ISSN 0975 – 2595

PRAJÑĀ

Volume 18, 2010

Journal of Pure and Applied Sciences

SARDAR PATEL UNIVERSITY
VALLABH VIDYANAGAR
Gujarat – 388 120, INDIA
www.spuvvn.edu

PRAJÑĀ- Journal of Pure and Applied Sciences, Vol. 18: 163 - 166 (2010)
ISSN 0975 - 2595

A STATISTICAL STUDY ON SPATIAL AUTOREGRESSIVE MODELS WITH REGIONAL RURAL POVERTY DIFFERENCE IN INDIA

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ABSTRACT

The purposes of this paper are to study the literature concerning the spatial autoregressive models and then to examine the influences of different variables, in particular, spatial effects on the population under poverty line of different regions in India by employing 14 states data. Spatial econometrics is a subfield of econometrics that deals with spatial effects in regression models for spatial data. The subject of regional difference primarily focuses on inequality causes by factors of geography matters. This paper uses data of 1994 for 14 major states in India to explore whether spatial effects play a crucial role in Indian rural regional poverty difference in 1994. The basis findings are that the spatial error model reveals a strong positive relationship between measures of difference in population under poverty line and spatial heterogeneity.

***Key words:** spatial econometrics, spatial effects, regional difference and spatial error.*

INTRODUCTION

In regional science, space is a central concept. During the 1970s, attention was paid to a growing body of geographic science literature. Historically, spatial econometrics, first coined in the early 1970s , originates as an identifiable field in Europe because sub-country data in regional econometric models are needed to deal with and been fast developed & grown during the 1990s [1]. According to Anselin [2], spatial econometrics addresses issues causes by space in statistical analysis of regional science regressions. In other words, spatial econometrics is the combination of statistical and econometrics methods that deal with problems concerning spatial effects that usually consist of two sections, spatial dependence and spatial heterogeneity, which are causes by using spatial data such as cross-sectional data and panel data.

The subject of regional difference has recently received a great attention in literature of regional economic growth. Romer [3] and Lucas [4] are the pioneers of this field, who address the issue of long term growth of average income in regions and with comparisons among regional long term growth tracks. Same way, we study spatial effect in the analysis of regional difference of rural poverty in India in this paper. We have studied spatial autoregressive models and applied to the Indian rural poverty data for 14 major states in India in 1994. These models are used to explore and examine what determines regional rural poverty difference, and to investigate spatial effects and the other variables that influence rural poverty in India. The paper is organized in 4 sections. Spatial econometrics and spatial autoregressive models described and interpreted in section 2. In section 3 the 14 states Indian spatial data set and the specified estimate models are described to examine spatial effects on rural poverty. Section 4 contains conclusions.

2 SPATIAL ECONOMETRICS

We usually use a database that includes information concerning geographical locations or regional units to estimate a set of regression in social sciences. However, the traditional econometric modeling has largely ignored or overlooked such available information. Therefore, if we want to use such valuable information in an efficient approach, we must take spatial effects into account. Spatial econometrics is the collection of methods that deal with the peculiarities caused by spatial interaction (spatial dependence) and spatial structure (spatial heterogeneity) in the statistical analysis of regional science models for cross- sectional and panel data [2]. As stated above, traditional econometrics does not often take geographical information into account. Hence, two issues occur when the sample data set has a locational component. First, spatial dependence exists between the sample observations. Second, spatial heterogeneity occurred in residuals of the regressions.

According to theoretical studies of Anselin [2], spatial dependence or spatial autocorrelation usually stands for dependence that often exists among the sample observations in cross-sectional data sets. In other words, the sample observations collected at one point in space are not independent on the sample observations collected at other locations. That is, we need to consider spatial dependence, if data collection associates with units such as states, provinces, countries and so on. There are rich examples concerning issues of spatial dependence such as data on population and employment, as well as other economic activities collected for location or distance. The term spatial heterogeneity is the second category of spatial effects and denotes instability or variation in relationships over space; namely, functional forms and parameters vary with location and are not homogeneous throughout the data set [2]. In general, a different relationship should hold for every point in space.

