THE STUDY ON SPATIAL STATISTICS AND ITS APPLICATION IN THE SPATIAL DISTRIBUTION AND EVOLVEMENT RULE OF RADIO AND TV INDUSTRY

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KEY WORDS: Spatial Statistics, Methods and Models, Radio and TV Industry, Spatial Distribution, Evolvement Rule

ABSTRACT:

Because of its researching object always be provided with spatial attribute, spatial statistics differs from traditional statistics. In this paper, besides of the definition of Spatial Statistics, the difference between them is discussed. Compared to statistics, spatial statistics is a very young one. Five models are introduced in this paper. They are Spatial Autoregressive Model, Spatial Aotucorrelated Model, The mixed Autoregressive-regressive Model, Spatial autoregressive error mode and The General Spatial Mode. On the application aspect, by Using the Spatial Autoregressive Model, SAR (the spatial autocorrelative mode) and SAC (the general spatial model)., from the Moran's I statistics, the marginal probability, the spatial autocorrelation parameter and R-square values we could gain the spatial dependence and evolvement rule of radio and TV industry in China. And the conclusion is that they are fitting the data famously, and the quantities could be explained fully.

1. INTRODUCTION

An attention to location, spatial interaction, spatial structure and spatial processes lies at the heart of research in several subdisciplines in the social sciences. Empirical studies in these fields routinely employ data for which locational attributes are an important source of information. Such data typically consist of one or a few cross sections of observations for either micro-units, such as households, store sites, settlements, or for aggregate spatial units, such as electoral districts, counties, states or even countries. In the social sciences, they have been utilized in a wide range of studies, such as archeological investigations of ancient settlement patterns (e.g., in Whitley and Clark, 1985, and Kvamme, 1990), sociological and anthropological studies of social networks (e.g., in White et al., 1981, and Doreian et al., 1984), demographic analyses of geographical trends in mortality and fertility (e.g., in Cook and Pocock, 1983, and Loftin and Ward, 1983), and political models of spatial patterns in international conflict and cooperation (e.g., in O'Loughlin, 1985, and O'Loughlin and Anselin, 1991). Furthermore, in urban and regional economics and regional science, spatial data are at the core of the field and are studied to model the spatial structure for a range of socioeconomic variables, such as unemployment rates (Bronars and Jansen, 1987), household consumer demand (Case, 1991), and prices for gasoline (Haining, 1984) or housing (Dubin, 1992).

The statistical treatment of such data is the subject of an abundant literature. During these studies, many problems relating to spatial connection encountered. And traditional statistic method could not do it. Then, the study on spatial statistics, spatial data analysis began. Spatial statistics is a new subject, which has developing with the application of spatial high-technology in prospecting for oil, aerial survey and remote sensing. There are many problems have to be settled on spatial relations in the study of spatial information and other phenomena correlated with them, such as selection of representational spatial specimen, spatial estimating, correlation of two group or multi-group spatial data. On the other hand, because there are many different directions, and the reciprocity among different elements with different distance shows complexity with vary degree, all of these make it difficult to solve the foregoing problems only with traditional symbolic statistical tools drastically. And then the study on spatial statistics, spatial data analytical method began, just the practical demand which brought about the naissance of spatial statistics.

2. THE DISTINGUISH BETWEEN TRADITIONAL STATISTICS AND SPATIAL STATISTICS

Just as its name implies，spatial statistics applies itself to analysis spatial information and settle spatial problem. Two characters are the maximal difference between spatial statistics and traditional statistics, spatial multi-dimension character of spatial statistical data and the base hypothesis of space-time correlation. There are some important distinguishes (Zhengquan Wang, 1999; Cressie, 1993; Haining, 2003) could not be ignored. They are,

First, the objects studied by classical statistics must be pure stochastic variables, and the value of variable is changing

Foundation Item: Supported By Open Research Fund Program of the Geomatics and Applications Laboratory, Liaoning Technical University; The High tech Research and Development (863) Program, No.2001AA135080 and The National Natural Science Foundation of China, No. 40371047.

