Fitting Spatial Stochastic Frontier Models in Stata

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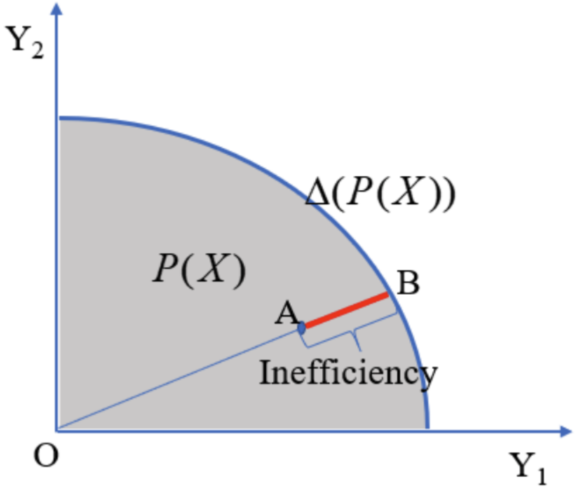
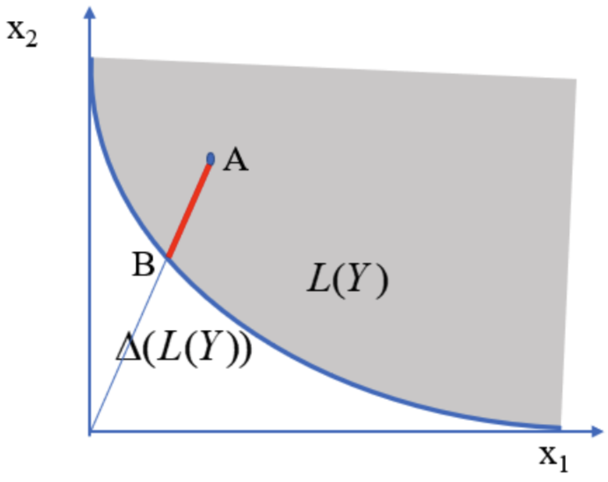
Efficiency analysis and Stochastic Frontier Models

- Classical production theory assumes that firms formulate optimal production plans in a given market environment. In reality, firms may deviate from their optimal production plans, resulting in output below potential output levels or costs that exceed the minimum cost.
- Economics researchers have proposed the concept of technical efficiency to measure and analyze the extent to which economic agents deviate from the optimal production state. Technically efficient firms can fully utilize production resources to maximize output or minimize costs. Technically inefficient firms, on the other hand, either produce output below potential levels given the resources or use excessive production resources for a given output level.

Efficiency analysis and Stochastic Frontier Models





Efficiency analysis and Stochastic Frontier Models

- Aigner et al. (1977) and Meeusen and van Den Broeck (1977) first propose SF models

$$Y_{it} = X_{it}'\beta + v_{it} - u_{it}$$
$$v_{it} \sim N(0, \sigma_v^2)$$
$$u_{it} \sim N^+(0, \sigma_u^2)$$

v and u are independent.