2.1 SPATIAL AUTOREGRESSIVE MODELS

This section in detail is a class of spatial autoregressive models that will be employed in the empirical applications. A general spatial autoregressive model which is well known as spatial log model is labeled as SAR in this paper and has been introduced to model cross-sectional data, is described in Anselin [2] and given by

$$y = \rho W y + X\beta + \varepsilon ,$$

$$\varepsilon \in N(0, \sigma_\varepsilon^2 I_n) \qquad (2.1)$$

Where, **y** represents an (nx1) vector of the sample observations on a dependent variable collected at each of n locations. **X** contains a (n x k) matrix of exogenous variables, and β is an (k x 1) vectors of parameters associated with exogenous variables x, which reflects the influence of the explanatory variables on variation in the dependent variable y, as well as **ρ** is the coefficient on the spatially lagged

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dependent variable, **W** is regarded as (n x n) spatial weight matrix(CONTIGUITY matrix) **Wy** is the spatially lagged dependent variable.

W is a row standardized (n X n) matrix with positive elements W_{ij} which are associated with the spatially lagged dependent variable that indicates the potential interaction between contiguous positions

$$W_{ij} = \frac{W'_{ij}}{\sum_{j=1, i \neq j}^{n} W'_{ij}}$$

where, $W'_{ij} = 1$ if location i linked to j

0 Otherwise

that is, the elements of the weight matrix are derived from information on contiguity, which is defined as two sample observations sharing a common border. Model (2.1) is labeled as a "mixed regressive- spatial autoregressive model" in Anselin [2], because it combines the standard regression model with a spatially lagged dependent variable.

Another model studied in this paper is spatial error model (SEM). It provides another efficient method for dealing with the spatial data set that consists of 14 observations for states in India. The SEM model can be stated as follows:

$$LOG\ (y) = X\beta + u,$$
$$u = \lambda W_{u} + \varepsilon$$
$$\varepsilon \in N(0, \sigma_{\varepsilon}^{2} I_{n}) \quad (2.2)$$

where, W_u is the spatially correlated errors and u is the spatial error. λ is a coefficient on the spatially correlated errors and W, X, as well as β are the same as described in the SAR model.
LOG(y) is the logarithm of (nx1) vector of the sample observations on a dependent variable collected at each of n locations.

3 An Empirical Application

In the previous section the study has revolved around the fundamental knowledge of spatial econometrics and spatial autoregressive models. In this section the focus will in turn be put on attempting to address such an issue as: what are the significant factors that influence rural population under poverty line in India?

Since the 1970's, economists have investigated the effect of geography on the labour markets and poverty outcomes. Recently, it has become more and more popular to explore spatial econometrics. A good application of spatial econometric techniques is to test regional disparity on population under poverty line.

3.1 Spatial Data

According to Anselin [2], spatial data are the data collected in space or in both space and time. For instance, our familiar data such as cross-sectional data and panel data are spatial data. However, as applying spatial data, we must consider the issue regarding the presence of self-correlation or autocorrelation. To avoid these problems, spatial autoregressive models should be employed in such a situation.

The source of the data used for the analysis is from "IFPRI research report [5]. Linkages between Government Spending, Growth, and poverty in rural India. *International Food Policy Research Institute.,* "World Bank 1997". From this data 14 major states in India have been selected. Here, we attempt to examine whether there is an interaction between rural poverty and spatial effects. The analysis is not only focused on spatial influence, but also interested in exploring how rural poverty is affected by other variables such as rural work-employment status, literacy rate, irrigation facilities and so on. At the state level, World Bank contains information on demography. The selected variables under study are summarized in Table - 1.

Table – 1 List of Variables used in study

	LABELED
Dependent variable	
Rural Population under Poverty Line	PUPL
Independent variables	
Ratio of rural employment with total rural population. Total rural employment, which includes both agricultural and non- agricultural employment symbolized as **REMP**,	REMP
Total rural population	TRP
Rural agricultural population, includes agricultural laborers and Rural non- agricultural population that are doing non- agricultural economic activities	RAE and RANE
Production Growth is agricultural production growth index which is calculated by the authors of the IFPRI research report 110 report (*International Food Policy Research Institute.,* "World Bank 1997").	P-G
Percentage of villages electrified, villages having the facility of electrification, by state	PVE
Road density in rural India measured as the length of roads in kilometers per thousand square kilometers of geographic area	RD
Changes in rural wages includes the percentage change in the existing wage rates	CRW
Total Factor Productivity Growth index is also given in IFPRI research report 110, data source,	TFP
Percentage of rural population that is literate by state, the rural literacy rate	LR
Ratio of Development expenditures with total rural population. Development expenditure which includes total government spending on various rural development facilities	DEP
Ratio of Percentage of cropped area sown with high-yielding varieties with Percentage of cropped area irrigated, by state.	HYV
Percentage of cropped area irrigated that is area having irrigation facilities represented by state.	IRR