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according to certain probability distribution. And the objects studied by spatial statistics are not stochastic variables but regional variables. The regional variable gets different value based on its spatial position in certain area. It is stochastic function of stochastic variable correlating location.

Second, the variables studied by traditional statistics could be repeated illimitably or tested repeatedly by large numbers of times. But the variables studied by spatial statistics could not be tested repeatedly like this, because after having getting a sample in certain location, another sample of the regional variables could not been gotten on the same position.

Third, sampling each time must be independent in traditional statistics, and every value in sample is kept independent. But regional variables in spatial statistics are gotten by sampling in different location in space, then values in two samples with same border are not always independent, by contraries, they have certain degree correlation in space.

Four, frequency distribution charts are base to study diversified data characteristics of samples in traditional statistics, and to spatial statistics besides of data characteristics of samples, more important the spatial distribution characteristics of regional variables are studied.

3. THE THEORY AND MODELS OF SPATIAL STATISTICS

The treatment of spatial data analysis from the lattice data perspective focuses on two main issues: testing for the presence of spatial association, and the estimation of regression models that incorporate spatial effects. Examples are selected materials in textbooks on "statistics for geographers," such as in Ebdon (1985) and Griffith and Amrhein (1991), and the small pedagogic volumes devoted to the topic of "spatial autocorrelation" by Griffith (1987) and Odland (1988).

A more technical treatment of these issues can be found in the classic works of Cliff and Ord (1973, 1981) and in Upton and Fingleton (1985). In addition to dealing with spatial autocorrelation, these texts also cover several aspects of spatial regression modeling. A more specific focus on spatial effects in regression analysis can be found in Haining (1990) at the intermediate level, and in Anselin (1988), Griffith (1988), and also Cressie (1991) at the more advanced level. An extensive discussion of operational implementation issues, including extensive listings of software code, is given in Anselin and Hudak (1992), and Anselin and Griffith (1993).

3.1.1 Spatial AutoCorrelated Model

If we consider spatial phenomena as stochastic processes, we must make some assumptions on the stationarity of the processes. We then define spatial autocorrelation is the situation where the presence of some quality in one area makes its presence in neighboring areas more or less likely.

In the spatial context, however, causality is assumed to be bidirectional, and therefore spatial correlations cannot be interpreted as causal components. Thus spatial autocorrelation is defined only as the linear relationship between two stochastic variables, which contains information about the nature of the joint distribution of all airs of variables which are a constant lag apart. In the situation where the stochastic processes are Gaussian, the coefficient determines a parameter of their joint distribution.

However where the processes aren't Gaussian isotropic and the spatial autocorrelation coefficient is invalid, and only the spatial autoregressive coefficient still remains valid. Thus these models focus on the estimation of spatial autoregressive structures and not on spatial autocorrelation. (Anselin, 1980, pg 10).

There are many methods to describe spatial autocorrelation, while the most usually used ones are Moran's I−statistic(Cliff and Ord, 1973), G statistics, Gi statistics(Getis and Ord, 1992, 1995) , Local Moran (Anselin, 1995) and so on. Here we only introduce the Moran' I method.

Moran’s I is defined as:

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \times \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2}$$

Under the assumption of normal distribution, there goes

$$E(I) = \frac{-1}{(n-1)},$$

$$Var(I) = \frac{n^2 S_1 - nS_2 + 2S_0}{(n^2-1)S_0} - E(I)^2$$

The standardized form

$$Z = \frac{[I - E(I)]}{\sqrt{Var(I)}}$$

is called Moran’s I statistics, which is asymptotically normal distributed. Positive spatial autocorrelation is when high values of Moran’s I statistics a variable in a location are associated with high values of the variable in neighboring locations, and negative spatial autocorrelation is when alternating high and low values occur in neighboring locations.