Efficiency analysis and Stochastic Frontier Models

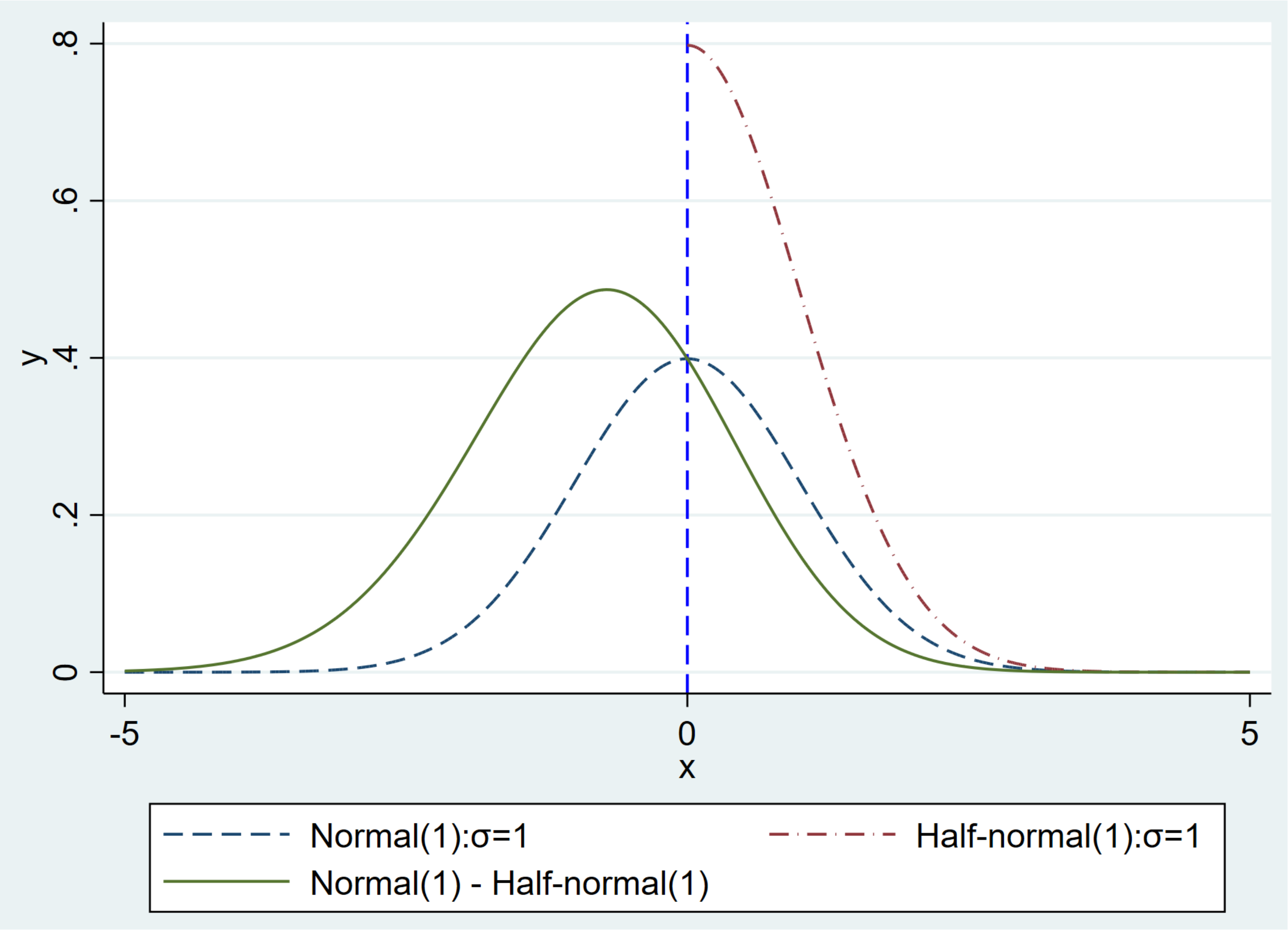
Denote $\varepsilon = v - u$. The PDF of ε can be obtained as follows:

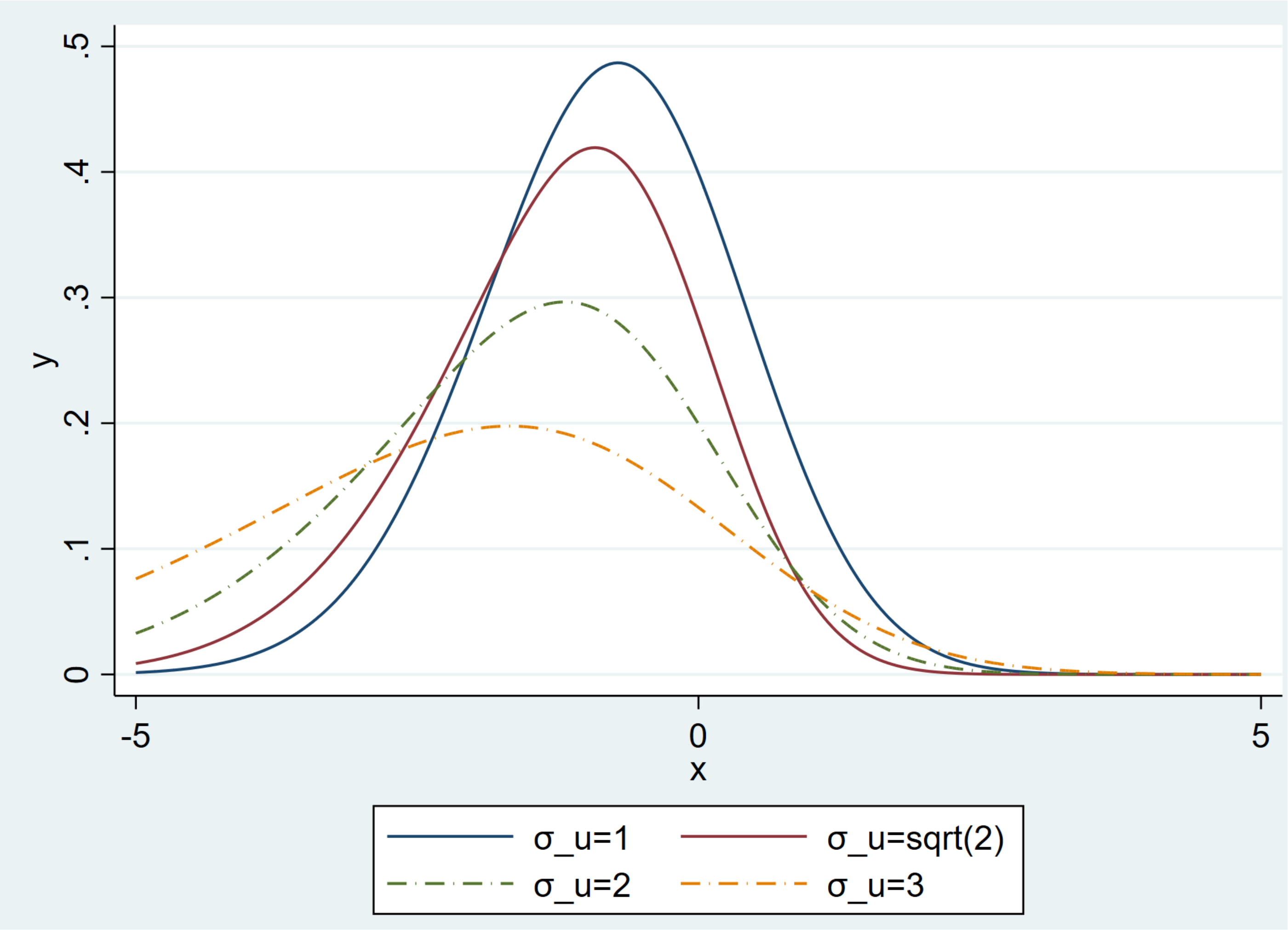
$$f(v,u) = f(v)f(u) = f(\varepsilon + u)f(u)$$

