or not. `ematrix()` is required.

`fe` uses the fixed-effects estimator.

`type(type_option[, leeyu])` specifies fixed-effects type. *type\_option* may be `ind` for individual-fixed effects, `time` for time-fixed effects, or `both` for time- and individual-fixed effects. The `leeyu` suboption transforms the data according to Lee and Yu (2010).

`effects` computes direct, indirect, and total effects and adds them to `e(b)`.

`vceeffects(vcee.type[, nsim(#)])` sets how the standard errors for the direct, indirect, and total effects are computed. *vcee.type* may be `dm` for delta method standard errors, `sim[, nsim(#)]` for Monte Carlo standard errors, where `nsim(#)` sets the number of simulations for the LeSage and Pace (2009) procedure, or `none` for no standard errors.

### Options for the SEM model

`ematrix(name)` specifies the weight matrix for the SAC error term. *name* can be a Stata matrix or an `spmat` object. This matrix can be standardized or not. `ematrix()` is required.

`re` uses the random-effects estimator; `re` is the default.

`fe` uses the fixed-effects estimator.

`type(type_option[, leeyu])` specifies fixed-effects type. *type\_option* may be `ind` for individual-fixed effects, `time` for time-fixed effects, or `both` for time- and individual-fixed effects. The `leeyu` suboption transforms the data according to Lee and Yu (2010).

`noconstant` suppresses the constant term in the model. It is used only for the `re` estimator.

`hausman` performs the robust Hausman test, automatically detecting the alternative estimator. The test is computed estimating the VC matrix of the difference between `fe` and `re` estimators as in [White \(1982\)](#). It is allowed only for static models.

### Options for the GSPRE model

`wmatrix(name)` specifies the weight matrix for the SAC RE. *name* can be a Stata matrix or an `spmat` object. This matrix can be standardized or not. `wmatrix()` is required.

`ematrix(name)` specifies the weight matrix for the SAC error term. *name* can be a Stata matrix or an `spmat` object. This matrix can be standardized or not.

`re` uses the random-effects estimator.

`error(error_options)` defines the random-effect error structure with *error\_options* = 1, ..., 4. In particular, `error(1)` (the default) for  $\phi \neq \lambda \neq 0$ , `error(2)` for  $\phi \neq 0$  and  $\lambda = 0$ , `error(3)` for  $\phi = 0$  and  $\lambda \neq 0$  (SEM model), and `error(4)` for  $\phi = \lambda$ .

`noconstant` suppresses the constant term in the model. It is used only for the `re` estimator.

## 3.2 Postestimation command after `xsmle`

After an `xsmle` estimation, the `predict` command can be used to compute predicted values. Moreover, `predict` allows postestimation of FE or RE. The methods implemented in this command are the panel-data extension of those available in Kelejian and Prucha (2007) and [Drukker, Prucha, and Raciborski \(2013b\)](#). See section 4.1 for details.

### Syntax for `predict`

The syntax of the command is the following:

```
predict [type] newvar [if] [in] [, rform full limited naive xb a noie]
```

### Options for `predict`

`rform`, the default, calculates predicted values from the reduced-form equation,  $y_{it} = (\mathbf{I}_n - \rho \mathbf{W})^{-1}(x_{it}\boldsymbol{\beta} + \alpha_i)$ .

`full` calculates predicted values based on the full information set. This option is available only with `model(sac)`.

**limited** calculates predicted values based on the limited information set. This option is available only with **model(sac)**.

**naive** calculates predicted values based on the observed values of  $y_{it} = \rho \mathbf{W} y_{it} + x_{it} \beta + \alpha_i$ .

**xb** calculates the linear prediction including the FE or RE  $x_{it} \beta + \alpha_i$ .

**a** estimates  $\alpha_i$ , the FE, or RE. With FE models, this statistic is allowed only with **type(ind)**.

**noie** excludes the estimated  $\alpha_i$ , the FE, or RE from the prediction.

## 4 Examples

### 4.1 Simulated data

In this section, we use simulated data to illustrate the **xsmle** command's estimation capabilities, focusing on model selection, prediction, and estimation in the presence of missing data.<sup>9</sup> In particular, we consider the following FE SDM model,

$$y_{it} = 0.3 \sum_{j=1}^n w_{ij} y_{jt} + 0.5 x_{1it} - 0.3 x_{2it} - 0.2 x_{3it} + 0.3 \sum_{j=1}^n w_{ij} x_{1it} + 0.6 \sum_{j=1}^n w_{ij} x_{2it} + 0.9 \sum_{j=1}^n w_{ij} x_{3it} + \mu_i + \epsilon_{it} \quad (2)$$

where the nuisance parameters ( $\mu_i$ ) are drawn from an independent and identically distributed (i.i.d.) standard Gaussian random variable. To allow for dependence between the unit-specific effects and the regressors, we generate the latter as follows,

$$x_{kit} = 0.4 \mu_i + (1 - 0.4^2)^{1/2} z_{kit} \quad (3)$$

where  $z_{kit}$  is standard Gaussian with  $k = 1, 2, 3$ . The sample size is set to 940 ( $n = 188$  and  $T = 5$ ) observations.<sup>10</sup>

Let us begin by importing a first-order spatial contiguity matrix of the Italian local health authorities using the **spmat** command:

```
. use ASL_contiguity_mat_ns.dta
. spmat dta W W*, replace
```

The **spmat dta** command allows users to store an **spmat** object called **W** in the Stata memory. Notice that, to fit a model using **xsmle**, one must use the spatial weight matrix as a Stata matrix or an **spmat** object. The following **spmat** entry allows users to easily summarize the **W** object:

9. We report the code used for each example in the **sj\_examples\_simdata.do** accompanying file.

10. The chosen cross-sectional dimension ( $n = 188$ ) depends on the dimension of the used weight matrix, a contiguity matrix of the Italian local health authorities.



```
. spmat summarize W, links
```

Summary of spatial-weighting object W

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

As can be seen, the imported spatial matrix consists of 188 cross-sectional units with at least 1 neighbor, with about 4.8 contiguous units on average. Because `xsmle` does not make this transformation automatically, the next step consists in the row-normalization of the `W` object. This can easily be performed using the following:

```
. spmat dta W W*, replace normalize(row)
```

In particular, the syntax for fitting an FE SDM is

```
. xtset id t
      panel variable:  id (strongly balanced)
      time variable:  t, 1 to 5
      delta:  1 unit

. xsmle y x1 x2 x3, wmat(W) model(sdm) fe type(ind) nolog
Warning: All regressors will be spatially lagged
SDM with spatial fixed-effects                Number of obs =      940
Group variable: id                            Number of groups =     188
Time variable: t                             Panel length =       5
R-sq:    within = 0.3852
          between = 0.3705
          overall = 0.3635
Mean of fixed-effects =  0.0314
Log-likelihood = -1204.1194
```

	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Main							
	x1	.5456416	.034473	15.83	0.000	.4780758	.6132075
	x2	-.2798453	.0356246	-7.86	0.000	-.3496683	-.2100224
	x3	-.1896873	.0356751	-5.32	0.000	-.2596093	-.1197654
Wx							
	x1	.3093954	.0716979	4.32	0.000	.16887	.4499207
	x2	.5063665	.0759508	6.67	0.000	.3575057	.6552273
	x3	.9072591	.0748364	12.12	0.000	.7605825	1.053936
Spatial							
	rho	.2274947	.0425135	5.35	0.000	.1441699	.3108196
Variance							
sigma2_e		.7500305	.0347637	21.58	0.000	.6818948	.8181661

```
. estimates store sdm_fe
```

When the `fe` option is specified, `xsmle` fits a model with a unit-specific FE. This means that, in the example above, we might omit the `type(ind)` option.<sup>11</sup> The latter allows users to specify alternative forms for the FE: `type(time)` allows for time FE, while `type(both)` specifies both time and unit FE. In the case of SDM, `xsmle` also allows users to specify a different set of spatially lagged explanatory variables through the `durbin(varlist)` option. As the warning message reports, the default is to lag all independent variables in `varlist`.