3.1.2 Spatial Autoregressive Model

The general form of the SAR model is the SAR[p], where the values of some variable are proportional to those of its neighbors at different spatial lags, plus some error:

$$\underset{(N\times1)}{y} = \underset{1\times1}{\rho_1} \underset{N\times N}{W_1} \underset{N\times1}{y} + \underset{1\times1}{\rho_2} \underset{N\times N}{W_2} \underset{N\times1}{y} + \cdots + \underset{1\times1}{\rho_p} \underset{N\times N}{W_p} \underset{N\times1}{y} + \underset{N\times1}{\varepsilon}$$

Where W is the normalized, contiguity, weights matrix discussed previously, and powers of W denote higher-order spatial-lag matrices, out to order ρ . The parameters to estimate are ρ_i , the spatial lag parameters. The error term ε is i.i.d. $N(0,\sigma^2 I_N)$. The simplest version of this is then the SAR[1] with just one lag:

$$\underset{(N\times1)}{y} = \underset{1\times1}{\rho} \underset{N\times N}{W} \underset{N\times1}{y} + \underset{N\times1}{\varepsilon}$$

3.1.3 The mixed Autoregressive-Regressive Model

This model extends the first-order spatial autoregressive model to include a matrix X of explanatory variables such as those used in traditional regression models. Anselin (1988) provides a maximum likelihood method for estimating the parameters of this model that he labels a ‘mixed regressive -

spatial autoregressive model'. The model takes the form:

$$y = \rho Wy + X\beta + \varepsilon$$

$$\varepsilon \sim N(0, \sigma^2 I_n)$$

Where y contains an nx1 vector of dependent variables, X represents the usual nxk data matrix containing explanatory variables and W is our spatial contiguity matrix. The parameter ρ is a coefficient on the spatially lagged dependent variable, Wy, and the parameters β reflect the influence of the explanatory variables on variation in the dependent variable y. The model is termed a mixed regressive - spatial autoregressive model because it combines the standard regression model with a spatially lagged dependent variable, reminiscent of the lagged dependent variable model from time-series analysis.

3.1.4 Spatial Autoregressive Error Model

Here we turn attention to the spatial errors model shown below, where the disturbances exhibit spatial dependence. Anselin (1988) provides a maximum likelihood method for this model which we label SEM here.

$$y = X\beta + \varepsilon$$

$$\varepsilon = \rho W\varepsilon + u$$

$$u \sim N(0, \sigma^2 I_n)$$

The nx1 vector y contains the dependent variable and X represents the usual nxk data matrix containing explanatory variables. W is the spatial weight matrix and the parameter ρ is a coefficient on the spatially correlated errors, analogous to the serial correlation problem in time series models. The parameters β reflect the influence of the explanatory variables on variation in the dependent variable y.

In models with serial correlation in the disturbance, Generalized Least-Squares gives the best linear unbiased estimate. While OLS will be unbiased, it won't be efficient, and inferences based upon the estimated variance of the coefficients may be erroneous (Anselin 1988, pg 59).

3.1.5 The General Spatial Model

A general version of the spatial model that we label SAC includes both the spatial lag term and a spatially correlated error structure as shown here:

$$y = \rho W_1 y + X\beta + u$$

$$u = \lambda W_2 u + \varepsilon$$

$$\varepsilon \sim N(0, \sigma^2 I_n)$$

One point to note about this model is that W1 can equal W2, but there may be identification problems in this case. When might one rely on this model? If there were evidence that spatial dependence existed in the error structure from a spatial autoregressive (SAR) model, the SAC would represent an appropriate approach to modeling this type of dependence in the errors. We might also rely on this model if we believe that the disturbance structure involves higher-order spatial dependence, perhaps due to second-round effects of a spatial phenomena being modeled.

4. SPATIAL ANALYSIS OF RADIO AND TV INDUSTRY IN CHINA

As we know, the industry of Radio and TV is provided with economical attribute besides its political attribute, and economical standard in China is imbalance, particularity and complexity is certainly in this study. Then pretreatment has to be done with the original data and several methods are required. Variable-classification and spatial sampling analysis are two most important course of pretreatment. During this course, spatial clustering is used too.