$$f(\varepsilon) = \int_0^{+\infty} f(\varepsilon + u)f(u)du$$

$$f(\varepsilon) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left[-\frac{1}{2\sigma^2}\varepsilon^2\right] * 2(1 - \Phi(\lambda\varepsilon/\sigma))$$

$\sigma^2 = \sigma_u^2 + \sigma_{v'}^2 \lambda = \sigma_u/\sigma_v$


.8
.6
.4
.2
0
y
-5
0
5
x
Normal(1):σ=1
Half-normal(1):σ=1
Normal(1) - Half-normal(1)


y
0
.1
.2
.3
.4
.5
-5
0
5
x
σ_u=1
σ_u=sqrt(2)
σ_u=2
σ_u=3

Efficiency analysis and Stochastic Frontier Models

Similar with linear regression models, we can get the log-likelihood function

$$\ln L = \sum_{it} \left[\ln(\frac{1}{\sigma}\phi(\varepsilon/\sigma)) + \ln\left[1 - \Phi\left(\varepsilon_{it}\lambda\sigma^{-1}\right)\right] + \ln(2) \right]$$

- Inefficiency estimates: $E(u|\varepsilon)$
- efficiency estimates: $E(exp(-u)|\varepsilon)$

Recent development of Stochastic Frontier Models

- Fixed effects panel SF models
- SF models with endogenous variables
- SF models with crossectional dependence and spatial spillover

Fixed effects

Inefficiency in technology refers to deviations from the common frontier, which may be partially due to individual heterogeneity. Fixed effects are commonly used to capture individual heterogeneity.


Y2
O
Y1

Fixed effects

- Greene (2005): “true” fixed effect SF model

$$Y_{it} = X_{it}'\beta + \alpha_i + v_{it} - su_{it}$$

$$v_{it} \sim N(0, \sigma_v^2)$$

$$u_{it} \sim N^+(0, \sigma_u^2)$$

$s = 1$ for production function; $s = -1$ for cost function

Fixed effects

- Greene (2005) proposed the 'brute force' method to estimate the model.
- Remark: The incidental parameters problem does not affect the slope coefficients of a stochastic frontier model, while there is also evidence suggesting that the variance parameters are more likely to be affected when T is not large.