Table - 2 Variable definitions in estimated models

	VARIABLE TYPE	**LABELED**
Dependent variable		
Logarithm of population under poverty line	**C**	LOG(PUPL)
Independent variables		
Ratio of rural employment with total rural population.	**R**	REMP/TRP
Ratio of rural agricultural employment with total rural employment	**R**	RAE
Ratio of rural non-agricultural employment with total rural employment	**R**	RANE
Production growth in agriculture	**C**	P-G
Percentage of villages electrified, by state	**C**	PVE
Road density in rural India	**C**	RD
Changes in rural wages, by state	**C**	CRW
Total factor productivity growth in Indian agriculture, by state	**C**	TFP
Percentage of rural population that is literate, by state	**C**	LR
Ratio of Development expenditures with total rural population.	**R**	DEV/TRP
Ratio of Percentage of cropped area sown with high-yielding varieties with Percentage of cropped area irrigated.	**R**	IRR/HYV

NOTE:- C= continuous variable and **R=** ratio variable.

All the variables (Ratio and Continuous) employed in the estimated models are in Table - 2. These variables will be examined in the empirical models in the next section as well.

3.2 MODELS AND RESULTS

Our proposed model (1) for population under poverty line is as following:

$$LOG\ (PUPL) = \beta_1\ (REMP/TRP) + \beta_2(RAE) + \beta_3(RANE) + \beta_4(P\text{-}G) + \beta_5(PVE) + \beta_6(RD) + \beta_7(CRW) + \beta_8(TFP) + \beta_9(LR) + \beta_{10}(DEV/TRP) + \beta_{11}(IRR/HYV) + \varepsilon \quad (3.1)$$

Where, LOG(PUPL) is an (14×1) vector of observations on logarithm of population under poverty line. β is an (11×1) vector of parameters, and $\boldsymbol{\varepsilon}$ is an (14×1) vector of disturbances.

The aim of setting up the following linear regression models estimated by OLS is to filter the variables that are used in spatial autoregressive models. The test steps are as follows:

1. Build up model 1 that contains all the variables described in Table - 2.
2. Model 2 consists of the significant variables in Model1.
3. Remove the insignificant variables from Model 2 to obtain Model 3.

This procedure is done until all the independent variables in one model are found to be statistically significant at 5% level. In our case, the experiment is carried out until step 4, which indicates that the variables in Model 4 are significant to explain reduction in dependent variable, the logarithm of population under poverty line. The results of the OLS estimation are shown in Table 3. According to the results given in Table 3, it can be seen that IRR/HYV is found to be statistically insignificant at 5% and will not be included in model 2.

Therefore, in model 2 there are 10 explanatory variables left in addition to the constant. After removing the insignificant variable RD from model 2, we gain model 3. Then, we obtain model 3 that contains these 9 significant variables and are shown in Table 3. Here, we found Production Growth and Total Factor Productivity growth are highly correlated and statistically insignificant. So, both the variables are removed and finally we got model 4 that consist of 7 significant variables.

The estimated model 4 is,

$$LOG\ (PUPL) = 11.023 - 92.64\ (REMP/TRP) - 0.00803\ (RAE) - 1.25\ (RANE) - 0.018\ (PVE) -0.17\ (CRW) -0.014\ (LR) - 3613\ (DEV/TRP) \quad (3.2)$$

Hence, these variables included in Model - 4 will be used as explanatory variables in the spatial autoregressive models and model 4 is regarded as the final model for adding the spatial effects.

We will now present a set of two spatial autoregressive models to analyze the sample data. There are 14 states in the sample dataset. Our interest is to calculate the proportion of the total variation in the population under poverty line that is explained by the spatial dependence. This relies on estimating the spatial lag model (SAR) that is brought up in Section 2.1.

The **SAR model** can be written as

$$LOG(PUPL) = \rho WLOG(PUPL) + X\beta + \varepsilon,$$
$$\varepsilon \in N\left(0, \sigma_\varepsilon^2 I_n\right) \quad (3.3)$$

where, LOG(PUPL)= [LOG $(PUPL)_1,\ldots,LOG(PUPL)_{14}$] is a 14 dimensional vector of log of population under poverty line for 14 states, ρ is the coefficient on the spatially lagged dependent variable, it denotes a estimated regression parameter, which reflects the spatial dependence characteristic in the sample data set, and measure the average influence of states on states in population under poverty line, W is 14×14 spatial weight matrix that is row-standardized and each row sum to one (see 2.1) and X represents a (14 ×7) matrix containing explanatory variables, which are used in Model 4, as well as β is the parameters that reflect the influence of the exogenous variables on variation in the dependent variable population under poverty line.

