Proceedings of the 11th International Conference "Reliability and Statistics in Transportation and Communication" (RelStat'11), 19–22 October 2011, Riga, Latvia, p. 19-27. ISBN 978-9984-818-46-7
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EFFICIENCY OF BROADBAND INTERNET ADOPTION IN EUROPEAN UNION MEMBER STATES

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This paper is devoted to econometric analysis of broadband adoption efficiency in EU member states. Stochastic frontier models are widely used for efficiency estimation. We enhanced the stochastic frontier model by adding a spatial component into the model specification to reflect possible dependencies between neighbour countries. A maximum likelihood estimator for the model was developed.

The proposed spatial autoregressive stochastic frontier model is used for estimation of broadband adoption efficiency. We confirmed a negative impact of average prices of broadband services on broadband adoption in a country and also discovered a significant negative influence of a level of population income inequality.

Significant positive spatial effects also have been revealed, so higher broadband penetration rates in neighbour countries have a positive impact on broadband adoption in a given country.

Keywords: spatial stochastic frontier, broadband adoption, efficiency

1. Introduction

Internet technologies are widely used by companies, government bodies and individuals. They support information flows in the economy, and provide people with access to information and services for work, schooling, and leisure time.

A significant positive impact of Internet spreading is acknowledged by researchers. There are a significant number of studies dedicated to analysis of broadband Internet impact on economic development [1, 2, 3]. Nowadays Internet is an essential part of economics and prevalence of up-to-date Internet connections becomes one of key factors of sustainable economic growth. Availability of broadband services significantly improves general productivity of population and country's GDP, employment situation and almost all sectors of the national economy. According to [3], availability of broadband gives competitive advantages to a country and stimulates business and overall economy growth.

A level of broadband access is usually estimated using a broadband penetration rate – a number of broadband connections per capita. This indicator is widely used as a key statistics of information society.

Efficiency of broadband Internet adoption is a subject of some recent researches [4]. Usually authors consider a broadband penetration rate as a "product" of country-specific economic and demographic factors. Ford et al. [4] successfully applied a modern stochastic frontier model [5] for estimation of broadband efficiency index in OECD countries.

Based on previous researches, we can assume that a distribution of broadband in Europe has significant spatial patterns [6] – adoption of broadband services in a given county is closely related with the same process in neighbour countries. These spatial effects are supported both from supply and demand sides. For suppliers it is easier and cheaper to provide broadband connection in adjacent areas, and for customers the network effect increases the utility of broadband connections.

Despite its importance, there are no researches of broadband efficiency taking a spatial structure into consideration (to the best of our knowledge), which can lead to biased estimates of model parameters and incorrect conclusions. There are two separate econometric tools for analysis of efficiency and spatial dependencies. Stochastic frontier models are widely used by researchers for estimation of units' efficiency, while spatial autoregressive models are taking spatial dependencies into consideration. In this research we develop a spatial autoregressive stochastic frontier model, which allows estimating efficiency levels in case of spatial dependencies between objects in a data set. There are some recent researches related to this issue. Schmidt et al. (2009) [7] proposed a stochastic frontier model with latent spatial components in the inefficiency term and a Bayesian approach to its estimation. Barrios and Lavado (2010) [8] extended the stochastic frontier model with a spatial component and suggested a back fitting algorithm for its estimation. Affuso (2010) [9] formulated maximum likelihood estimator for the spatial autoregressive stochastic frontier model with a half-normal inefficiency term, and used it for estimation of farmers' productivity growth.

The article includes a formulation of the spatial autoregressive stochastic frontier model, a proposed maximum likelihood estimator for this model, and an empirical application of this model to analysis of broadband adoption in EU member states.

2. The Spatial Autoregressive Stochastic Frontier (SARSF) Model

In this section we present a sequential formulation of the spatial autoregressive stochastic frontier model and describe its main features.

2.1. The classical regression model and spatial dependence

The classical regression model is widely used for analysis of a stochastic relationship between a dependent variable and a set of determinants:

$$y = X\beta + v, \tag{1}$$

where

y is an (n x 1) vector of a dependent variable (n is a size of the sample);
X is an (n x k+1) matrix of explanatory variables (k is a number of explanatory variables);
β is a (1 x k+1) vector of unknown coefficients (model parameters);
v is an (n x 1) vector of independent identically distributed (i.i.d) error terms.