4.1 Spatial Dependence Analysis

In common sense, the development of any Industry in a particular province, including Radio and TV industry, should be in certain extent related to that of the other provinces in close proximity. In this part, we focus on the spatial dependence analysis of the efficiency of Radio and TV industry, and try to find the spatial clustering effect of this industry. Therefore, the ratio of net income to gross income is used to evaluate the market efficiency of Radio and TV Industry in different provinces in China. The data are over 17 years from 1987 to 2003.

To make a clear and visible understanding of the spatial structure of market efficiency of Radio and TV Industry we divide the 31 provinces into four groups according to the value of ratio we compute beforehand and draw the scatter plot which is shown in figure 1.

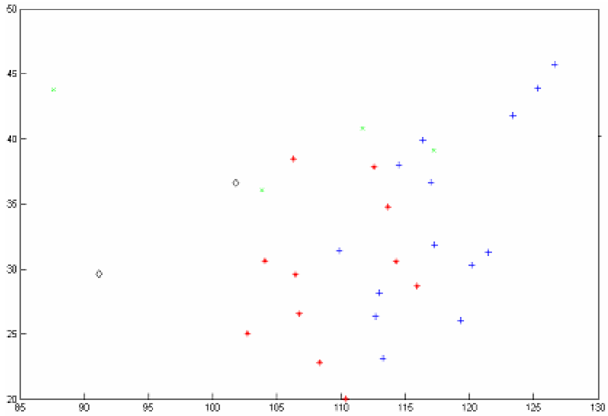

Figure 1：The scatter plot of market efficient level of Radio and TV Industry in China

In figure 1, the x-coordinate represents the longitude of the metropolis of each province and the y-coordinate represents the latitude of it. Different color and type of the point denotes different market efficiency, with the blue plus sign denotes the highest market efficiency (from 75 percent to 100 percent), the red star sign denotes the higher market efficiency (from 50 percent to 75 percent), the green 'x' sign denotes the lower market efficiency (from 25 percent to 50 percent), and the black diamond sign denotes the lowest market efficiency (from 0 percent to 25 percent). It can be clearly seen from the figure that the same level of market efficiency displays considerable spatial clustering effect. Those provinces with the blue plus sign (which means that they are among the provinces of the highest market efficiency) are located in the northeast areas, the southeast coastal areas and the drainage areas of Yangtse River. This conforms to the economic development level and resident consume level of these provinces. In the northeast part of China, Radio and TV Industry grew in the earlier days and due to the geographical characteristic, people there tend to stay at home in most of the time. So listening to the radio and watching TV are the most popular relaxation. Consequently, the market efficiency of Radio and TV Industry is relatively high. The southeast coastal areas and the drainage areas of Yangtse River are the rich parts in China, therefore it is rational that they are among the highest market efficient group. For the other groups, there are similar understandable reasons for them and we omit them to keep concision.

To confirm the existence of spatial dependence of market efficiency of Radio and TV Industry quantificationally, we turn to the methods of spatial statistics which we have described in the former part. We firstly compute the Moran's I statistics to explore the spatial dependence of this industry by using the spatial contiguity matrix W. The value of Moran's I statistics and the marginal probability from year 1987 to 2003 are shown below in table 1.