To simplify the task of producing publication-quality tables, `xsmle` reports labeled estimation results. The **Main** equation contains the  $\beta$  vector, the **Wx** equation reports (only for SDM) the  $\theta$  vector, the **Spatial** equation reports the spatial coefficients (in this case  $\rho$ ), and the **Variance** equation reports ancillary parameters as the variance of the error ( $\sigma_\epsilon^2$  in this case).<sup>12</sup>

Even if we already know the FE SDM is correctly specified in this example, we might be interested in testing the appropriateness of a RE variant using the official Stata `hausman` command:

---

11. The `nolog` option is seldom used and allows users to omit the display of the log-likelihood function iteration log. `xsmle` allows users to use all `maximize` options available for `ml` estimation commands (see `help maximize`) plus the additional `postscore` and `posthessian` options, which report the score and the hessian as an `e()` matrix. Note that the usual limit for matrix dimension does apply in this case.

12. Notice that for models other than SDM, the ancillary equations will be different following the specific parametrization used.

```
. xsmle y x1 x2 x3, wmat(W) model(sdm) re type(ind) nolog
```

```
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 = 0.3671
```

```
between = 0.5567
```

```
overall = 0.4429
```

```
Log-likelihood = -1461.5464
```

	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Main							
	x1	.6278704	.0383441	16.37	0.000	.5527173	.7030236
	x2	-.1595226	.0402597	-3.96	0.000	-.2384301	-.0806151
	x3	-.0807422	.0400913	-2.01	0.044	-.1593197	-.0021648
	_cons	.0214849	.0669073	0.32	0.748	-.109651	.1526208
Wx							
	x1	.3042129	.0784076	3.88	0.000	.1505368	.4578889
	x2	.5215032	.0805461	6.47	0.000	.3636356	.6793707
	x3	.9631849	.0813256	11.84	0.000	.8037896	1.12258
Spatial							
	rho	.2558274	.040904	6.25	0.000	.175657	.3359977
Variance							
	lgt_theta	-.0751917	.1284863	-0.59	0.558	-.3270202	.1766369
	sigma2_e	.9648846	.0515123	18.73	0.000	.8639224	1.065847

```
. estimates store sdm_re
```

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

		Coefficients			
		(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
		sdm_fe	sdm_re	Difference	S.E.
comp1					
	x1	.5456416	.6278704	-.0822288	.
	x2	-.2798453	-.1595226	-.1203227	.
	x3	-.1896873	-.0807422	-.1089451	.
comp2					
	x1	.3093954	.3042129	.0051825	.
	x2	.5063665	.5215032	-.0151366	.
	x3	.9072591	.9631849	-.0559257	.
comp3					
	rho	.2274947	.2558274	-.0283326	.011587

```

b = consistent under Ho and Ha; obtained from xsmle
B = inconsistent under Ha, efficient under Ho; obtained from xsmle
Test: Ho: difference in coefficients not systematic
      chi2(7) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            =  -75.83      chi2<0 ==> model fitted on these
                                data fails to meet the asymptotic
                                assumptions of the Hausman test;
                                see suest for a generalized test

```

In this example, the Hausman statistic fails to meet its asymptotic assumptions. This problem can be overcome by adding the `hausman` option to the estimation command:

```

. xsmle y x1 x2 x3, wmat(W) model(sdm) fe type(ind) hausman 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 =       5
R-sq:    within  = 0.3852
          between = 0.3705
          overall = 0.3635
Mean of fixed-effects = 0.0314
Log-likelihood = -1204.1194

```

	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Main							
	x1	.5456416	.034473	15.83	0.000	.4780758	.6132075
	x2	-.2798453	.0356246	-7.86	0.000	-.3496683	-.2100224
	x3	-.1896873	.0356751	-5.32	0.000	-.2596093	-.1197654
Wx							
	x1	.3093954	.0716979	4.32	0.000	.16887	.4499207
	x2	.5063665	.0759508	6.67	0.000	.3575057	.6552273
	x3	.9072591	.0748364	12.12	0.000	.7605825	1.053936
Spatial							
	rho	.2274947	.0425135	5.35	0.000	.1441699	.3108196
Variance							
	sigma2_e	.7500305	.0347637	21.58	0.000	.6818948	.8181661
Ho: difference in coeffs not systematic chi2(7) = 91.10      Prob>=chi2 = 0.0000							

As expected, in this case, we strongly reject the null hypothesis, with a  $\chi^2$  test statistic equal to 91.10 and a  $p$ -value lower than 1%. Note that, if specified, the `hausman` option automatically detects the alternative model, which in our example is the RE.

Another common task routinely undertaken by spatial practitioners is model selection. Following the strategy described in [LeSage and Pace \(2009\)](#) and [Elhorst \(2010b\)](#), investigators should start with the SDM as a general specification and test for the alternatives. That is, we fit an SDM but would like to know whether it is the best model for the data at hand. This kind of procedure can be easily implemented using `xsmle`. For

instance, one may be interested in testing for SAR or SEM specifications. Because the SDM may be easily derived starting from a SEM, one can easily show that if  $\theta = 0$  and  $\rho \neq 0$ , the model is a SAR, while if  $\theta = -\beta\rho$ , the model is a SEM. After the estimation of the SDM, these tests can be performed by exploiting the `xsmle` “equation-labeled” vector of estimated coefficients and using the official Stata `test` and `testnl` commands as follows:

```
. test [Wx]x1 = [Wx]x2 = [Wx]x3 = 0
( 1)  [Wx]x1 - [Wx]x2 = 0
( 2)  [Wx]x1 - [Wx]x3 = 0
( 3)  [Wx]x1 = 0
      chi2( 3) =    203.77
      Prob > chi2 =    0.0000
. 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) =    193.70
      Prob > chi2 =    0.0000
```

Finally, because the SAC and SDM are nonnested, information criteria can be used to test whether the most appropriate model is the SAC using the following:

```
. estimates restore sdm_fe
(results sdm_fe are active now)
. estat ic
Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
sdm_fe	940	.	-1204.119	8	2424.239	2463.006

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

and

```
. xsmle y x1 x2 x3, wmat(W) emat(W) model(sac) fe type(ind) 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 = 0.2208  
              between = 0.0007  
              overall = 0.0667

Mean of fixed-effects = 0.0831  
Log-likelihood = -1290.9574

	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Main							
	x1	.4860935	.0415495	11.70	0.000	.4046579	.5675291
	x2	-.3332588	.0370124	-9.00	0.000	-.4058019	-.2607158
	x3	-.3039008	.0371472	-8.18	0.000	-.3767081	-.2310936
Spatial							
	rho	-.134535	.1106866	-1.22	0.224	-.3514768	.0824067
	lambda	.4760945	.0877639	5.42	0.000	.3040804	.6481085
Variance							
	sigma2_e	1.073918	.0469018	22.90	0.000	.9819918	1.165844

```
. estat ic
```

Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	940	.	-1290.957	6	2593.915	2622.99

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

In this case, all tests point toward an FE SDM. Finally, one may be interested in the postestimation of the FE or predicted values of the outcome variable. In section 4.1, we summarize the spatial predictors implemented in `xsmle`. They are the panel-data extension of the predictors discussed in [Kelejian and Prucha \(2007\)](#), which range from the suboptimal naïve predictor to the efficient minimum mean square error (MSE) full-information predictor. Here we give some examples of the `xsmle` postestimation syntax. For instance, to postestimate the FE once an FE spatial model has been fit, we type

```
. estimates restore sdm_fe
(results sdm_fe are active now)
. predict alphahat, a
```

Now, to immediately visualize the deviation between the true (simulated) and estimated  $\mu_i$  values, we may plot them using

```
. twoway (kdensity alpha, lpattern(dot) lwidth(*2))
> (kdensity alphahat, lpattern(dash)),
> legend(row(1) label(1 "True") label(2 "Estimated"))
```

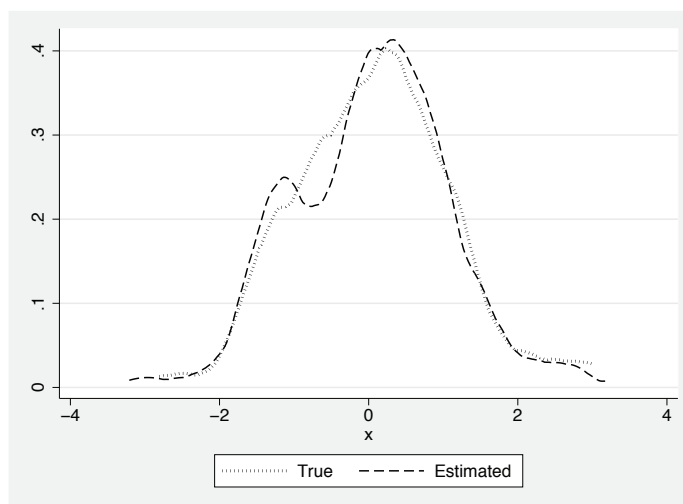
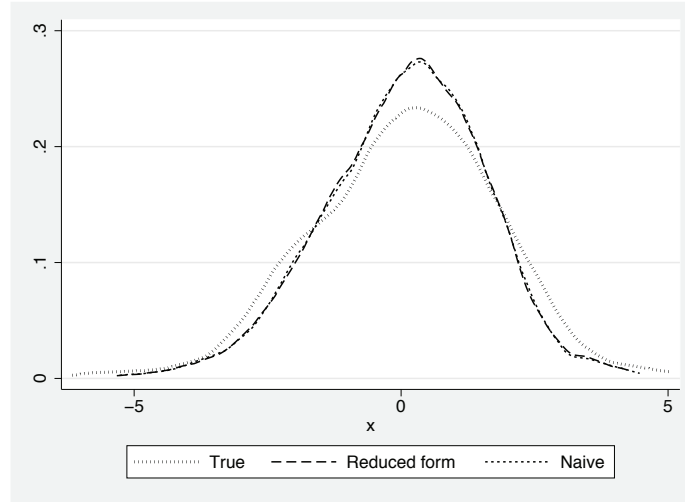


Figure 1. `xsmle` postestimation: predicted FE

The resulting plot is shown in figure 1. Similarly, we can obtain a reduced form and naïve prediction of the outcome variable using (the resulting plot is shown in figure 2)

```
. predict yhat_rform
(option rform assumed)
. predict yhat_naive, naive
. twoway (kdensity y, lpattern(dot) lwidth(*2))
> (kdensity yhat_rform, lpattern(dash))
> (kdensity yhat_naive), legend(row(1) label(1 "True")
> label(2 "Reduced form") label(3 "Naive"))
```

Figure 2. `xsmle` postestimation: reduced form and naïve predictors

### Postestimation

In this section, we briefly discuss the predictors available in `xsmle` and replicate the [Kelejian and Prucha \(2007\)](#) Monte Carlo study, extending it to the case of panel data. Let us consider the following SAR with a SAC errors model,

$$\mathbf{y}_t = \rho \mathbf{W} \mathbf{y}_t + \mathbf{X}_t \boldsymbol{\beta} + \boldsymbol{\mu} + \boldsymbol{\nu}_t \quad (4)$$

$$\boldsymbol{\nu}_t = \lambda \mathbf{M} \boldsymbol{\nu}_t + \boldsymbol{\epsilon}_t \quad (5)$$

for which we use the same notation discussed in section 2. In this model,  $y_{it}$  is determined as

$$y_{it} = \rho \mathbf{w}_{i.} \mathbf{y}_t + \mathbf{x}_{it} \boldsymbol{\beta} + \mu_i + \nu_{it}$$

$$\nu_{it} = \lambda \mathbf{m}_{i.} \boldsymbol{\nu}_t + \epsilon_{it}$$

where, for  $t = 1, \dots, T$ ,  $\mathbf{w}_{i.}$  and  $\mathbf{m}_{i.}$  are the  $i$ th rows of  $\mathbf{W}$  and  $\mathbf{M}$ ,  $\mathbf{x}_{it}$  is the  $i$ th row of  $\mathbf{X}_t$ ,  $\nu_{it}$  and  $\epsilon_{it}$  are the  $i$ th elements of  $\boldsymbol{\nu}_t$  and  $\boldsymbol{\epsilon}_t$ ,  $\mu_i$  is the  $i$ th element of  $\boldsymbol{\mu}$ , and  $\mathbf{w}_{i.} \mathbf{y}_t$  and  $\mathbf{m}_{i.} \boldsymbol{\nu}_t$  denote the  $i$ th elements of the spatial lags  $\mathbf{W} \mathbf{y}_t$  and  $\mathbf{M} \boldsymbol{\nu}_t$  with  $\mathbf{w}_{i.} \mathbf{y}_t$  that does not include  $y_{it}$ . By making the same assumptions of [Kelejian and Prucha \(2007\)](#), we have (see [Kelejian and Prucha \[2007\]](#) for more details on model assumptions)

$$\boldsymbol{\nu}_t \sim \mathcal{N}(0, \sigma_\epsilon^2 \boldsymbol{\Sigma}^{\nu_t})$$

$$\mathbf{y}_t \sim \mathcal{N}(\boldsymbol{\xi}_t, \sigma_\epsilon^2 \boldsymbol{\Sigma}^{\mathbf{y}_t})$$



with

$$\begin{aligned}\xi_t &= (\mathbf{I} - \rho \mathbf{W})^{-1}(\mathbf{X}_t \boldsymbol{\beta} + \boldsymbol{\mu}) \\ \boldsymbol{\Sigma}^{\nu_t} &= (\mathbf{I} - \lambda \mathbf{M})^{-1}(\mathbf{I} - \lambda \mathbf{M}')^{-1} \\ \boldsymbol{\Sigma}^{\mathbf{y}_t} &= (\mathbf{I} - \rho \mathbf{W})^{-1} \boldsymbol{\Sigma}^{\nu_t} (\mathbf{I} - \rho \mathbf{W}')^{-1}\end{aligned}$$