An important potential problem of the classical model (1) is omitting of significant explanatory variables. If a significant determinant of the dependent variable isn't included into the model, estimates of model parameters will be biased and inconsistent (well-known omitted variables bias [10]). If objects in a study sample have a spatial structure and a level of the spatial dependence between them is significant, then the omitted variable problem will arise. Spatial effects should be included into the set of determinants to prevent this problem. Also estimation of possible spatial effects can be a subject of empirical researches.

Spatial effects appear for objects located near to each other. Tobler's law [11] says that "everything is related to everything else, but near things are more related than distant things", so usually researchers expect that a level of the spatial relationship is a function of a distance between objects. This metric is called a spatial weight. There are some different approaches to calculation of spatial weights as well as different definition of distance itself. A distance between two point objects can be estimated not only as a physical metric, but also as a travel time or cost, and even as a closeness of contacts between objects (for example, import-export volumes or a number of visitors between two cities). Objects with area (like countries) require another, border-based approach. There are some popular ways to calculate spatial weights for objects with area [6]. Distance-based neighbours approach defines two objects as related if the distance between them is less than a predefined maximum distance. When list of neighbours is created, we can assign spatial weights to each relationship. The relationship can be binary (1 is present, 0 if not) or variable (for example, standardised). Standardization is used to create proportional weights in cases where objects have different numbers of neighbours and lays in division of each neighbour weight by the sum of all neighbour weights. A set of spatial weights for every two objects in a sample are usually compiled into a contiguity matrix W. The matrix W is a square n x n matrix, where each element w_{ij} represents a distance (generally, a relationship) between objects i and j. Diagonal elements of the matrix W are set to 0.

There are two basic forms of spatial dependency:

1. Spatial lags – a value of the dependent variable for a given object is affected by variables (both explanatory and dependent ones) in neighbour objects. This dependence directly follows from Tobler's law of geography.
2. Spatial errors – there are some factors (not included into the model and possibly unobserved) which have an influence on all object inside an area and lead to common direction of errors of prediction of the dependent variable.

Both types of spatial dependency lead to problems with the classical regression model. Neglected spatial lags lead to the omitted variable problem and inconsistent estimates, and neglected spatial errors make model estimate inefficient.

There are diagnostic statistics developed to discover spatial relationships.

Moran's I is a test statistics for global spatial dependence [12]:

$$MoranI = \frac{e^T We}{e^T e} \sim N(0,1), \tag{2}$$

where

$$e = y - X\hat{\beta},$$

$\hat{\beta}$ are estimates of model parameters β.

Moran's I coefficient allows to discover spatial autocorrelation of model residuals, but cannot distinguish between spatial lags and spatial errors.

Lagrange Multiplier statistics [6] are used to test spatial lags (LM-lags statistic) and spatial errors (LM-errors statistic) separately:

$$\begin{aligned} LM-lags &= \frac{1}{nJ}\left(\frac{e^T W y}{\sigma_\varepsilon^2}\right)^2 \sim \chi^2(1), \\ LM-errors &= \frac{1}{T}\left(\frac{e^T W e}{\sigma_\varepsilon^2}\right)^2 \sim \chi^2(1), \end{aligned} \tag{3}$$

where

$$\sigma_\varepsilon^2 = \frac{1}{n} e^T e, \quad t = trace\left(WW + W^T W\right), \quad J = \frac{\left(WX\hat{\beta}\right)^T \left(I - X\left(X^T X\right)^{-1} X\right)\left(WX\hat{\beta}\right)}{e^T e} + \frac{t}{n}.$$

If both statistics are significant, robust modifications of these test statistics should be used. We don't require robust modifications for empirical purposes of this research, so we skip formulas for them for space saving.

2.2. The spatial autoregressive (SAR) model

If diagnostic statistics show presence of spatial dependence in the sample, it should be included into the model for proper estimation. The spatial autoregressive model includes spatial effects and can be written as:

$$y = \rho \cdot spatial.lag(y) + X\beta + v, \tag{4}$$

where

$$spatial.lag(y) = Wy.$$

The feature of the model is the spatial lag component, reflecting a relationship between the dependent variable in a given region with the same variable in neighbour regions. Model parameter ρ and its significance represent a direction and a power of this relationship and usually is a subject of researchers' interest. A detailed description of the SAR model can be found at [6].