Table - 3 Results of OLS estimation

Dependent variable : LOG(PUPL)				
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
REMP/TRP	-144.36 (-2.65)	-141 (-3.43)	-136.24 (-4.10)	-92.64 (-3.15)
RAE	-0.07978 (-1.24)	-0.0768 (-1.49)	-0.06852 (-1.88)	-0.00803 (-0.25)
RANE	-3.165 (-1.18)	-2.75 (-2.22)	-2.57 (-2.80)	-1.2456 (-1.45)
P-G	-0.006882 (-0.9)	-0.00609 (-1.17)	-0.00493* (-1.87)	-
PVE	-0.02633 (-2.26)	-0.0257 (-2.78)	-0.0249 (-3.24)	-0.017801 (-2.03)
RD	-0.00000752 (-0.28)	-0.000006* (-0.27)	-	-
CRW	-0.1 (-0.77)	-0.0917 (-0.92)	-0.08861 (-1.02)	-0.17124 (-1.77)
TFP	0.005203 (0.57)	0.00399 (0.77)	0.002822* (1.10)	-
LR	-0.00340 (-0.23)	-0.0045 (-0.42)	-0.00636 (-0.85)	-0.013896 (-1.71)
DEV/TRP	-4412 (-1.13)	-4866 (-1.94)	0.002822 (-2.24)	-3613 (-1.36)
IRR/HYV	0.0841* (0.19)	-	-	-
Constant	14.270 (4.80)	14.119 (5.99)	13.824 (7.35)	11.023 (7.31)
N	14	14	14	14
Adj-R^2	75.1%	83.1%	87%	77%

Note:- t-statistics in parentheses. * indicates a p-value that is not statistically significant at 5% significance level. N is the number of observations.

The spatial error model (SEM) provides another efficient method for dealing with the spatial data set that consists of 14 observations for states in India.

The **SEM model**, which is introduced in section 2.1, is stated as follows:

$$LOG\ (PUPL) = X\beta + u,$$
$$u = \lambda W_u + \varepsilon$$
$$\varepsilon \in N\left(0, \sigma_\varepsilon^2 I_n\right) \quad (3.4)$$

where, **λ** is a coefficient on the spatially correlated errors and LOG(PUPL), W, X, as well as β are the same as described in the SAR model. The estimates of the SAR and SEM models are shown in Table - 4.

Table - 4 Results of spatial autoregressive model estimation

Dependent variable : LOG(PUPL)			
Variables	**SAR**	**SEM**	**Model 4**
Constant	10.616 (4.04)	10.673 (6.52)	11.023 (7.31)
REMP/TRP	-90.77 (-2.71)	-96.20 (-3.11)	-92.64 (-3.15)
RAE	-0.00567 (-0.15)	-0.01382 (-0.41)	-0.00803 (-0.25)
RANE	-1.1997 (-1.24)	-1.2983 (-1.45)	-1.2456 (-1.45)
PVE	-0.01703 (-1.77)	-0.00930 (-0.64)	-0.017801 (-2.03)
CRW	-0.1703 (-1.61)	-0.2269 (-1.81)	-0.17124 (-1.77)
LR	-0.014249 (-1.58)	-0.012485 (-1.44)	-0.013896 (-1.71)
DEV/TRP	-3476 (-1.17)	-4567 (-1.50)	-3613 (-1.36)
Rho	0.066 (0.20)	-	-
Lambda	-	0.1493 (0.75)	-
N	14	14	14
Adj-R^2	75.8%	78%	77%

Note:- t-statistics in parentheses. N is the number of observations. * indicates a p-value that is not statistically significant at 5% significance level.

Table - 4 displays the result of both SAR and SEM as well as OLS estimation of model 4. The reason why the estimate results model 4 are shown in Table - 4 is that it is an easy and clear way to compare the model with spatial effects and without spatial effects.

In Table - 4, the adjusted R^2 values of these three regressions range between 0.75 and 0.78. All coefficients of the independent variables, except rho in SAR model, are found to be statistically significant. Interpretations for the coefficients of the explanatory variables are not our chief focus here.

The SAR estimates in Table - 4 show that after taking into account the influence of the independent variables, we do not have spatial correlation in the model, since the spatial autoregressive coefficient ρ is statistically insignificant and not large at all. That is, the dependent variable LOG(PUPL) exhibits insignificant spatial dependence. This indicates that we cannot estimate the SAR model successfully. Therefore, we do believe that the OLS estimates are correct, as there are insignificant spatial autoregressive parameters in the SAR model.