Year	Moran's I	Moran's I-statistic	Marginal Probability
1987	0.28881856	2.74524717	0.00604653
1988	0.31966303	3.00809115	0.00262894
1989	0.29424118	2.79145656	0.00524714
1990	**0.15046073**	**1.56621815**	**0.11729756**
1991	**-0.04528988**	**-0.10188885**	**0.9188449**
1992	0.3096874	2.92308294	0.00346584
1993	0.34861726	3.25482735	0.00113461
1994	0.2721242	2.60298467	0.00924161
…	…	…	…
2002	0.37081296	3.44397004	0.00057324
2003	0.4208254	3.87015564	0.00010877

Table 1：Spatial dependence analysis of the industry of Radio and TV in China

As we can see from the table, except in 1990, Moran's I is a positive value which means that certain province tends to have the similar market efficiency as that of its 'neighbors' . In all the years except 1990 and 1991, the marginal probability are almost all under 0.005 which strongly shows that there exists considerable spatial dependence among the 31 provinces in China. As for the untypical result in 1990 and 1991, it may be ascribed to the policy of the government or the incorrect data, or the improper choice of the spatial continuity matrix W.

4.2 Spatial Autoregressive Model Analysis

In the preceding section, we found that in all the years except 1990 and 1991, considerable spatial dependence of market efficiency of Radio and TV Industry in the 31 provinces in China exists. Here, we'll estimate the spatial autocorrelation coefficient for a SAR[1] model to detect if the degree with which the market efficiency of one province's radio and TV industry is affected by its neighbors, and then consider the changes in the spatial autocorrelation parameter over time. The corresponding results are tabled below.

Year	R-square	Coefficient	Asymptotic t-stat	z-probability
1987	0.2996	0.875993	8.700447	0.000000
1988	0.1995	0.819992	6.154491	0.000000
1989	0.2157	0.864944	8.039392	0.000000
1990	**-0.0158**	**0.821000**	**6.186997**	**0.000000**
1991	**-0.5210**	**0.777982**	**5.040774**	**0.000000**
1992	0.0630	0.892967	9.974017	0.000000
1993	0.2793	0.936975	16.461685	0.000000
1994	0.0706	0.937971	16.716575	0.000000
…	…	…	…	…
2002	0.1813	0.953987	22.369079	0.000000
2003	0.3014	0.933994	15.745476	0.000000

Table 2：The result of SAR [1] model

It's very easy to see that all the years are statistically significant. Since the coefficient is a measure of the relationship between the market efficiency of one province's radio and TV industry and that of its neighbors, we can say that the spatial neighbors' effect is rather high in this industry (expect in 1991, all the Coefficient s are more than 0.8.). And there is an increasing tendency of this effect over time. Although the tendency is slight and fluctuating every now and then, considering the random disturbance to the data and the narrow changing range (0.8~1.0), it is undeniable. But to the value of R-square, almost all of them are less than 0.3. (For year 1990 and 1991, the value of R-square is incredibly negative! Yet, that's coincident with the untypical Moran' I statistics mentioned above.) We also show the actual vs. predicted data plot of in 2003 to make a more visible understanding (Figure 2).

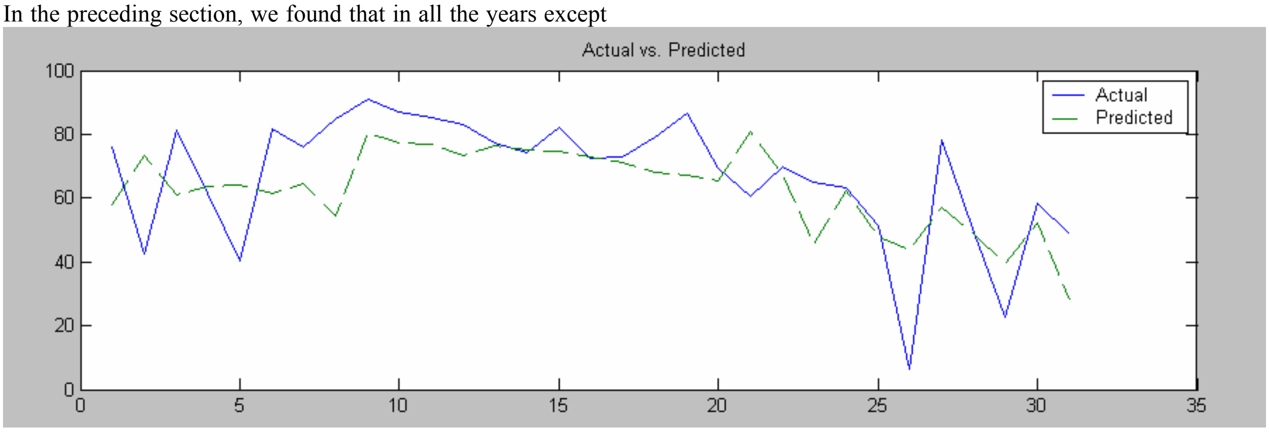

Figure 2：The actual vs. cted data of 2003 (SAR [1])