Note that it is supposed that Gauss-Markov conditions are satisfied for model's error component v.

2.3. The stochastic frontier (SF) model

The classical regression approach (including the SAR model) is widely used to predict an average value of a dependent variable (for given values of determinants). Another very practically important issue is estimation of unit's efficiency level. Efficiency is usually considered as a ratio of results (a dependent variable) and resources used (determinants). There are some methodologies developed to estimate unit's efficiency; many of them take a relative nature of the efficiency indicator into account. Frontier-based methods consist in constructing of a hypothetical set of 100% efficient units (an efficiency frontier) and estimating of unit's efficiency as a distance from this frontier. Stochastic frontier model utilises probabilistic approach to the efficiency frontier and can be formalised as [5, 10]:

$$\begin{aligned} &y = f(x, \beta) + \varepsilon, \\ &\varepsilon = v - u, \\ &v \sim N(0, \sigma_v^2), u \geq 0, \end{aligned} \tag{5}$$

where

ε is an (n x 1) vector of composite error terms,

u is an (n x 1) vector of inefficiency terms with non-negative values.

The main feature of the SF model is a composite error terms, which includes not only i.i.d. random errors v, but also an inefficiency component u. The inefficiency term u represents a distance from the efficiency frontier and is supposed to be non-negative. A distribution law of the inefficiency term can be selected by a researcher (subject to mandatory non-negativity).

Selection between the classical and the SF model is based on variances of u and v error terms. If the variance of u is significantly large relative to the total variance of the error term, then inefficiency presents in data. A γ statistic is used to check this hypothesis:

$$\gamma = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2}. \tag{6}$$

If γ is significantly different from 0, the SF model is preferred.

Detailed description of stochastic frontier models is presented in [5].

2.4. Formulation of the spatial autoregressive stochastic frontier (SARSF) model

In this research we try to combine the SF and SAR models to construct and estimate an efficiency frontier model in case of presence of spatial dependencies.

We introduce the spatial autoregressive stochastic frontier (SARSF) model as:

$$\begin{aligned} &y = \rho W y + X\beta + \varepsilon, \\ &\varepsilon = v - u, v \sim N(0, \sigma_v^2), u \geq 0. \end{aligned} \tag{7}$$

The model is a composition of the SF and SAR models and includes features of both – spatial lags in the functional form and the inefficiency component in the random errors.

3. Maximum Likelihood Estimation of the SARSF Model

A task of SARSF model parameter estimation is very important from applications, but includes some difficulties. In this work we apply well-known maximum likelihood estimator.

The classical maximum likelihood approach requires an exact distribution law for the composite error term, inherited from the SF model. We assume normal – half-normal specification of the error term:

$$\begin{aligned} &\varepsilon = v - u, \\ &v \sim N(0, \sigma_v^2), u \sim N^+(0, \sigma_u^2) \end{aligned} \tag{8}$$

A probability distribution function for the composite error term ε in this case is presented as [5]:

$$f(\varepsilon) = \frac{2}{\sigma}\varphi\left(\frac{\varepsilon}{\sigma}\right)\Phi\left(\frac{-\varepsilon\lambda}{\sigma}\right),$$

where

$$\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}, \lambda = \frac{\sigma_u}{\sigma_v},$$

φ and Φ are standard normal probability density and distribution functions accordingly.

Applying a usual algorithm of likelihood function construction and taking the endogeneity problem into consideration [13] we receive the log-likelihood function for the SARSF model:

$$\begin{aligned} LogL(\rho, \beta, \sigma, y, X, W) = n\ln\left(\sqrt{\frac{2}{\pi}}\right) - n\ln(\sigma) - \frac{\varepsilon^T\varepsilon}{2\sigma^2} + \\ + \sum_{i=1}^{n}\ln\left(\Phi\left(\frac{-\varepsilon\lambda}{\sigma}\right)\right) + \\ + \sum_{i=1}^{n}\ln(\det(I - \rho W)) \end{aligned} \tag{9}$$

where the component

$$\sum_{i=1}^{n} \ln\left(\Phi\left(\frac{-\varepsilon\lambda}{\sigma}\right)\right)$$

is inherited from the log-likelihood function of the SF model and the component

$$\sum_{i=1}^{n} \ln\left(\det\left(I - \rho W\right)\right)$$

is inherited from the log-likelihood function of spatial models.

