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A SPATIAL APPROACH TO CONTROL FOR UNOBSERVED ENVIRONMENTAL CONDITIONS WHEN MEASURING FIRMS´TECHNOLOGY: AN APPLICATION TO NORWEGIAN ELECTRICITY DISTRIBUTION NETWORKS

INTRODUCTION

- Since the 1990s many network utilities are incentive regulated with the aim of improving their operating and investment efficiency. Using parametric and non-parametric techniques (Haney and Pollit, 2013). However, there are **many characteristics** of the electricity distribution networks that affect their production costs but **are not observed** (Farsi and Filippini, 2004). Several statistical methods have recently been developed to address this issue: TRE and TFE models introduced by Greene (2005) and Latent Class Stochastic Frontier Models (Llorca et al., 2014: Orea and Jamasb, 2016).
- In this paper we advocate using a **new empirical strategy** to deal with unobserved differences based on their geographic location and neighboring networks.
- The underlying idea behind our empirical proposal is that we can use **data from neighboring firms** in order to proxy *unobserved* cost drivers that are likely to be spatially correlated, such as weather and geographic conditions, population structure, electricity demand patterns, input prices, etc.
- Therefore, the main contribution of this paper is to link benchmarking methods addressing unobserved heterogeneity with the literature on spatial econometrics. To the best of our knowledge, our paper is one of the first to apply **spatial econometric models** which make use of **individual firm cost data**.

METHODOLOGY

Predicting omitted but spaltially correlated variables

Assume that firms' technology can be modelled as follows:

$$\ln C_{it} = \beta X_{it} + Z_{it} + v_{it} + u_{it}$$

where Z_{it} is a vector of unobserved cost drivers that are spatially correlated:

$$Z_{it} = \lambda W_i Z_t$$

Where Z_t is a vector of Nx1 unobserved cost drivers, W_i is a known 1xN spatial weight vector, λ is a coefficient that measures the degree of spatial correlation between unobserved cost drivers. Using our cost model, we get that:

$$Z_{it} = \ln C_{it} - \beta X_{it} - v_{it} - u_{it}$$

If we replace Zit and Z_t with their "observable" counterparts we get:

$$(\ln C_{it} - \beta X_{it} - v_{it} - u_{it}) = \lambda W_i (\ln C_t - \beta X_t - v_t - u_t)$$

The model to be estimated can be rewritten as follows:

$$\ln C_{it} = \beta X_{it} + \overbrace{\underbrace{\lambda W_i \ln C_t - \lambda \beta W_i X_t + h_{it}}_{Z_{it}}}^{\hat{Z}_{it}} + v_{it} + u_{it}$$

Where,

$$h_{it} = -\lambda W_i v_t - \lambda W_i u_t$$

Complete spatial econometric SFA model

A complete model with two spatially correlated error terms:

$$\ln C_{it} = [\beta X_{it} + \lambda W_i \ln C_t - \lambda \beta W_i X_t] + \Delta v_{it} + \Delta u_{it}$$

Where

$$\Delta v_{it} = v_{it} - \lambda W_i v_t$$

$$\Delta u_{it} = u_{it} - \lambda W_i u_t$$

and

$$\Delta v_{it} \sim \mathrm{N}\left[0, \left(1 + \lambda^2 \Sigma W_i^2\right)^{1/2} \sigma_v\right]$$

but

The distribution of Δu_{it} is not known and therefore intractable MLE.

Estimation Method

First-step spatial econometric model

Model to be estimated:

$$\ln C_{it} = \beta X_{it} + \lambda W_i \ln C_t - \lambda \beta W_i X_t + \varepsilon_{it}$$

In the first step the parameters β and λ are estimated ignoring both the spatial and frontier structures of ε_{it} using GMM because $W_i \ln C_t$ is endogenous.

The first-step estimates are aiming to get a prediction of Zit that is used as an additional explanatory variable later on.

$$\hat{Z}_{it} = \lambda W_i \ln C_t - \lambda \beta W_i X_t \qquad Z_{it} = \hat{Z}_{it} + h_{it}$$

Two-step SFA model with generated regressor

In the second stage, we estimate a SFA cost frontier model with a generated regressor $\hat{Z}_{it}$

$$\ln C_{it} = \beta X_{it} + \gamma_{it} \hat{Z}_{it} + v_{it} + u_{it}(m_{it})$$

Where, $\gamma_{it} = \frac{Z_{it}}{\hat{Z}_{it}} = \frac{\hat{Z}_{it} + h_{it}}{\hat{Z}_{it}} \longrightarrow \gamma < 1$

We model γ_{it} as a simple function:

$$\gamma_{it} = \gamma_0 + \gamma_1 N_i + \gamma_2 W_i m_{it}$$

DATA

Norwegian distribution utilities (2004-2011) from sector regulator Norwegian Water Resources and Power Directorate (NVE).

