Retraction

Retracted: Application and Analysis of Spatial Spillover Effects of an Improved Panel Data Econometric Model in Universities, Population, and Industrial Parks in Guiyang

Mobile Information Systems

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] S. Xu, "Application and Analysis of Spatial Spillover Effects of an Improved Panel Data Econometric Model in Universities, Population, and Industrial Parks in Guiyang," *Mobile Information Systems*, vol. 2022, Article ID 9654342, 10 pages, 2022.

Research Article

Application and Analysis of Spatial Spillover Effects of an Improved Panel Data Econometric Model in Universities, Population, and Industrial Parks in Guiyang

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In the field of econometrics, panel data are an extremely important type of data. In macroeconomic research, panel data models are widely used in exchange rate determination theory, testing of cross-border economic growth and convergence theory, analysis of industrial structure, research on technological innovation, etc. The agglomeration and population distribution of colleges and universities, and the economic support of industrial parks play an important role in economic and social development as a source of research and development and a source of talents. The panel data model usually assumes that the error term follows a normal distribution, but the actual data are difficult to satisfy this assumption, and the estimation obtained by traditional methods may be biased or even invalid. This paper proposes a more robust and effective estimation method (ELS-EL) based on the panel data mean regression model, and extends this method to complex panel data models such as generalized linear models and partial linear models; in addition, this paper is based on panel data. We proposed a two-stage instrumental variable method (2S-IVFEQR) to reduce the computational complexity and generalized the new method to the quantile regression model of dynamic panel data. At the same time, this paper uses the above-improved panel data econometric model to analyze the spatial spillover effects of college aggregation, population distribution, and industrial parks in Guiyang. This study found that the agglomeration of colleges and universities has significantly promoted the economic growth of our country. These promotion effects come from both the direct contribution of college agglomeration and the positive external spillover effect of college agglomeration.

1. Introduction

In the field of econometrics, panel data are an extremely important type of data. As early as the mid-1960s, the NLS in the United States began to collect labor force data information of different age-groups; another well-known panel dataset is the PSID of the University of Michigan, which has collected more than 6,000 representative data from across the United States since 1968 [1]. Annual economic information about 15000 families and more than 15000 individuals. Many countries in Europe have annual or higher-frequency national survey data, such as BHPS in the UK and GSOEP in Germany [2]. While many developing countries have not yet developed a tradition of collecting statistics, panel data are also increasingly common in these countries. In our country, the National Bureau of Statistics has included panel data of some important economic indicators in the National Statistical Yearbook and published it on the official website.

Since the reform and opening up, combined with the law of industrial adjustment, Guiyang has actively promoted the transformation of industrial structure from low level to high level [3]. In the development of the three industries, from the perspective of output value composition as shown in Figure 1, the proportion of the primary industry dropped from 20% to 13%, the proportion of the secondary industry dropped from 60% to 47%, and the tertiary industry increased by 20 percentage points [4]; the structural characteristics of Gansu's modern economy are becoming more and more obvious, but compared with developed areas, there are still problems such as the low proportion of service industry, uncoordinated development among the three
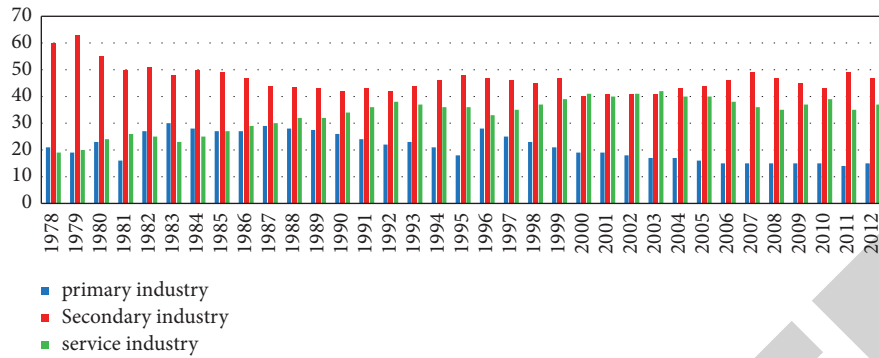
FIGURE 1: The proportion of three industries in Guiyang (%).

industries, and insignificant role of modern industrial sectors [5].