We skip a formal derivation of the log-likelihood function in this paper.

Maximisation of the log-likelihood function with respect to its parameters is a separate computational problem (the function can have many local maximums, so selection of initial values becomes a highly important task). Consideration of the computational problems lies outside of this research scope.

4. Data and Model Specification

The empirical part of this research is devoted to analysis of broadband adoption in European countries and estimation of this process efficiency. For the model specification we require information about the dependent variable (broadband adoption), a set of explanatory variables (which determines the dependent variable) and geographical information.

Three main data sources are used for this research:

1. The Eurostat (the Statistical Office of the European Communities) database [14] is a source of general information about EU member states. The information about each country includes:
   a. Broadband penetration rate, a number of broadband services subscribers per 100 inhabitants (in 2009). This is the dependent variable of our research.
   b. Population density, persons per square kilometre (2010).
   c. Gini coefficient, a measurement of income distribution inequality (2009).
   d. Phones, a number of fixed phone lines per 100 inhabitants (2010).
   e. Mobiles, a number of active mobile phone numbers per 100 inhabitants (2009).
2. "Measuring the Information Society 2010" executive summary [15] from International Telecommunication Union (ITU) used for information about prices of broadband services:
   a. Price GNI, a fixed broadband sub-basket as a % of gross national income per capita (2009).
3. ThematicMapping web site [16] is used for information about borders of European countries in form of shape files.

Descriptive statistics of characteristics above are presented in the Table 1.

Table 1. Data descriptive statistics

Parameter	Mean	Standard deviation	Min	Max
Broadband, *subscribers per 100 inhabitants*	24.43	7.05	13.7	38.5
PopulationDensity, *persons/km^2*	171.89	247.34	15.81	1306.87
Gini	29.49	3.94	22.7	37.4
PriceGNI, *fixed broadband sub-basket as a % of GNI per capita*	1.42	0.78	0.59	3.24
Phones, *lines per 100 inhabitants*	38.33	13.39	20	62
Mobiles, *lines per 100 inhabitants*	124.3	21.32	83	180

Regarding the dependent variable, the broadband penetration rate is the most frequently used metric for broadband adoption. There are some other indicators proposed (for example, traffic volume), but they are quite specific and used relatively rare.

We expect a positive relationship between the population density and broadband adoption. This expectation is supported by a higher level of broadband adoption in urban areas. Also providing of broadband connection is technically easier and cheaper in densely populated areas.

Income distribution inequality is supposed to be negatively related to the broadband penetration rate. At this moment broadband Internet connection still can be classified as a superior product, so we expect that a higher level of income inequality should lead to lower percent of broadband subscribers.

An average price of broadband services is supposed to have a negative impact on broadband adoption (although we don't claim that the estimated relationship is a demand curve due to possible complexity of the latter). This metric is constructed as a share of broadband cost in gross personal income and is comparable between countries. This property is necessary for our purposes and implicitly excludes an influence of country-specific price and economic development levels.

Phones (both fixed and mobile) adoption levels are frequently used [4] as a metric of technical preparedness of a country and a level of potential demand. Generally, broadband services can be considered as competitor for fixed phone lines, due to widely used VoIP software, so from our point of view it shouldn't be used as a resource at least for the efficiency frontier model. But we include these variables out of regards to other researchers to check the difference.

Using the SARSF model specification (7) and the Cobb-Douglas functional form, we constructed the empirical econometric model:

$$\begin{aligned} \ln Broadband &= \beta_0 + \rho \cdot sp.lag(\ln Broadband) + \\ &+ \beta_1 \cdot \ln Gini + \beta_2 \cdot \ln PriceGNI + \beta_3 \cdot \ln PopulationDensity + \\ &+ \beta_4 \cdot \ln Phones + \beta_5 \cdot \ln Mobiles + \\ &+ v - u \end{aligned} \tag{10}$$

We understand that under selected specification the dependent variable is limited (0 ≤ Broadband Penetration Rate ≤ 1*number of homes/offices/other places to have broadband connection), and the linear model is not quite appropriate in this case ([10]). Due to the lower bound (the upper bound is not a real restriction in practice), a limited dependent variable modification of the model should be theoretically used. We leave this shortcoming of our model for simplicity; it didn't lead to problems of interpretation and to a significant bias of the estimates.