We consider three information sets,

$$\begin{aligned}\boldsymbol{\Lambda}_1 &= \{\mathbf{X}_t, \mathbf{W}\} \\ \boldsymbol{\Lambda}_2 &= \{\mathbf{X}_t, \mathbf{W}, \mathbf{w}_{i \cdot} \mathbf{y}_t\} \\ \boldsymbol{\Lambda}_3 &= \{\mathbf{X}_t, \mathbf{W}, \mathbf{y}_{t,-1}\}, \quad t = 1, \dots, T\end{aligned}$$

where  $\boldsymbol{\Lambda}_3$  is the full-information set containing all  $n - 1$  observations on  $\mathbf{y}_t$  and  $\boldsymbol{\Lambda}_1$  and  $\boldsymbol{\Lambda}_2$  are both subsets of  $\boldsymbol{\Lambda}_3$ . We consider the following four predictors of  $y_{it}$  (denoted as  $y_{it}^{(p)}$  with  $p = 1 \dots, 4$ ),<sup>13</sup>

$$\begin{aligned}y_{it}^{(1)} &= E(y_{it} | \boldsymbol{\Lambda}_1) \\ &= (\mathbf{I} - \rho \mathbf{W})_{i \cdot}^{-1}(\mathbf{X}_t \boldsymbol{\beta} + \boldsymbol{\mu}) \\ y_{it}^{(2)} &= E(y_{it} | \boldsymbol{\Lambda}_2) \\ &= \rho \mathbf{w}_{i \cdot} \mathbf{y}_t + \mathbf{x}_{it} \boldsymbol{\beta} + \mu_i + \frac{\text{cov}(\nu_{it}, \mathbf{w}_{i \cdot} \mathbf{y}_t)}{\text{var}(\mathbf{w}_{i \cdot} \mathbf{y}_t)} \{\mathbf{w}_{i \cdot} \mathbf{y}_t - E(\mathbf{w}_{i \cdot} \mathbf{y}_t)\} \\ y_{it}^{(3)} &= E(y_{it} | \boldsymbol{\Lambda}_3) \\ &= \rho \mathbf{w}_{i \cdot} \mathbf{y}_t + \mathbf{x}_{it} \boldsymbol{\beta} + \mu_i + \text{cov}(\nu_{it}, \mathbf{y}_{t,-i}) \{\text{VC}(\mathbf{y}_{t,-i})\}^{-1} \{\mathbf{y}_{t,-i} - E(\mathbf{y}_{t,-i})\} \\ y_{it}^{(4)} &= \rho \mathbf{w}_{i \cdot} \mathbf{y}_t + \mathbf{x}_{it} \boldsymbol{\beta} + \mu_i\end{aligned}$$

where

$$\begin{aligned}E(\mathbf{w}_{i \cdot} \mathbf{y}_t) &= \mathbf{w}_{i \cdot} (\mathbf{I} - \rho \mathbf{W})^{-1}(\mathbf{X}_t \boldsymbol{\beta} + \boldsymbol{\mu}) \\ \text{var}(\mathbf{w}_{i \cdot} \mathbf{y}_t) &= \sigma_\epsilon^2 \mathbf{w}_{i \cdot} \boldsymbol{\Sigma}^{\mathbf{y}_t} \mathbf{w}_{i \cdot}' \\ \text{cov}(\mu_i, \mathbf{w}_{i \cdot} \mathbf{y}_t) &= \sigma_\epsilon^2 \boldsymbol{\Sigma}_{i \cdot}^{\nu_t} (\mathbf{I} - \rho \mathbf{W}')^{-1} \mathbf{w}_{i \cdot}' \\ E(\mathbf{y}_{t,-i}) &= \mathbf{S}_{t,-i} (\mathbf{I} - \rho \mathbf{W})^{-1}(\mathbf{X}_t \boldsymbol{\beta} + \boldsymbol{\mu}) \\ \text{VC}(\mathbf{y}_{t,-i}) &= \sigma_\epsilon^2 \mathbf{S}_{t,-i} \boldsymbol{\Sigma}^{\mathbf{y}_t} \mathbf{S}_{t,-i}' \\ \text{cov}(\nu_{it}, \mathbf{y}_{t,-i}) &= \sigma_\epsilon^2 \boldsymbol{\Sigma}_{i \cdot}^{\nu_t} (\mathbf{I} - \rho \mathbf{W}')^{-1} \mathbf{S}_{t,-i}'\end{aligned}$$

In the above expressions,  $(\mathbf{I} - \rho \mathbf{W})_{i \cdot}^{-1}$  and  $\boldsymbol{\Sigma}_{i \cdot}^{\nu_t}$  denote the  $i$ th rows of  $(\mathbf{I} - \rho \mathbf{W})^{-1}$  and  $\boldsymbol{\Sigma}^{\nu_t}$ , respectively, while  $\mathbf{S}_{t,-i}$  is the  $n - 1 \times n$  selector matrix identical to the  $n \times n$  identity matrix  $\mathbf{I}$ , except that the  $i$ th row of  $\mathbf{I}$  is deleted.

13.  $p = 1$  indicates the reduced-form predictor,  $p = 2$  indicates the limited-information predictor,  $p = 3$  indicates the full-information predictor, and  $p = 4$  indicates the naïve predictor.

We now compare the above predictors in terms of predictive efficiencies, extending the Kelejian and Prucha (2007) Monte Carlo design to FE models like the one reported in (4)–(5). In particular, we consider the following FE SAC model,

$$\begin{aligned} y_{it} &= \rho \sum_{j=1}^n w_{ij} y_{jt} + 0.5x_{1it} + \mu_i + \nu_{it} \\ \nu_{it} &= \lambda \sum_{j=1}^n w_{ij} \nu_{jt} + \epsilon_{it} \end{aligned}$$

where the nuisance parameters,  $\mu_i$ , are drawn from an i.i.d. standard Gaussian random variable, while the  $x_{1it}$  regressor is generated according to (3). The simulation is based on what Kelejian and Prucha (2007) describe as the “two ahead and two behind” weight matrix, in which each unit is directly related to the two units immediately after it and immediately before it in the ordering. The matrix is row normalized, and all of its nonzero elements are equal to  $1/4$ .<sup>14</sup> As in Kelejian and Prucha (2007), we report results for 25 combinations of  $\rho, \lambda = -0.9, -0.4, 0, 0.4, 0.9$  and set  $\sigma_\epsilon^2 = 1$ . The sample size is set to 500 ( $n = 100$  and  $T = 5$ ) observations. Note that when  $\rho = 0$ , results refer to the SEM.

Simulation results in terms of sample averages over  $i = 1, \dots, 100$  and  $t = 1, \dots, 5$  for  $\text{MSE}(y_{it}^{(p)})$  for  $p = 2, \dots, 4$  are given in table 3.<sup>15</sup> As expected, even in the panel-data case, numerical results are fully consistent with the theoretical notions reported in Kelejian and Prucha (2007): the biased **naïve** predictor is the worst, especially when  $\rho = \lambda = 0.9$ , while the **full information** predictor is always the best.

14. See Kelejian and Prucha (2007) for more details on the structure of this weight matrix. Clearly, the results reported here depend on the structure of this matrix.