Fixed effects

- The fixed effects can be removed by the first difference or within-tansfromation.

$$\tilde{Y}_{it} = \tilde{X}'_{it}\beta + \tilde{v}_{it} - \tilde{u}_{it}$$

$$\tilde{v}_{i.} \sim MN(0, \Omega)$$

$$\tilde{u}_{i.} \sim ?$$

$$\tilde{\varepsilon}_{i.} = \tilde{v}_{i.} - \tilde{u}_{i.} \sim ?$$

Fixed effects

- Wang and Ho (2010) assume $u_{it} = h(z_{it})u_i^*, u_i^* \sim N^+(0, \sigma_u^2)$

  $\tilde{u}_{i.} = \tilde{h}(z_{i.})u_i^*$

  $f(\tilde{v}_{i.}, \tilde{u}_{i.}|z_{i.}) = f(\tilde{v}_{i.}|z_{i.})f(\tilde{u}_{i.}|z_{i.}) = f(\tilde{\varepsilon}_{i.} + \tilde{u}_{i.}|z_{i.})f(\tilde{u}_{i.}|z_{i.})$

Fixed effects

- Chen et al. (2014) relax the WH model without assuming the scaling property of the inefficency term.

$$\tilde{\varepsilon}_{it} = M\varepsilon_{it}$$

$$M = I_T - \frac{l_T l_T'}{T}$$

$\tilde{\varepsilon}_{it}$ is a linear combinantion of ε_{it}.

Fixed effects

- Chen et al. (2014) relax the WH model without assuming the scaling property of the ineffiency term.

It is well known that the normal distribution has some important and convenient properties. (i) If two random variables are marginally normal and independent, they are jointly normal. (ii) If two random variables are jointly normal, they are marginally normal. (iii) If two random variables are jointly normal, the distribution of either one conditional on the other is normal. (iv) Linear combinations of jointly normal random variables are normal. The *CSN* family has analogous properties, as the following results show.

Fixed effects

- Chen et al. (2014) relax the WH model without assuming the scaling property of the inefficency term.

Theorem 2.

$$\tilde{\varepsilon}_i^* \sim CSN_{T-1,T}\left(0_{T-1}, \sigma^2\left(I_{T-1} - \frac{1}{T}E_{T-1}\right),\right.$$
$$\left. -\frac{\lambda}{\sigma}\begin{bmatrix} I_{T-1} \\ -1'_{T-1} \end{bmatrix}, 0_T, I_T + \frac{\lambda^2}{T}E_T\right), \quad \text{(A)}$$

$$\bar{\varepsilon}_i \sim CSN_{1,T}\left(0, \frac{\sigma^2}{T}, -\frac{\lambda}{\sigma}1_T, \left(1+\lambda^2\right)I_T - \frac{\lambda^2}{T}E_T\right), \quad \text{(B)}$$

$\tilde{\varepsilon}_i^*$ *and* $\bar{\varepsilon}_i$ are not independent (except when $\lambda = 0$). (C)

Handling endogenous variables

Endogeneity problems can arise in stochastic frontier models due to a couple of major reasons: First, the determinants of the frontier and the two-sided error term can be correlated. Secondly, the inefficiency term and two-sided error term can be correlated, or in particular, the determinants of the inefficiency can cause this correlation. Endogeneity in a stochastic frontier model would lead to inconsistent parameter estimates.

Handling endogenous variables

- Karakaplan, Mustafa U. (2017) and Karakaplan, Mustafa U. and Kutlu, Levent (2017)

The stochastic frontier panel data model is given as follows:

$$
\begin{aligned}
y_{it} &= \boldsymbol{x_{yit}}'\boldsymbol{\beta} + v_{it} - \mathrm{s}u_{it} \\
x_{it} &= Z_{it}\delta + \varepsilon_{it} \\
\begin{bmatrix} \tilde{\boldsymbol{\varepsilon}}_{\boldsymbol{it}} \\ v_{it} \end{bmatrix} &\equiv \begin{bmatrix} \boldsymbol{\Omega}^{-1/2}\boldsymbol{\varepsilon}_{it} \\ v_{it} \end{bmatrix} \sim \mathbf{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} I_p & \sigma_v\boldsymbol{\rho} \\ \sigma_v\boldsymbol{\rho}' & \sigma_v^2 \end{bmatrix}\right) \\
u_{it} &= \boldsymbol{h}\left(\boldsymbol{x}'_{uit}\varphi_u\right)\boldsymbol{u}^*_{it} \\
s &= \begin{cases} 1 & \text{for production functions} \\ -1 & \text{for cost functions} \end{cases}
\end{aligned}
$$

Handling endogenous variables

- Karakaplan, Mustafa U. (2017) and Karakaplan, Mustafa U. and Kutlu, Levent (2017)

By a Cholesky decomposition of the variance-covariance matrix of $(\tilde{\varepsilon}'_{it}, v_{it})'$, we can represent $(\tilde{\varepsilon}'_{it}, v_{it})'$ as follows:

$$\begin{bmatrix} \tilde{\varepsilon}_{it} \\ v_{it} \end{bmatrix} = \begin{bmatrix} I_p & 0 \\ \sigma_v \rho' & \sigma_v \sqrt{1-\rho'\rho} \end{bmatrix} \begin{bmatrix} \tilde{\varepsilon}_{it} \\ \tilde{w}_{it} \end{bmatrix}$$

where $\tilde{\varepsilon}_{it}$ and $\tilde{w}_{it} \sim \mathbf{N}(0,1)$ are independent.