5. Empirical Results

We composed a study data set of information for all 27 EU member states in 2009 or 2010 (where data available) years; we don't consider a panel data set in this research). The empirical research includes the next steps:

1. Estimation of the classical regression model (1) parameters and analysis of its residuals for possible spatial dependency.
2. Estimation of the stochastic frontier model's parameters with different sets of explanatory variables.
3. Analysis of the SF model's efficiency estimates.
4. Estimation of the SARSF model's parameters and analysis of relationships discovered.

In terms of this research the most interesting part of the first step was analysis of spatial dependencies. Table 2 includes observed values for Moran's I (2), LM-lags, and LM-errors test statistics (3), p-values for them (a null hypothesis for all tests is an absence of spatial dependencies in residuals) and resulting conclusions.

Table 2. Results of the tests for spatial dependence of classical regression's OLS residuals

Test statistic	Observed value	p-value	Conclusion
Global Moran's I	0.189	0.007	Significant spatial dependence
Lagrange multiplier statistic for spatial lags	5.235	0.022	Significant spatial lags
Lagrange multiplier statistic for spatial errors	2.7052	0.100	Weakly significant spatial errors

Spatial dependency testing results with different test statistics are not contradictory – all statistics show a presence of spatial dependencies. The significant value of Moran's I indicates the presence of global spatial dependency, and LM-lags and LM-errors tests allow us to indentify its type. The value of

the LM-lags test statistic is significant (at the 5% level), and the value of the LM-errors test statistic is not, so following Anselin's [6] recommendation we choose the spatial lag type of dependency for our further research.

Separately we estimated the SF model (5) to discover possible inefficiencies in broadband adoption. We investigated two different sets of explanatory variables – with Phones and Mobiles indicators included and without them; estimation results for both models are presented in the Table 3.

Table 3. Comparison of stochastic frontier model with and without Phones in explanatory variables

	Estimates for the SF model with Phones in explanatory variables		**Estimates for the SF model without Phones in explanatory variables**	
Parameter	Coefficient	p-value	Coefficient	p-value
Intercept	4.739	0.000	5.376	0.000
Ln(Gini)	-0.678	0.014	-0.612	0.053
Ln(PriceGNI)	-0.280	0.001	-0.329	0.000
Ln(PopulationDensity)	0.016	0.677	0.028	0.456
Ln(Phones)	0.199	0.080		
Ln(Mobiles)	-0.004	0.984		
γ	0.000	0.999	0.817	0.007

The most interesting result of model comparison is related with the presence of inefficiencies in data. The γ statistic (6) indicates that there are no inefficiencies in the SF model with Phones and Mobiles, and there are highly significant inefficiencies in the SF model without these indicators. Technically it means that Phones are correlated with inefficiencies of the model without them, but there are two different ways to interpret this result. The first one is to denote the Phones indicators are a significant resource for the broadband penetration rate, which should be used for its prediction and managing. The second one is to conclude that countries, inefficient with respect to broadband adoption, are also less developed with respect to phone lines. We can't make a conclusion about the correct interpretation on the base of our model, so their comparison is a matter of a separate work. In this research we preferred the second way of interpretation and conclude that both Broadband and Phones are metrics of a general level of country's telecommunication development.

The stochastic frontier approach allows estimating inefficiency values for each country in the data set. We present the estimated values in form of the map (Figure 2).