15. Because the reduced-form predictor has by far the worst performance, we do not report its results.

Table 3. Simulation results (MSEs)

$\rho$	$\lambda$	naive	limited	full	$\hat{\alpha}$
-0.9	-0.9	1.441	0.488	0.308	0.398
-0.9	-0.4	0.931	0.547	0.464	0.263
-0.9	0	0.811	0.678	0.659	0.221
-0.9	0.4	0.940	0.932	0.913	0.244
-0.9	0.9	6.384	1.331	1.155	1.594
-0.4	-0.9	1.348	0.547	0.465	0.359
-0.4	-0.4	0.902	0.649	0.625	0.246
-0.4	0	0.809	0.764	0.761	0.224
-0.4	0.4	0.937	0.863	0.857	0.252
-0.4	0.9	6.362	0.856	0.849	1.586
0	-0.9	1.340	0.678	0.659	0.346
0	-0.4	0.887	0.764	0.761	0.240
0	0	0.803	0.793	0.792	0.220
0	0.4	0.937	0.765	0.762	0.257
0	0.9	6.019	0.702	0.660	1.548
0.4	-0.9	1.337	0.931	0.913	0.341
0.4	-0.4	0.885	0.863	0.857	0.233
0.4	0	0.811	0.765	0.762	0.229
0.4	0.4	0.966	0.673	0.651	0.274
0.4	0.9	5.541	0.659	0.518	1.445
0.9	-0.9	1.340	1.334	1.156	0.339
0.9	-0.4	0.887	0.857	0.849	0.230
0.9	0	0.805	0.702	0.660	0.215
0.9	0.4	1.445	0.659	0.518	0.758
0.9	0.9	8.150	1.127	0.391	2.250

### On marginal effects

As already mentioned in section 2.1, a peculiar feature of spatial regression models is the feedback process among spatially correlated units, which leads to the distinction between direct, indirect, and total marginal effects. To show how to compute these effects using `xsmle`, let us consider the data-generating process of the following dynamic FE SDM model,

$$\begin{aligned}
 y_{it} = & \tau y_{it-1} + \psi \sum_{j=1}^n w_{ij} y_{jt-1} + 0.2 \sum_{j=1}^n w_{ij} y_{jt} + 0.5 x_{1it} - 0.3 x_{2it} - 0.2 x_{3it} \\
 & + 0.3 \sum_{j=1}^n w_{ij} x_{1it} + 0.6 \sum_{j=1}^n w_{ij} x_{2it} + 0.9 \sum_{j=1}^n w_{ij} x_{3it} + \mu_i + \epsilon_{it}
 \end{aligned} \tag{6}$$

where, as for the data-generating process reported in (2), the nuisance parameters are drawn from an i.i.d. standard Gaussian random variable and the correlation between unit-specific effects and regressors is obtained according to (3). The sample size is set to 1,960 observations ( $n = 196$  and  $T = 10$ ) and  $\tau = \psi = 0.3$ .<sup>16</sup>

As documented in section 3.1, `xsmle` allows the estimation of (6) by specifying the `dlag(3)` option.<sup>17</sup> By adding the `effects` option, one can use `xsmle` to compute direct, indirect, and total effects:

```
. xsmle y x1 x2 x3, wmat(Wspmat) model(sdm) fe dlag(3) effects nolog
Warning: All regressors will be spatially lagged
Computing marginal effects standard errors using MC simulation...
Dynamic SDM with spatial fixed-effects          Number of obs =      1764
Group variable: id                             Number of groups =      196
Time variable: t                               Panel length =       9
R-sq:      within = 0.3876
           between = 0.9108
           overall = 0.8354
Mean of fixed-effects = 0.0708
Log-likelihood = -2396.3051
```

y		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Main	y						
	L1.	.278483	.0187886	14.82	0.000	.2416579	.315308
	Wy						
	L1.	.3371464	.0312009	10.81	0.000	.2759938	.3982989
	x1	.471855	.0261821	18.02	0.000	.420539	.523171
	x2	-.2774485	.0263341	-10.54	0.000	-.3290623	-.2258347
	x3	-.1814445	.0268751	-6.75	0.000	-.2341187	-.1287704
Wx							
	x1	.3501276	.0516946	6.77	0.000	.2488081	.4514471
	x2	.5557425	.0498404	11.15	0.000	.4580572	.6534278
	x3	.9499813	.0503458	18.87	0.000	.8513054	1.048657
Spatial							
	rho	.152554	.0287441	5.31	0.000	.0962165	.2088915
Variance							
	sigma2_e	.9612217	.0291937	32.93	0.000	.9040031	1.01844
SR_Direct							
	x1	.4920234	.0251053	19.60	0.000	.4428179	.541229
	x2	-.2567458	.0253696	-10.12	0.000	-.3064693	-.2070222
	x3	-.1435512	.0251039	-5.72	0.000	-.1927539	-.0943484

16. We thank Jihai Yu for sharing his MATLAB code for creating the rook spatial weights matrix used in this example. The original code has been translated into Mata for our purposes (see the accompanying `sj_examples_simdata.do` file for details).

17. `dlag(1)` allows the estimation of (6), in which  $\psi = 0$ , while `dlag(2)` is the case in which  $\tau = 0$ .

SR_Indirect						
x1	.4867733	.0582277	8.36	0.000	.372649	.6008975
x2	.5859261	.0604524	9.69	0.000	.4674416	.7044107
x3	1.052221	.0616699	17.06	0.000	.9313501	1.173092
SR_Total						
x1	.9787967	.0683064	14.33	0.000	.8449185	1.112675
x2	.3291804	.0681426	4.83	0.000	.1956234	.4627374
x3	.9086697	.0672656	13.51	0.000	.7768315	1.040508
LR_Direct						
x1	.8954026	.0504489	17.75	0.000	.7965245	.9942807
x2	-.2565021	.0444616	-5.77	0.000	-.3436452	-.1693589
x3	.0384557	.0470276	0.82	0.414	-.0537168	.1306282
LR_Indirect						
x1	2.750811	.4462418	6.16	0.000	1.876193	3.625428
x2	1.485876	.2744933	5.41	0.000	.9478791	2.023873
x3	3.352583	.4749726	7.06	0.000	2.421653	4.283512
LR_Total						
x1	3.646213	.4830534	7.55	0.000	2.699446	4.59298
x2	1.229374	.3028385	4.06	0.000	.6358214	1.822927
x3	3.391038	.5056929	6.71	0.000	2.399898	4.382178

When the **effects** option is specified, the marginal effects will be both displayed and added to the estimated vector **e(b)**. Given its dynamic nature, (6) implies both short- and long-run effects (see table 2). In these cases, short-run effects are reported under the three equations labeled **SR\_Direct**, **SR\_Indirect**, and **SR\_Total**, while long-run effects are reported under **LR\_Direct**, **LR\_Indirect**, and **LR\_Total**.<sup>18</sup> Equivalently, short-run total effects can be obtained through **margins** using the following syntax:

```
. margins, dydx(*) predict(rform noie)
```

Average marginal effects	Number of obs	=	1,764
Model VCE : OIM			
Expression : Reduced form prediction, predict(rform noie)			
dy/dx w.r.t. : x1 x2 x3			

	Delta-method dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]
x1	.9699528	.0681065	14.24	0.000	.8364665 1.103439
x2	.3283914	.0669413	4.91	0.000	.1971888 .459594
x3	.9068859	.0712236	12.73	0.000	.7672903 1.046481