From the two figures, we can find that the prediction curve well exhibit the shape of the actual curve, but there is large gap between the prediction and the true value. It is a graphic expression of the small R-square value.

4.3 General Spatial Model Analysis

One goal of our analysis of radio and TV industry is to predict the future productivity of the 31 provinces and then give reasonable advice for decision-makers. We've seen that from the simple SAR[1], only poor R-square value is got, so it's reasonable to add explanatory variables into the model.

Considering this goal of prediction, the nature of our data itself and by the method of stepwise, we finally chose the net income of the Radio and TV Industry as the dependent variable, and the two explanatory variables are, namely, the city resident consume (CRC) and GDP. The data we deal with here is from 1997 to 2003. In this application example several spatial models are used and compared them to a variety of competing spatial models. And then found that SAC (the general spatially model) is more appropriate for this dataset than the corresponding spatial autoregressive model. While the model competes very well against a variety of other standard spatial and non-spatial models, both in terms of in-sample statistics as well as out-of-sample predictive properties, in fact they do not perform significantly differently from a simpler, non-parametric specification because in which only absolute spatial effects been taken into account. Apparently the majority of predictive capabilities of the two models come from their non-linearity and the inclusion of absolute spatial effects; the inclusion of relative spatial effects only has a marginal benefit towards prediction. The another advantage to considering relative spatial effects when net income be predicted is that the general spatial models offer more accurate and stable estimates of the spatial and regressive parameters than do the alternative parametric models.

Using SAC (the general spatial model), more favorite results are given. They are shown below.

Year	***1998***	***Variable***	***Coefficient***	***Asymptotic t-stat***	***z-probability***
R-square	0.8178	CRC	19.684167	5.319672	0.000000
Rbar-square	0.8115	GDP	11.896106	3.316304	0.000912
		rho	-0.142883	-0.867772	0.385519
		lambda	0.883000	11.737434	0.000000
…		…	…	…	…
Year	***2003***	***Variable***	***Coefficient***	***Asymptotic t-stat***	***Z -probability***
R-square	0.9351	CRC	12.672466	6.007684	0.000000
Rbar-square	0.9329	GDP	23.102377	10.501906	0.000000
		rho	-0.347985	-3.781102	0.000156
		lambda	0.878998	12.210916	0.000000

Table 3：The SAC model result

From table 3, we can see a great increase in the R-square values. Most of them are more than 0.85, which means that the model can explain almost all of the variety of the dependent variable. Interestingly, all the coefficient of the parameter ρ(a parameter of spatial autocorrelation) is negative in this model which means a kind of spatial neighbor competition and a few of the values of the parameters ρ are not statistically significant, whereas the coefficient of the parameter λ(a parameter of spatial error autocorrelation) is rather close to 1 which means a strong spatial autocorrelation error. Yet spatial autoregressive error model with the same dependent and explanatory variables is less better than SAC model.

We also plotted the actual vs. predicted data in figure 4 and figure 5 (They are the normal years), and found that the prediction curve is almost identical with the actual one. It shows good fitness of the model just as expressed in the table 3.