Handling endogenous variables

The frontier equation can be written as

$$\begin{aligned} y_{it} &= x'_{yit}\beta + \sigma_v \rho' \tilde{\varepsilon}_{it} + w_{it} - su_{it} \\ &= x'_{yit}\beta + (x_{it} - Z_{it}\delta)'\eta + e_{it} \end{aligned}$$

where $e_{it} = w_{it} - \mathrm{s}u_{it}, w_{it} = \sigma_v \sqrt{1-\rho'\rho}\tilde{w}_{it} = \sigma_w \tilde{w}_{it}$ and $\eta = \sigma_w \Omega^{-1/2}\rho / \sqrt{1-\rho'\rho}$.

Handling endogenous variables

- $(x_{it} - Z_{it}\delta)'\eta$ is the biased corrected term. The random error v is decomposed into $(x_{it} - Z_{it}\delta)'\eta$ correlated with endogeneous variables x_{it} and w_{it} uncorrelated with endogeneous variables. This is the control function approach.
- Remark: The 2SLS method decomposes the endogenous variables x_{it} into $\hat{x}_{it}$ and $(x_{it} - \hat{x}_{it}) = [\varepsilon - Z(Z'Z)^{-1}Z'\varepsilon]_{it}$. The two stage method can not be applied in SF models with endogeneous variables.

$$y_{it} = \hat{x}'_{yit}\beta + [\varepsilon - Z(Z'Z)^{-1}Z'\varepsilon]'_{it}\beta + v_{it} - su_{it}$$

Handling endogenous variables

- The frontier equation can be written as

$$\begin{aligned} y_{it} &= x'_{yit}\beta + \sigma_v \rho' \tilde{\varepsilon}_{it} + w_{it} - su_{it} \\ &= x'_{yit}\beta + (x_{it} - Z_{it}\delta)'\eta + e_{it} \end{aligned}$$

where $e_{it} = w_{it} - \mathrm{s}u_{it}, w_{it} = \sigma_v \sqrt{1-\rho'\rho}\tilde{w}_{it} = \sigma_w \tilde{w}_{it}$ and $\eta = \sigma_w \Omega^{-1/2}\rho/\sqrt{1-\rho'\rho}$.

$$f_{YX|Z} = f_{Y|XZ} f_{X|Z}$$

Handling endogenous variables

Consider the case $u_{it} \sim N^+(0, \sigma_u^2)$

$$\ln(f_{Y|XZ})_{it} = \ln(2) + \ln[\phi(e_{it}/\sigma)/\sigma] + \ln\left[1 - \Phi\left(e_{it}\lambda\sigma^{-1}\right)\right]$$

$\sigma^2 = \sigma_u^2 + \sigma_w^2, \lambda = \sigma_u/\sigma_w$

$f_{X|Z}$ is a multivariable normal distribution, the same as in the systems of linear regression models.

$$f(\mathbf{x}|\mathbf{z}) = \frac{1}{\sqrt{(2\pi)^k|\boldsymbol{\Omega}|}}\exp\left(-\frac{1}{2}(\mathbf{x} - \mathbf{z}'\boldsymbol{\delta})^T\boldsymbol{\Omega}^{-1}(\mathbf{x} - \mathbf{z}'\boldsymbol{\delta})\right)$$

Crossectional dependence and Spatial spillover

Firms tend to concentrate in clusters, taking advantage of positive agglomeration externalities due to cooperation, shared ideas and emulation, resulting in increased productivity levels. Thus, producers cannot be regarded as isolated entities and the hypothesis of cross-sectional independence underlying the basic SF model must no longer be considered valid.