18. Equation names follow [Elhorst \(2014\)](#) terminology on short- and long-run marginal effects.

To ensure `margins` works, we added the `noie`'s `xsmle` postestimation option through the `predict()` option of `margins`. As can be seen, the two procedures produce slightly different results. This is because `xsmle`, by default, uses the Monte Carlo procedure outlined in [LeSage and Pace \(2009\)](#). Hence, the point estimates (standard errors) are averages (standard deviations) over the (default) 500 Monte Carlo replications. The same point estimates can be obtained using `xsmle` with the `vceeffects(none)` option.<sup>19</sup>

```
. quietly xsmle y x1 x2 x3, wmat(Wspmat) model(sdm) fe dlag(3) effects
> vceeffects(none)
. estimates store dsdm_fe
. estout dsdm_fe, keep(SR_Total:) c(b)
```

	dsdm_fe
	b
SR_Total	
x1	.9699528
x2	.3283914
x3	.9068859

Because the analytical formulas for direct, indirect, and total effects reported in [table 2](#) imply a linear (in variables) specification, `xsmle` suppresses the computation of these effects when factor variables are specified, as shown in the example below:

```
. xsmle y c.x1##c.x1 c.x1#c.x2 c.x2 c.x3, wmat(Wspmat) model(sdm) fe dlag(3)
> effects nolog
Warning: All regressors will be spatially lagged
Warning: direct and indirect effects cannot be computed if factor variables
        are specified option -effects- ignored. Notice that total effects
        can be obtained using -margins-
Dynamic SDM with spatial fixed-effects          Number of obs =      1764
Group variable: id                             Number of groups =      196
Time variable: t                               Panel length =       9
R-sq:      within = 0.3929
           between = 0.9122
           overall = 0.8378
```

19. The `vceeffects(none)` option suppresses the computation of standard errors.

Mean of fixed-effects = 0.0395

Log-likelihood = -2389.1429

	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Main	y						
	L1.	.282856	.0187596	15.08	0.000	.2460878	.3196242
	Wy						
	L1.	.3418741	.0311604	10.97	0.000	.2808008	.4029474
	x1	.4766421	.0261214	18.25	0.000	.4254451	.5278391
	c.x1#c.x1	.0446299	.017106	2.61	0.009	.0111027	.0781571
	c.x1#c.x2	-.0847021	.0243227	-3.48	0.000	-.1323737	-.0370306
	x2	-.2720875	.0263194	-10.34	0.000	-.3236725	-.2205025
x3	-.1824236	.0267751	-6.81	0.000	-.2349018	-.1299453	
Wx	x1	.3633111	.0517657	7.02	0.000	.2618521	.4647701
	c.x1#c.x1	.0073658	.0327561	0.22	0.822	-.056835	.0715667
	c.x1#c.x2	-.0608174	.0472681	-1.29	0.198	-.1534612	.0318264
	x2	.5585988	.0496918	11.24	0.000	.4612047	.6559929
	x3	.9484272	.0501452	18.91	0.000	.8501445	1.04671
	Spatial						
rho	.1509144	.0287019	5.26	0.000	.0946597	.2071691	
Variance							
sigma2_e	.9534039	.0289549	32.93	0.000	.8966533	1.010154	

Nonetheless, when the specification includes factor variables, `xsmle` allows for the use of `margins` to compute total marginal effects:

```
. margins, dydx(x1 x2 x3) predict(rform noie)
Warning: cannot perform check for estimable functions.
Average marginal effects      Number of obs      =      1,764
Model VCE      : OIM
Expression      : Reduced form prediction, predict(rform noie)
dy/dx w.r.t.    : x1 x2 x3
```

	Delta-method					
	dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	.9952611	.0683488	14.56	0.000	.8613	1.129222
x2	.3278821	.0665554	4.93	0.000	.1974359	.4583284
x3	.9021512	.0707735	12.75	0.000	.7634377	1.040865

xsmle also offers the opportunity to compute standard errors using the Delta method through the `vceffets(dm)` option.<sup>20</sup>

```
. xsmle y x1 x2 x3, wmat(Wspmat) model(sdm) fe dlag(3) effects vceffects(dm)
> nolog
Warning: All regressors will be spatially lagged
Computing marginal effects standard errors using delta-method...
Dynamic SDM with spatial fixed-effects          Number of obs =      1764
Group variable: id                             Number of groups =      196
Time variable: t                               Panel length =       9
R-sq:      within = 0.3876
           between = 0.9108
           overall = 0.8354
Mean of fixed-effects = 0.0708
Log-likelihood = -2396.3051
```

	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
<b>Main</b>						
	y					
	L1.	.278483	.0187886	14.82	0.000	.2416579 .315308
	Wy					
	L1.	.3371464	.0312009	10.81	0.000	.2759938 .3982989
	x1	.471855	.0261821	18.02	0.000	.420539 .523171
	x2	-.2774485	.0263341	-10.54	0.000	-.3290623 -.2258347
	x3	-.1814445	.0268751	-6.75	0.000	-.2341187 -.1287704
<b>Wx</b>						
	x1	.3501276	.0516946	6.77	0.000	.2488081 .4514471
	x2	.5557425	.0498404	11.15	0.000	.4580572 .6534278
	x3	.9499813	.0503458	18.87	0.000	.8513054 1.048657
<b>Spatial</b>						
	rho	.152554	.0287441	5.31	0.000	.0962165 .2088915
<b>Variance</b>						
	sigma2_e	.9612217	.0291937	32.93	0.000	.9040031 1.01844
<b>SR_Direct</b>						
	x1	.4889378	.0262506	18.63	0.000	.4374875 .5403881
	x2	-.2566706	.0262086	-9.79	0.000	-.3080385 -.2053026
	x3	-.144119	.02613	-5.52	0.000	-.1953328 -.0929052
<b>SR_Indirect</b>						
	x1	.481015	.058585	8.21	0.000	.3661905 .5958395
	x2	.585062	.0580324	10.08	0.000	.4713206 .6988034
	x3	1.051005	.0630431	16.67	0.000	.9274428 1.174567

20. While using the Delta method ensures the results do not depend on stochastic variability, it is a more computationally intensive procedure.



SR_Total							
	x1	.9699528	.0681065	14.24	0.000	.8364665	1.103439
	x2	.3283914	.0669413	4.91	0.000	.1971888	.459594
	x3	.9068859	.0712236	12.73	0.000	.7672903	1.046481
LR_Direct							
	x1	.8860048	.0680006	13.03	0.000	.7527261	1.019283
	x2	-.25736	.0472579	-5.45	0.000	-.3499839	-.1647362
	x3	.0347029	.0566012	0.61	0.540	-.0762334	.1456392
LR_Indirect							
	x1	2.659826	.5536009	4.80	0.000	1.574789	3.744864
	x2	1.457852	.2844823	5.12	0.000	.9002767	2.015427
	x3	3.280576	.5347181	6.14	0.000	2.232548	4.328604
LR_Total							
	x1	3.545831	.6090295	5.82	0.000	2.352155	4.739507
	x2	1.200492	.3154343	3.81	0.000	.582252	1.818732
	x3	3.315279	.5776118	5.74	0.000	2.183181	4.447377

### Unbalanced panels

Missing data can pose major problems when fitting econometric models because it is unlikely that missing values are missing completely at random. Most important here is that `xsmle` generally cannot handle unbalanced panels. A strategy to address this issue without relying on more complex econometric approaches is by multiple imputation, that is, the process of replacing missing values by multiple sets of plausible values. This section provides a simple example in which `xsmle` is used together with `mi`, Stata's suite of commands dealing with multiple data imputation, to overcome the hurdle. Let us consider the same data-generating process reported in (2). The following syntax allows users to randomly assign 5% missing values to the  $x_{1it}$  covariate:<sup>21</sup>

```
. set seed 12345
. replace x1 = . if uniform()<0.05
(49 real changes made, 49 to missing)
```

The first step is to declare the dataset as an `mi` dataset using `mi set`. Data must be `mi set` before other `mi` commands can be used. In this example, we choose the `wide` style. The second step is to register (declare) the variables with missing values using the `mi register` command:

```
. mi set wide
. mi register imputed x1
```

21. As usual, a good practice to obtain reproducible results is to set the seed of Stata's pseudorandom number generator using the command `set seed #`, where `#` is any number between 0 and  $2^{31} - 1$ .