Cost definition:
- C= TOTEX + quality costs.

Cost drivers:
- CUS = number of customers
- NL = network length in kilometers
- DE = delivered energy in megawatt-hours
- PK = capital price
- PE = energy price
- PL = labor price
- OH = percentage of overhead lines
- NS = number of stations
- WIND = average reference wind
- WINDEX = average wind exposure
- DIS = distance to coast
- Forrest = forrest measure
- AveSlope = average terrain slopeness
- MaxSlope = maximum terrain slopeness

Outputs (CUS, NL, DE); Economic variables (CUS–PL); technological variables (OH, NS); Environmental variables (WIND–MaxSlope)

We consider firms operating in distribution áreas and capture spatial interdependence based on physical contiguity.

Norwegian electricity distribution areas

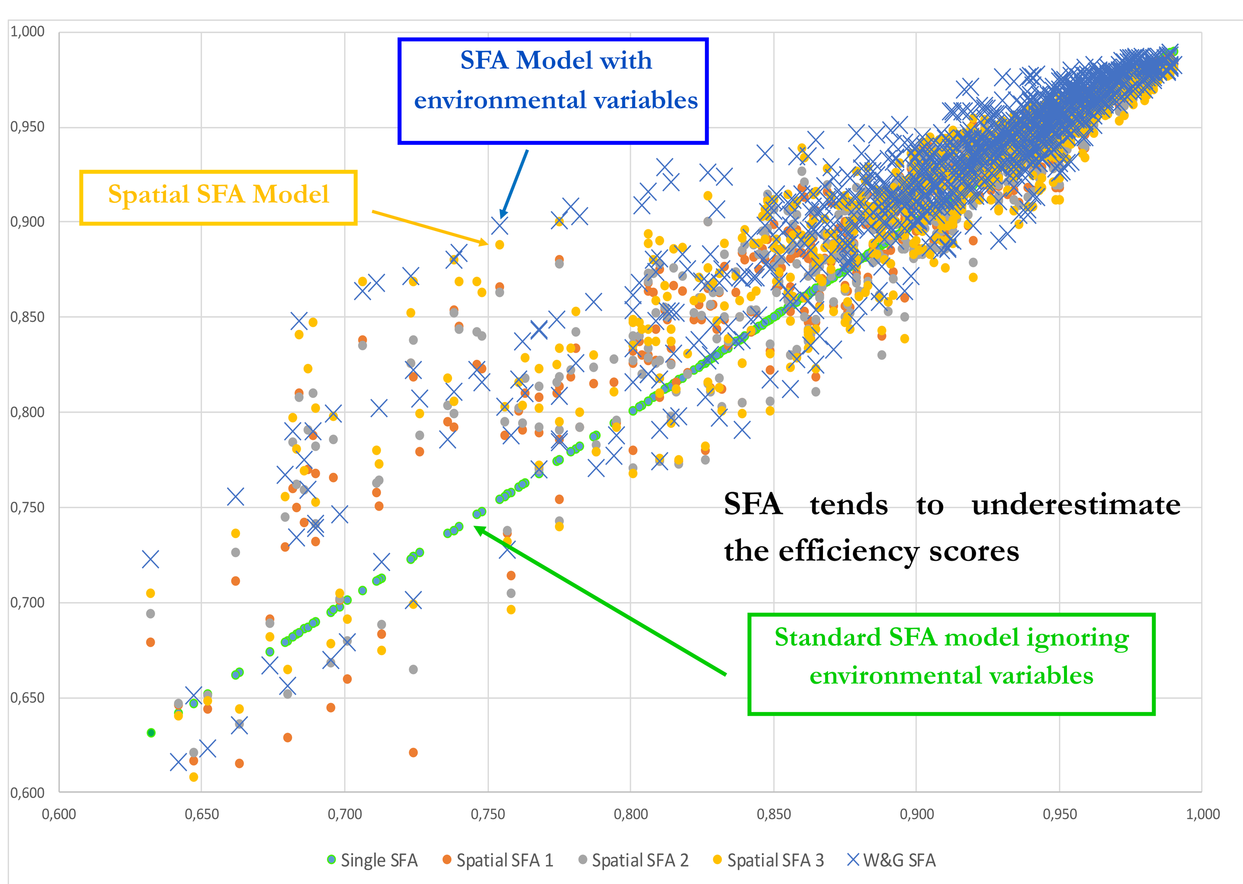
Source: Norwegian Water Resources and Power Directorate (NVE)