Spatial Stochastic Frontier Models (SSFM)

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- Glass et al. (2016): SAR-SFA

$$Y_{it} = \rho \sum_j w_{ij} Y_{jt} + X'_{it}\beta + v_{it} - s u_{it}$$

$$v_{it} \sim N(0, \sigma_v^2)$$

$$u_{it} \sim N^{+}(0, \sigma_u^2)$$

$$Y_t = (I - \rho W)^{-1}(X_t\beta + v_t - s u_t)$$

Denote $Z_t = X_t\beta + \varepsilon_t$

$$f_{Z_t|X_t} = \Pi_i \frac{2}{(2\pi\sigma^2)^N} e^{-\frac{(Z_t - X'_t\beta)'(Z_{it} - X'_{it}\beta)}{2\sigma^2}} (1 - \Phi(\lambda(Z_{it} - X'_{it}\beta)\sigma^{-1}))$$

$$Z_t = [I - \rho W] Y_t$$

$$f_{Y_t|X_t} = |I - \rho W| f_{Z_t|X_t}$$

$$\log(f_{Y_t|X_t}) = \log(|I - \rho W|) + \log(f(Z_t|X_t))$$

Spatial Stochastic Frontier Models (SSFM)

- Kultu et al. (2020): SAR-SFA with endogeneous variables

$$y_{it} = \rho \sum_{j} w_{ij} y_{jt} + \boldsymbol{x_{yit}}' \boldsymbol{\beta} + v_{it} - \mathrm{s} u_{it}$$

$$x_{it} = Z_{it}\delta + \varepsilon_{it}$$

$$\begin{bmatrix} \tilde{\boldsymbol{\varepsilon}}_{\boldsymbol{it}} \\ v_{it} \end{bmatrix} \equiv \begin{bmatrix} \boldsymbol{\Omega}^{-1/2} \boldsymbol{\varepsilon}_{it} \\ v_{it} \end{bmatrix} \sim \mathbf{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} I_p & \sigma_v \boldsymbol{\rho} \\ \sigma_v \boldsymbol{\rho}' & \sigma_v^2 \end{bmatrix} \right)$$

$$u_{it} = \boldsymbol{h}\left(\boldsymbol{x}'_{uit}\varphi_u\right)\boldsymbol{u}^*_{it}$$

$$s = \begin{cases} 1 & \text{for production functions} \\ -1 & \text{for cost functions} \end{cases}$$

Spatial Stochastic Frontier Models (SSFM)

- Orea and Álvarez (2019) include the cross-sectional dependence of v_{it} and u_{it}

$$v_{it} = \gamma \sum_j w_{ij} v_{it} + v_{it}^*$$

$$u_{it} = \tau \sum_j w_{ij} u_{jt} + u_{it}^*$$

$$v_t = [I - \gamma W]^{-1} v_t^*$$

$$u_t = [I - \tau W]^{-1} u_t^*$$

$$\varepsilon_t = v_t - u_t$$

$$f(v_t, u_t) = f(\varepsilon_t + u_t, u_t)$$

Remark: It is difficult to intergrate N-dimension random variables $u_t = (u_{1t}, \ldots, u_{Nt})'$ of $f(\varepsilon_t + u_t, u_t)$.

Spatial Stochastic Frontier Models (SSFM)

Orea and Álvarez (2019) assume $u_{it}^* = h(Z_{it})\tilde{u}_t$ where $\tilde{u}_t$ is a **scalar** random variable which does not vary across individuals given time t. The N-dimension degenerates to *one dimension*.

The spatial SF model is a a transposed version of the WH model.

$$\tilde{h}(Z_t) = [I - \tau W]^{-1} h(Z_t)$$

$$\tilde{v}_t \sim MN(0, \sigma_v^2 [I - \gamma W]^{-1} ([I - \gamma W]^{-1})^T)$$

Spatial Stochastic Frontier Models (SSFM)

- Galli (2022)
  - Global spatial spillovers Wy_t
  - Local spatial spillovers Wx_t
  - Cross-sectional dependence of error term
  - Cross-sectional dependence of inefficiency term

$$Y_{it} = \rho \sum_j w_{ij} Y_{jt} + X'_{it}\beta + \sum_j W_j X'_{it}\theta + v_{it} + su_{it}$$

$$Y_t = (I - \rho W)^{-1}(X_t\beta + \sum_j W_j X'_{it}\theta + v_{it} + su_{it})$$

Spatial Stochastic Frontier Models (SSFM)

- Galli (2022)

Table 1: Specific models with restricted parameters

	yuv	xuv	yv	yu	y	xuv	xv	xu	uv	u	v
ρ		0				0	0	0	0	0	0
θ	0		0	0	0				0	0	0
γ				0	0			0		0	
τ			0		0		0				0

Estimating SF models in Stata

- Stata official: *frontier*, *xtfrontier*
- Belotti et al. (2013): *sfcross*, *sfpanel*
- Karakaplan (2017): *sfkk*
- Karakaplan (2018): *xtsfkk*
- Lian et al. (2013): *sftt*
- Kumbhakar et al. (2015) provides a practitioner's guide to stochastic frontier analysis with a suite of Stata commands (including sfmodel, sfpan, sf_fixeff, and sfprim).