On the other hand, estimations in the SEM model display the results we expect, so that our analysis will be focused on comparing estimate results between SEM model and Model 4. The following three aspects are considered in particular.

Firstly, taking the spatial heterogeneity into account improves the fit of the model, as the adjusted R^2 statistic rises from 0.77 in Model 4 to 0.78 in SEM model. That is, around one percent of the variation in the logarithm of population under poverty line is explained by spatial structure, because the adjusted R^2 is 0.78 in SEM model that takes the spatial effect into account and 0.77 in the least-square model that ignores such an effect.

Secondly, the t-value on the spatial autocorrelation parameter λ is 0.75, indicating that this explanatory variable has a coefficient estimate that is significantly different from zero. Equivalently, the spatial coefficient is found to be statistically significant, showing that there exists spatial heterogeneity in the residuals of the model. However, Model 3 based on OLS ignores the spatial information that is provided by the sample dataset.

CONCLUSIONS

Our purpose of this study is to focus on the theoretical study of spatial econometrics and to explore an empirical application of spatial autoregressive models used on Indian rural poverty cross-sectional data.

Recently, spatial econometric techniques have grown rapidly and have increasingly been applied in empirical researches. In general, spatial econometrics is related to spatial statistics and is a subfield of econometrics that deals with the combination of spatial dependence and spatial heterogeneity in regression analysis. Spatial dependence relates to the fact that observations in the sample data set display correlation with regard to location in space. Spatial heterogeneity relates to the fact that the regression models that we estimate may vary systematically over space.

The basic regressions used in this paper are simply OLS regressions of the logarithm of population under poverty line on the explanatory variables to obtain Model 4 that contains 7 significant variables and one constant. The results from the empirical investigation indicate that there are many variables that influence the rural population under poverty line. With respect to our major interest, spatial effects, we do find that in the SAR model there is a positive sign on rho, but it is not statistically significant, indicating there is no spatial dependency in the model.

However, in the SEM model lambda is found to be both positive and significant at 5% significance level, indicating that spatial heterogeneity presents in the residuals of the model. Thus, Model 4 associated with OLS estimation is an inappropriate regression model for the sample data that are the spatial data.

The findings are that relative to model 4, the SEM model reveals larger influences on the ratios of the development expenditure and rural employed population with total rural population and a smaller influence on literacy rate. Additionally, the proportion of employed population with total rural population has the strongest negative influences on population under poverty line in our models.

In addition, the empirical models of SAR and SEM are selected primarily to illustrate the various spatial effects, and are not supposed to contribute to a substantive understanding of spatial patterns of population under poverty line.

ACKNOWLEDGEMENT

The authors would like to thank the referee for the valuable comments and for the pain taken to read the paper thoroughly, which maid the paper published.

REFERENCES

[1] Anselin, L. (1999) Spatial econometrics, Bruton Center, School of Social Sciences,University of Texas at Dallas, Richardson, TX 75083-0688.

[2] Anselin, L. (1988) *Spatial econometrics: Methods and models*, Kluwer Academic Publishers, Dordrecht.

[3] Romer, P. M. (1986) Increasing Returns and Long-Run Growth, *Journal of Political Economy*, 94(5): 1002-1037.

[4] Lucas, R. E. (1988) On the mechanics of development planning, *Journal of Monetary Economics* 22(1): 3-42.

[5] IFPRI research report 110, (1999) Linkages between Government Spending, Growth, and poverty in rural India. *International Food Policy Research Institute.,* Washington, D.C.

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Books

[16] Stebbins, G. L. (1974) *Flowering plants: Evolution above the species level,* Arnold Press, London, pp. 1 – 399.

Chapters from a book

[19] Schafer, H. and Muyzer, G. (2001) Denaturing gradient gel electrophoresis in marine microbial ecology. In *Methods in Microbiology* (Ed. Paul, J. H.), Academic Press, London, Vol. 30, pp. 425 – 468.

Thesis or other diplomas

[21] Nayaka, S. (2004) *The visionary studies on the lichen genus Lecanora sensu lato in India.* Ph. D. Thesis, Dr. R. M. L. Avadh University, Faizabad, India.

Conference proceedings

[4] Mohapatra, G. C. (1981) Environment and culture of early man in the valley of rivers Chenab and Ravi, western sub-Himalayas. In *Proceedings X Congress of IUPPS*, Mexico, pp. 90 – 123.

Online documentation

[9] Koning, R. E. (1994). Home Page for Ross Koning. Retrieved 26-6-2009 from *Plant Physiology Information Website*: http://plantphys.info/index.html.

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