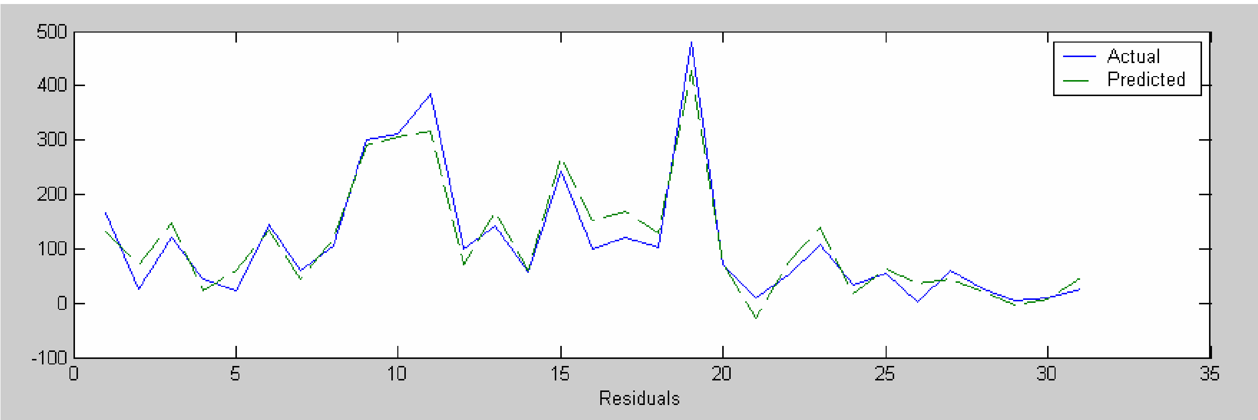

Figure 3：The actual vs. predicted data of 2003 (SAC)

5. DISCUSSION AND CONCLUSION

In this paper, the difference between traditional statistics and spatial statistics are introduced in detail. Then some important models of spatial statistics are introduced. Not only the conception, but the details of the models are represented.

On the other hand, some preliminary applications are attempted to study the efficiency and productivity of radio and TV industry of the 31 China provinces over 17 years. There are three aspects just as the following.

Firstly, to explore the spatial dependence of the market efficiency of radio and TV industry of the 31 China provinces, a spatial structure scatter plot was drawn and found that the existence of the spatial clustering visibly. It shows that those provinces with the highest market efficiency conform to the economic development level, resident consume level and geography attributes of these provinces. In other words, these provinces are in the most productive area in China. Furthermore, Moran's I statistics is computed over 17 years to confirm spatial dependence. From the results, we can see that there is considerable spatial dependence among the 31 provinces in China which means that a certain province tends to have the similar market efficiency as that of its "neighbors".

Secondly, to analysis the market efficiency of radio and TV industry of the 31 China provinces deeply and detect the degree with which it is affected in a certain province by its neighbors, and then consider the changes in the spatial autocorrelation parameter over time. The spatial autocorrelation coefficient for a SAR[1] model was estimated. Judging from the results, the spatial effect of neighbors is rather high in this industry, and almost all of the R-square values are more than 0.8. There is also an increasing tendency of this effect over time. And we know that if the value of

R-square is little, it means that neighbors' effect can not explain fully the variety of the marked efficiency of radio and TV industry in different provinces. On the other hand, the actual vs. predicted data in several years are plotted which makes a more visible expression to show the similar results.

Thirdly, to predict the future productivity of the 31 provinces then provide useful advices to decision-making, with the consideration of the nature of our data itself and by the method of stepwise, a general spatial model is chosen with the net income of the Radio and TV Industry as the dependent variable, and city resident consume (CRC) and GDP as the two explanatory variables. We get a favorite R-square value which means that the model can explain almost all of the variety of the dependent variable. The figures of the actual vs. predicted data exhibit the good fitness of the model as well.

To make a summary, based on the economic database and Radio-TV information database at the territory of China, by applying spatial statistics modules and spatial economics technique, consulting regulation and repository of distribution of radio and TV industry, the spatial distribution and evolvement rule of radio and TV industry in varying level districts at the territory of China can be mined, the correlation between radio and TV industry and region economy can be found, and the developing trend of radio and TV industry in different area and different geographical conditions can be forecasted.

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