Our *spxtsfa* command

spxtsfa: a new command for fitting spatial stochastic frontier models in the style of Orea and Álvarez (2019) and Galli(2022). We use Stata ml model routine with the method-*d0* evaluator to program the spxtsfa command.

Our *spxtsfa* command

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- install from github

> net install spxtsfa, from("https://raw.githubusercontent.com/kerrydu/spxtsfa/main/spxtsfa-statafiles/") replace
> net get spxtsfa, from("https://raw.githubusercontent.com/kerrydu/spxtsfa/main/spxtsfa-statafiles/") replace

- install from gitee

> net install spxtsfa, from("https://gitee.com/kerrydu/spxtsfa/raw/main/spxtsfa-statafiles") replace
> net get spxtsfa, from("https://gitee.com/kerrydu/spxtsfa/raw/main/spxtsfa-statafiles") replace

Our *spxtsfa* command

Estimation syntax

spxtsfa *depvar* [*indepvars*], *uhet(varlist)* [noconstant cost wy(*wyspec*)
wx(*wxspec*) wu(*wuspec*) wv(*wvspec*) normalize(*norm_method*)
wxvars(*varlist*) initial(*matname*) mlmodel(*model_options*)
mlsearch(*search_options*) mlplot mlmax(*maximize_options*) nolog
mldisplay(*display_options*) level(#) lndetmc(*numlist*)
te(*newvarname*) genwxvars delmissing constraints(*constraints*)]

Version syntax

spxtsfa , version

Replay syntax

spxtsfa [, level(#)]

Our *spxtsfa* command

wy(*wyspec*) specifies the spatial weight matrix for lagged dependent variable. The expression is wy(W_1 $[W_2 ... W_T]$ [,mata array]). By default, the weight matrices are Sp objects. mata declares weight matrices are mata matrices. If one weight matrix is specified, it assumes a time-constant weight matrix. For time-varying cases, T weight matrices should be specified in time order. Alternatively, using array to declare weight matrices are stored in an array. If only one matrix is stored in the specified array, the time-constant weight matrix is assumed. Otherwise, the keys of the array specify time information, and the values store time-specific weight matrices.

Examples

We first consider the $yxuv$-SAR model specified by the following data-generating process (DGP 1) with $i = 1, \ldots, 300$ and $t = 1, \ldots, 20$,

$$Y_{it} = 0.3W_iY_{.t} + 2X_{it} + 0.3W_iX_{.t} + \tilde{v}_{it} - \tilde{u}_{it}$$

where $\tilde{v}_{it}$ and $\tilde{u}_{it}$ are defined with $\gamma = 0.3$, $\tau = 0.3$, $\delta = 2$, $\sigma_u^2 = 0.2$ and $\sigma_v^2 = 0.2$. All the spatial matrices for the four spatial components are the same and time-invariant, created from a binary contiguity spatial weight matrix. We generate the exogenous variables X_{it} and Z_{it} from the standard normal distribution, respectively. With the sample generated by DGP 1, we can fit the model in the following syntax.

```
. use spxtsfa_DGP1.dta

. xtset id t

Panel variable: id (strongly balanced)
 Time variable: t, 1 to 20
         Delta: 1 unit

. * importing spatial weight matrix from spxtsfa_wmat1.mmat
. mata mata matuse spxtsfa_wmat1.mmat,replace
(loading w1[300,300])

. * fitting the model
. spxtsfa y x, uhet(z) noconstant  wy(w1,mata) wx(w1,mata) wu(w1,mata) wv(w1,mata) wxvars(x) nolog

Spatial frontier model(yxuv-SAR)                     Number of obs =      6,000
                                                     Wald chi2(2)  = 118937.24
Log likelihood = -1727.016                           Prob > chi2   =     0.0000
```

y	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
frontier						
x	1.993915	.0065251	305.58	0.000	1.981126	2.006704
W_x	.4435823	.0373189	11.89	0.000	.3704386	.516726
uhet						
z	2.000371	.0013412	1491.49	0.000	1.997742	2.002999
/lnsigma2_u	-2.098104	.3163094	-6.63	0.000	-2.718059	-1.478149
/lnsigma2_v	-1.637609	.018401	-89.00	0.000	-1.673674	-1.601544
Wy						
_cons	.6605993	.0317043	20.84	0.000	.5984599	.7227386
Wu						
_cons	.5806681	.0318346	18.24	0.000	.5182735	.6430627
Wv						
_cons	.5745429	.051903	11.07	0.000	.4728148	.676271
sigma2_u	.1226888	.0388076	3.16	0.002	.0660027	.2280593
sigma2_v	.1944444	.003578	54.34	0.000	.1875567	.2015851
rho	.3187581	.0142397	22.39	0.000	.2905787	.3463849
tau	.282414	.014646	19.28	0.000	.2534626	.3108598
gamma	.2795936	.02392	11.69	0.000	.2320763	.3257792