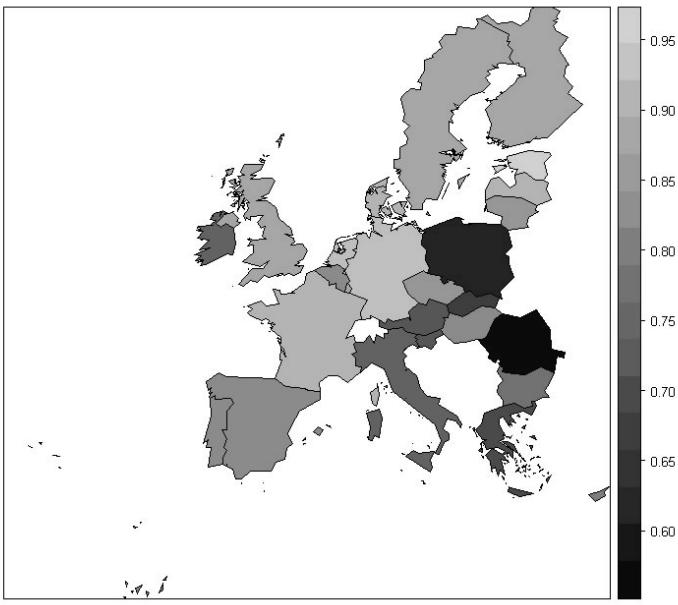

Figure 2. Efficiency of broadband adoption in EU member states

An average value of the estimated efficiency levels is 81.73% with minimum 57.78% (Romania) and maximum 94.79% (Estonia). The overall distribution of efficiency levels has obvious traces of spatial dependencies – areas with relatively high and relative low efficiency levels are clustered.

The SARSF model embodies both spatial dependencies and efficiency levels. To estimate the parameters of the SARSF model (10) we utilised maximum likelihood estimation technique (9). Estimates, calculated using our own module for CRAN R software, are presented in the equation (we put corresponding p-values in brackets underneath the model parameters' estimates):

$$\begin{aligned}
\ln Broadband &= \underset{(0.004)}{3.938} + \\
&+ \underset{(0.047)}{0.465}\, sp.lag(\ln Broadband) - \\
&- \underset{(0.046)}{0.612} \ln Gini - \\
&- \underset{(0.021)}{0.231} \ln PriceGNI + \\
&+ \underset{(0.65)}{0.015} \ln PopulationDensity + \\
&+ v - u
\end{aligned}$$

The model is formulated in the Cobb-Douglass functional form, so estimated values are elasticities of explanatory factors.

Signs of estimated coefficients completely match our expectations. Gini coefficient has a significant negative influence on broadband adoption (a higher level of income inequality leads to worse broadband adoption in a country). Prices of broadband services also have an expected negative elasticity. Population density is detected as an insignificant factor for broadband adoption (perhaps due to its "average" nature – a metric of population distribution should be tested for a strong conclusion).

A significant positive value is revealed for the spatial lag of the broadband penetration rate, so a high value of broadband penetration rate in neighbour countries enforces broadband adoption in a given country. The presence of spatial dependency can be justified in different ways – technical possibilities, installation and maintenance costs. Additional investigations are required to provide a strong explanation of the positive spatial lag discovered.

6. Conclusions

Recently significant interest has been given to impact of broadband services' adoption on sustainable national economic growth. Efficiency of broadband adoption becomes one of important long-term competitive advantages of countries. At the same time, broadband adoption in a given country has significant spatial effects and enhances development of broadband and other services in neighbour countries.

In this article we combine the stochastic frontier model, frequently used for efficiency estimation, with spatial econometric models. The proposed spatial autoregressive stochastic frontier model is used for estimation of broadband adoption efficiency in EU countries.

A maximum likelihood estimator for the spatial autoregressive stochastic frontier model was proposed and implemented as a module for R software.

We use the data sample for 2009–2010 years to analyse factors, influencing on broadband adoption in EU member states. A significant negative relationship between broadband penetration rate and average prices for broadband service is confirmed. A higher level of population income inequality (in form of the Gini coefficient) is also discovered as a significantly negative factor of broadband adoption.

We have discovered significant spatial lags of broadband penetration rates, which make the proposed spatial autoregressive stochastic frontier model a preferred one in this case. The estimated sign of the spatial lag is positive as expected, so higher broadband penetration rates in neighbour countries have a positive impact on broadband adoption in a given country.

Another considerable output of this research is estimates of broadband adoption efficiency in EU member states. From our point of view, these estimates, calculated on the base of the proposed model, perform better than the conventional ones, because it includes both influence of country-specific resources and spatial effects.

Acknowledgement

The author is grateful to Ermanno Affuso, researcher at the Department of Agricultural Economics and Rural Sociology of Auburn University, for providing very useful comments about maximum likelihood estimation of the spatial autoregressive stochastic frontier model.

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