We then use `mi impute regress` to fill in `x1`'s missing values using the linear regression method with the `z` covariate as the predictor.<sup>22</sup> The `add(50)` option specifies the number of imputations to be added (currently, the total number of imputations cannot exceed 1,000).

```
. mi impute regress x1 = z, add(50) rseed(12345)
Univariate imputation          Imputations =      50
Linear regression              added =      50
Imputed: m=1 through m=50      updated =      0
```

Variable	Observations per <i>m</i>			
	Complete	Incomplete	Imputed	Total
x1	891	49	49	940

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

After `mi impute` has been executed, 50 new variables `_#x1` (with `# = 1, ..., 50`) are added to the dataset, each representing an imputed version of `x1`. Finally, we type

```
. mi estimate, dots post: xsmle y x1 x2 x3, wmat(W) model(sdm) fe type(ind) nolog
Imputations (50):
.....10.....20.....30.....40.....50 done
Multiple-imputation estimates          Imputations      =      50
SDM with spatial fixed-effects        Number of obs    =      940
                                      Average RVI       =      0.0452
                                      Largest FMI       =      0.1304
DF adjustment: Large sample           DF: min         = 2,908.95
                                      avg             = 126,717.41
                                      max             = 516,684.95
Model F test: Equal FMI               F( 8,205401.9)   =      130.14
Within VCE type: OIM                 Prob > F         =      0.0000
```

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
Main						
x1	.509667	.0367065	13.88	0.000	.4377079	.581626
x2	-.2737751	.0363977	-7.52	0.000	-.3451134	-.2024368
x3	-.1947675	.036523	-5.33	0.000	-.2663518	-.1231832
Wx						
x1	.2788079	.0769524	3.62	0.000	.1279211	.4296947
x2	.5316003	.0779399	6.82	0.000	.3788391	.6843615
x3	.8991836	.0768688	11.70	0.000	.748522	1.049845
Spatial						
rho	.2471005	.042971	5.75	0.000	.1628754	.3313257
Variance						
sigma2_e	.7751222	.0364928	21.24	0.000	.7035961	.8466484

22. See `help mi impute` for details on the available imputation methods. The `z` covariate is a standard Gaussian random variable specifically designed to be correlated with `x1`. See the code reported in the `sj_examples_simdata.do` file for details.

to exploit `xsmle` to fit the FE SDM using the 50 imputed versions of the `x1` variable. In this way, both the coefficients and standard errors will be adjusted for the between-imputations variability according to the combination rules given in [Rubin \(1987\)](#). We replicated the same exercise by assigning (at random) a higher percentage (10% and 20%) of missing values to the `x1` covariate. To offer an example in which the multiple imputation strategy directly affects the  $\rho$  parameter value, we used the same strategy, assigning 5%, 10%, and 20% missing values to the dependent variable.<sup>23</sup>

The upper panel of table 4 reports the results for the case in which `x1` is the missing variable. As expected, the bias affecting the  $\beta_1$  parameter increases when the number of imputed values grows. The same is true for the  $\rho$  parameter when the missing values are in the dependent variable (lower panel of table 4). Note that even if these are not the results of a Monte Carlo simulation, the effect of missing values is seemingly stronger on  $\rho$  than  $\beta_1$ .

Table 4. Summary of estimation results by % of missing values<sup>†</sup>

Missing <code>x1</code>				
	No missing	5% missing	10% missing	20% missing
$\beta_1$	0.546 (0.034)	0.510 (0.037)	0.471 (0.040)	0.425 (0.043)
Missing <code>y</code>				
	No missing	5% missing	10% missing	20% missing
$\rho$	0.227 (0.043)	0.192 (0.047)	0.171 (0.053)	0.103 (0.060)

<sup>†</sup> Standard errors in parentheses. True values:  $\beta_1 = 0.5$ ,  $\rho = 0.3$ .

## 4.2 Real data

As an example of using spatial panel models with real data, we use a dataset on electricity usage at the state level in the United States. The data cover the 48 states in the continental United States plus the District of Columbia for the period 1990–2010. The data are drawn from the Electric Power Annual compiled by the Department of Energy's Energy Information Agency together with general economic, demographic, and weather information from other U.S. statistical agencies, including the Bureau of Labor Statistics and the Census Bureau.<sup>24</sup>

23. Interested readers can find the related Stata code in the accompanying `sj_examples_simdata.do` file.

24. Interested readers can find the Stata code and data used for this application in the accompanying `sj_empirical_application.do`, `wstate_rook.spmat`, and `state_spatial.dbf.dta` files.

The analysis focuses on the response of residential electricity demand to prices and weather or climate conditions. The spatial dimension arises in at least two ways:

- Relative prices in neighboring states may influence decisions about the location of economic activities and subsequently of the residence. Electricity prices in California are high in comparison with prices in the Northwest and parts of the Midwest, but one would expect that location decisions and thus electricity demand will be more strongly influenced by prices in the Northwest than in the Midwest. In modeling terms, this behavior may be manifested as a significant coefficient on spatially weighted prices or on the spatially lagged dependent variable.
- Both weather and climate variables may serve as proxies for short- and long-term regional influences on the location of economic activity, the energy efficiency of buildings, and other determinants of electricity use. Given the physical capital stock, annual variations in weather will affect electricity demand for air conditioning or heating. Hence, it is interesting to determine whether local or regional weather variables have a statistically distinct influence on electricity demand.

Note that the logic suggesting a role for spatial influences on electricity demand in each state does not imply direct spatial interactions for the dependent variable, as in cases where it is argued that policy decisions in one state—for example, taxes on property—are influenced by decisions made by neighboring states. Instead, the arguments reflect a combination of omitted variables that may be spatially correlated plus the spatially distributed influence of variables that would be included in any model of electricity demand.

Tables 5–7 summarize the results obtained when FE models are used to examine residential demand for electricity using the log of residential consumption per person as the dependent variable. Elhorst and others argue that FE models are more appropriate for such data because the sample represents the complete population of U.S. continental states rather than a random sample drawn from that population. This claim is supported by the evidence given in the last two lines of table 5, where all static RE specifications are strongly rejected by the Hausman test. The models do not provide a comprehensive analysis of factors that may influence demand, but they have been refined to focus on key variables that explain changes in electricity demand over the last two decades. For residential consumption, the large differences between the within and between  $R^2$  statistics, other than for the models that include the lagged (in time) dependent variable, confirm the importance of state FE associated with variables that are not included in the analysis or that cannot be identified in this specification. Nonetheless, the within  $R^2$  statistics, at least equal to 0.82, show that the models can account for a large proportion of variation over time in electricity consumption for residential usage by state. Weather variables, both heating and cooling degree days, have an important influence on residential consumption, and so does the size of the housing stock.<sup>25</sup>

25. We test for alternative measures of income; the best indicator seems to be personal disposable income adjusted for differences in the cost of living across states (using the ACCRA cost of living index) and for changes in the CPI over time.