$$\eta = \left(\frac{1}{r_{\min}}\right)(1-p) + \left(\frac{1}{r_{\max}}\right)p$$

$$0 \leq p = \frac{\exp\left(\delta_0\right)}{1+\exp\left(\delta_0\right)} \leq 1$$

Examples

We consider the restricted model uv-SAR with time-varying spatial weight matrices as the second example. The DGP 2 is described as
$Y_{it} = 1 + 2X_{it} + v_{it} - u_{it}, i = 1, . . , 300; t = 1, . . , 10.$

```
. use spxtsfa_DGP2.dta

. xtset id t

Panel variable: id (strongly balanced)
 Time variable: t, 1 to 10
         Delta: 1 unit

. * importing spatial weight matrices from spxtsfa_wmat2.mmat
. mata mata matuse spxtsfa_wmat2.mmat,replace
(loading w1[300,300], w10[300,300], w2[300,300], w3[300,300], w4[300,300],
 w5[300,300], w6[300,300], w7[300,300],  w8[300,300], w9[300,300])

. * fitting the model
. local w w1 w2 w3 w4 w5 w6 w7 w8 w9 w10

. spxtsfa y x, uhet(z) wu(`w´,mata) wv(`w´,mata) te(efficiency) nolog

Spatial frontier model(uv-SAR)                    Number of obs =     3,000
                                                  Wald chi2(1)  = 43686.91
Log likelihood = -1336.482                        Prob > chi2   =   0.0000
```

y	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
frontier						
x	2.015288	.0096419	209.01	0.000	1.99639	2.034186
_cons	.9415143	.0160786	58.56	0.000	.9100008	.9730278
uhet						
z	2.000242	.0020671	967.66	0.000	1.99619	2.004293
/lnsigma2_u	-2.006684	.4473506	-4.49	0.000	-2.883475	-1.129893
/lnsigma2_v	-1.300024	.0260099	-49.98	0.000	-1.351002	-1.249045
Wu						
_cons	.582383	.0031549	184.59	0.000	.5761995	.5885666
Wv						
_cons	.5374655	.0601775	8.93	0.000	.4195198	.6554113
sigma2_u	.1344337	.060139	2.24	0.025	.05594	.3230678
sigma2_v	.2725253	.0070883	38.45	0.000	.2589806	.2867784
tau	.2832028	.0014508	195.21	0.000	.2803569	.2860438
gamma	.262419	.0280135	9.37	0.000	.206716	.3164261

Examples

- Spatial weight matrix can be created by *spmatrix* and *spwmatrix*

```
copy "https://gitee.com/kerrydu/spxtsfa/raw/main/city.zip" .
unzipfile city.zip
cd ./city
spshape2dta province
spmatrix create contiguity M, normalize(row) rook
spmatrix create idistance W, normalize(row) replace
spmatrix matafromsp W id = M
```

Examples

- The likelihood function of spatial stochastic frontier models is complicated, and generally diffcult to obtain the optimal global solutions. Thus, good initial values would be helpful for fitting spatial stochastic models. Practitioners might fit the non-spatial stochastic models using fronteir and sfpanel commands to obtain the initial values of the parameters involved in the frontier and the scaling function and then use the mlplot option to search initial values for spatially-correlated parameters

Examples

```
use uvexample.dta
xtset id t
mata mata matuse spxtsfa_wmat.mmat,replace
frontier y x, noconst cost uhet(z)
mat b = e(b)
mat b = b[1,1],b[1,3],b[1,4],b[1,2]
mat b = b[1,1],b[1,3],b[1,4],b[1,2],0.2,0.2
spxtsfa y x, cost noconstant wu(w2,mata) wv(w1,mata) uhet(z) te(te) init(b) mlplot
```

Some issues

- "spxtsfa, version" which could potentially cause Stata to crash as it attempts to establish a connection with Github. Undocuemneted syntax: spxtsfa, version gitee
- Speed of spxtsfa is slow
- failure of convergence
- mata does not have routines of sparse matrix; consume a lot of memory for large spmatrix
- spxtfsa does not support vce(cluseter)

Thank you! Welcome your comments and suggestion