RESULTS

SFA MODELS WITHOUT W&G VARIABLES

	Single SFA		Spatial SFA 1		Spatial SFA 2		Spatial SFA 3	
PARAMETERS	Estimates	t-ratio	Estimates	t-ratio	Estimates	t-ratio	Estimates	t-ratio
INTERCEPT	10.511	677.658	10.518	665.138	10.518	636.091	10.517	624.989
LNCUS	0.291	10.809	0.273	10.724	0.276	10.740	0.271	10.309
LNNL	0.549	25.530	0.564	28.060	0.560	27.525	0.561	27.538
LNDE	0.142	6.011	0.146	6.454	0.147	6.506	0.148	6.529
OH	-0.312	-4.826	-0.298	-4.909	-0.294	-4.802	-0.285	-4.692
0.5·LNCUS²	0.130	6.460	0.124	5.852	0.120	5.754	0.121	5.662
0.5·LNNL²	-0.007	-0.080	-0.041	-0.502	-0.036	-0.448	-0.049	-0.608
0.5·LNDE²	0.196	4.994	0.202	5.243	0.199	5.256	0.204	5.359
0.5·OH²	0.227	0.398	0.349	0.639	0.445	0.812	0.465	0.855
LNCUS·LNNL	-0.007	-0.178	0.003	0.073	0.000	-0.004	0.006	0.157
LNCUS·LNDE	-0.109	-4.424	-0.114	-4.477	-0.110	-4.362	-0.113	-4.509
LNCUS·OH	-0.127	-1.073	-0.145	-1.202	-0.113	-0.935	-0.136	-1.099
LNNL·LNDE	-0.056	-1.223	-0.045	-1.000	-0.046	-1.027	-0.045	-1.020
LNNL·OH	-0.390	-1.874	-0.370	-1.817	-0.395	-1.959	-0.391	-1.942
LNDE·OH	0.483	3.342	0.492	3.371	0.483	3.335	0.505	3.461
LNPK	0.277	14.189	0.263	13.993	0.264	13.933	0.263	13.810
LNPL	0.662	16.887	0.664	17.979	0.663	17.884	0.661	17.784
Z			0.894	11.193	1.034	11.404	1.007	11.177
Z·N					-0.100	-2.741	-0.151	-3.829
Z·WLNKM							-0.302	-2.218
Z·WOH							0.111	0.594
Z·WLNNS							0.230	1.823
LNSV	-2.136	-51.024	-2.182	-51.687	-2.184	-49.280	-2.181	-48.556
LNSU	-2.376	-11.147	-2.447	-10.787	-2.436	-10.341	-2.462	-10.097
LNKM	-1.623	-3.552	-1.621	-3.558	-1.485	-3.278	-1.504	-3.192
OH	0.659	1.847	0.064	0.172	-0.004	-0.011	-0.167	-0.442
LNNS	1.012	2.638	1.085	2.835	0.971	2.558	1.014	2.554
MEAN LOG-LIKELIHOOD	0.553		0.612		0.616		0.621	
OBSERVATIONS	1032		1032		1032		1032	
LF	570.514		631.716		635.365		640.414	

Efficiency scores



CONCLUSIONS

- This study **combines SFA and spatial econometrics** to account for spatially correlated omitted variables when measuring inefficiency of regulated firms.
- Our empirical application suggests that **data from neighboring utilities improve goodness-of-fit** of models without collecting additional data on environmental conditions.
- Our spatial-SFA model yields **similar efficiency scores** to a more demanding SFA model that includes environmental variables, indicating than the spatial-SFA approach proposed here could be used in regulatory settings where collecting **environmental variables** is either **costly** of **unfeasible**.

FUTURE EXTENSIONS

- Add a **simulation exercise** to corroborate that ignoring spatially correlated variables still tends to underestimate efficiency scores. If not, why?
- Use a **complete spatial SFA model** with spatial error correlation in both v and u. This is not easy because the difference between two half-normal variables is not known (see Wang and Ho, 2010).

Universidad de Oviedo

EMEE 2016
9th International Workshop on "Empirical Methods in Energy Economics"

Oviedo, Spain, 7-8th July, 2016