Table 5. FE models for residential electricity demand

	FE	SAR	dynamic SAR	SDM	dynamic SDM	SEM	SAC
Real personal income	0.391***	0.203***	0.033	0.212***	0.039	0.375***	0.207***
Real average residential price	-0.235***	-0.239***	-0.144***	-0.293***	-0.165***	-0.271***	-0.241***
Housing units	1.019***	0.747***	0.150*	0.629***	0.128*	0.818***	0.748***
Cooling degree days	0.075***	0.057***	0.073***	0.057***	0.072***	0.071***	0.057***
Heating degree days	0.188***	0.140***	0.146***	0.131***	0.140***	0.156***	0.141***
L.Residential							
electricity consumption							
$\rho$		0.367***	0.554***	0.416***	0.534***		0.359***
$\lambda$			0.261***		0.284***	0.390***	0.018
Real average total price							
Log likelihood	2029.91	2108.54	2315.67	2144.51	2323.58	2071.08	2108.58
Observations	1078	1078	1029	1078	1029	1078	1078
$R^2_o$	0.82	0.82	0.89	0.85	0.89	0.82	0.82
$R^2_b$	0.12	0.14	0.91	0.16	0.91	0.21	0.14
$R^2_b$	0.18	0.20	0.89	0.22	0.90	0.26	0.20
Hausman $\chi^2$		28.24		27.33		33.19	
Hausman $p$ -value		0.00		0.00		0.00	

Significance levels: \*  $p < 10\%$ , \*\*  $p < 5\%$ , and \*\*\*  $p < 1\%$ .

Table 6. Residential electricity demand—test for model selection

	$\chi^2$	$p$ -value	Akaike's information criterion
SAR versus dynamic SAR	414.26	0.000	.
SDM versus dynamic SDM	358.14	0.000	.
dynamic SAR versus dynamic SDM	15.82	0.000	.
SEM versus dynamic SDM	505.00	0.000	.
SAC	.	.	−4201.0
dynamic SDM	.	.	−4629.0

Table 7. Direct, indirect, and total effects—residential electricity demand

	SAR	dynamic SAR	SDM	dynamic SDM	SAC
Long-run direct effects					
Real personal income	0.210***	0.082	0.223***	0.096	0.214***
Real average residential price	−0.247***	−0.359***	−0.307***	−0.401***	−0.249***
Housing units	0.775***	0.375**	0.660***	0.312*	0.775***
Cooling degree days	0.059***	0.182***	0.059***	0.174***	0.059***
Heating degree days	0.145***	0.366***	0.138***	0.339***	0.146***
Real average total price			0.020***	0.026*	
Long-run indirect effects					
Real personal income	0.110***	0.095	0.141***	0.121*	0.109***
Real average residential price	−0.130***	−0.417**	−0.194***	−0.508**	−0.126**
Housing units	0.406***	0.435*	0.417***	0.394	0.393*
Cooling degree days	0.031***	0.211***	0.038***	0.221***	0.030*
Heating degree days	0.076***	0.424**	0.087***	0.429**	0.074*
Real average total price			0.262***	0.285*	
Long-run total effects					
Real personal income	0.321***	0.177	0.364***	0.217	0.323***
Real average residential price	−0.377***	−0.777***	−0.502***	−0.909***	−0.375***
Housing units	1.180***	0.809**	1.077***	0.706*	1.168***
Cooling degree days	0.090***	0.393***	0.097***	0.395***	0.089***
Heating degree days	0.222***	0.790***	0.225***	0.768***	0.220***
Real average total price			0.282***	0.311*	
Short-run direct effects					
Real personal income		0.033		0.040	
Real average residential price		−0.146***		−0.169***	
Housing units		0.152*		0.131*	
Cooling degree days		0.074***		0.073***	
Heating degree days		0.149***		0.142***	
Real average total price				0.004*	
Short-run indirect effects					
Real personal income		0.011		0.015	
Real average residential price		−0.048***		−0.062***	
Housing units		0.050*		0.048	
Cooling degree days		0.024***		0.027***	
Heating degree days		0.049***		0.052***	
Real average total price				0.075*	
Short-run total effects					
Real personal income		0.044		0.055	
Real average residential price		−0.194***		−0.231***	
Housing units		0.203*		0.179	
Cooling degree days		0.098***		0.100***	
Heating degree days		0.198***		0.195***	
Real average total price				0.079*	

Significance levels: \*  $p < 10\%$ , \*\*  $p < 5\%$ , and \*\*\*  $p < 1\%$

Table 5 shows strong spatial interactions in residential consumption. The coefficients of the spatially lagged dependent variable ( $\rho$ ) and of the spatially weighted price are highly significant and appear to have quite separate influences on consumption. Spatial Durbin variables with coefficients not significantly different from zero have been dropped from the model. The results in table 6 reinforce recommendations from LeSage and Pace (2009) and Elhorst (2010a) that investigators should start with the SDM as a general specification and test for the exclusion of variables for nested models using likelihood-ratio tests; for the SAC model, we adopted the modified Akaike's information criterion as in Burnham and Anderson (2004). The positive  $\rho$  coefficient is consistent with omitted regional factors that vary over time and affect residential consumption. The positive coefficient on the spatially weighted average price in neighboring states indicates a clear displacement effect by which an increase in electricity prices in one state encourages a shift in demand from that state to neighboring states. That is an important constraint on the impact of state programs to promote renewable energy or reduce CO<sub>2</sub> emissions. The coefficients on the lagged dependent variable are both highly significant in columns (3) and (5) of table 5. The series within panel time are too short to carry out reliable tests, but the coefficient on the lagged dependent variable is so far from one that it is unlikely the equations have a unit root. The  $\lambda$  coefficient in the SEM column, (6), is highly significant, but this specification is dominated by the SAC model in column (7). The inclusion of the spatially lagged dependent variables reduces the estimate of  $\lambda$  from 0.39 to about 0.02 so that it is no longer significantly different from 0. Overall, the results in table 5 together with the test reported in table 6 suggest that the dynamic SDM (column 5) provides the best specification.

One of the reasons for studying such models is to fit the price elasticities of demand. In the nonspatial specification, the elasticity is simply the coefficient of the log price. As discussed in section 2, the marginal effect of price on electricity demand may differ across states because of spatial interactions. The key difference between the direct and total impacts is that the direct impact measures the impact of a unit change in variable  $x_k$  in state  $i$  on demand in state  $i$  averaged over all states. In contrast, the total impact measures the impact of the same unit change in variable  $x_k$  in all states on demand in state  $i$ , again averaged over all states. `xsmle` displays values for the direct, indirect, and total impact of changes in each of the independent variables. Unlike the values reported in table 5, table 7 reports elasticities accounting for spatial feedback. Moreover, for the SAR and SDM dynamic specifications, table 7 also distinguishes between short- and long-run marginal effects. Note that marginal effects in static models have been labeled as long run, but they should be compared with short-run effects from dynamic models (see table 2). These additional results are consistent across all spatial specifications, with the controls being significant and with the expected signs. The inclusion of the time-lagged dependent variable makes the coefficient for the real personal income not significant anymore and greatly reduces the elasticity of residential consumption with respect to the other controls.



## 5 Conclusions

In this article, we described the new `xsmle` command, which can be used to fit an extensive array of spatial models for panel data. `xsmle` supports weight matrices in the form of both Stata matrices and `spmat` objects, allows the computation of direct, indirect, and total effects and related standard errors, and provides various postestimation features for obtaining predictions, including the use of `margins`. Furthermore, `xsmle` is fully compatible with the `mi` Stata suite of commands. We used simulated data to illustrate `xsmle` estimation capabilities, focusing on model selection, prediction, and estimation in the presence of missing data, and provided an empirical application based on electricity usage data at the state level in the United States.

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