The development level of higher education is an important symbol of a country's educational level, and it is also an important manifestation of a country's comprehensive national strength. The development of higher education is a priority in the national development strategy. It provides talents and intellectual support for economic and social development. It is an indispensable driving force for the sustainable and stable development of the national economy, and has attracted great attention from all over the world. Since the 1990s, our country has successively put forward the "Strategy of Rejuvenating the Country through Science and Education" and the "Action Plan for Educational Revitalization in the 21st Century" [6], and the cause of higher education has achieved rapid development and achieved world-renowned achievements [7]. At the end of 2005, the overall scale of higher education in our country ranked first in the world, marking that higher education has entered the stage of popularization [8]. In 2014, the overall scale of higher education in our country continued to expand. There were 2,824 general higher education institutions and adult higher education institutions nationwide [9], the total number of students in various types of higher education nationwide reached 35.59 million, and the gross enrollment rate of higher education reached 37.5% [10]. Among them, a total of 7,214,000 students were enrolled in general higher education undergraduate programs, and 25,477,000 undergraduate students were enrolled [11]. In 2014, the national total investment in education was 3,280.646 billion yuan, accounting for 5.16% of GDP [12]. Among them, the public finance expenditure on education (including education expenses, infrastructure funds, and education surcharges) was 2,257.601 billion yuan, accounting for 14.87% of the public finance expenditure [13]. On the other hand, with the continuous expansion of the scale of higher education, profound changes have taken place in the higher education management system, and the fragmentation of higher education institutions has been fundamentally reversed. The main system has promoted the rapid development of local colleges and universities, including Guiyang and other central and western regions [14].

However, the further prominence of differences in the agglomeration of colleges and universities in Guiyang, differences in population distribution, and economic differences in industrial parks will also have a profound impact on regional economic growth, as shown in Figure 2 [15]. Therefore, what we should be concerned about is whether there is a spillover effect of higher education resource agglomeration, population distribution, and industrial parks on economic growth [16]? If so, what is the impact on economic growth? Under the background of "deepwater area" and the implementation of strategic adjustment of education structure [17], is it necessary to further adjust regional higher education resources and population and industrial park allocation to narrow regional differences in economic development [18]? In response to the above problems, this paper proposes a mean regression model based on panel data. This method is a more robust and effective estimation method, and this method is extended to complex panel data models such as generalized linear models and partial linear models; this paper proposes a two-stage quantile regression model based on panel data. The instrumental variable method reduces the computational complexity; further extends the new method to the quantile regression model of dynamic panel data to analyze the spatial spillover effects of colleges, population, and industrial parks in Guiyang; and then optimizes higher education, the population in Guiyang, and the regional layout of industrial park resources; it has important practical significance.

2. State of the Art

2.1. Panel Data Model

2.1.1. Definitions. Panel data refer to data obtained by tracking a given individual in different periods. It contains multiple observations of each individual in the sample, and is two-dimensional data with both a time dimension and a cross-sectional dimension [19]. In economic research, panel data have many advantages over traditional time-series or cross-sectional data. First, panel data can provide researchers with a large amount of data, so it can reduce the degree of collinearity between explanatory variables and increase the degree of freedom of the data, thereby
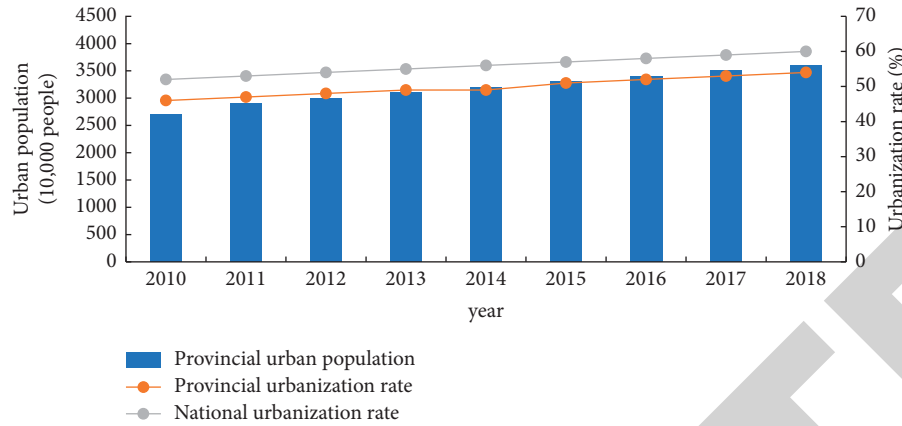
Figure 2: Population urbanization in Guiyang.

improving the effectiveness of model estimation [20]. Second, panel data can control for unobserved heterogeneity of each individual, usually expressed in terms of individual effects or within-group correlations. Third, the panel data model can analyze economic issues from multiple levels and can describe more complex variable structural relationships. Therefore, the panel data model is more and more widely used in the study of economic problems. In macroeconomic research, panel data models are widely used in exchange rate determination theory, testing of cross-border economic growth convergence theory, industrial structure analysis, and technological innovation research; in microeconomic research, panel data models are widely used in business cost analysis, employment, household consumption, and other fields.

2.1.2. Quantile Regression Model for Panel Data.

The quantile regression model was first proposed by Koenker and Bassett. Different from the mean regression, the quantile regression model describes the influence of the explanatory variables on the different quantiles of the explained variables and can make a regression relationship between the variables on the overall distribution. Subsequently, Koenker extended the quantile regression model to panel data and proposed a solution method with penalty terms. With the wide application of the panel data quantile regression model in the economic field, the problem of endogeneity in the model has gradually emerged, that is, if there is a correlation between the quantile level U and one or more explanatory variables, the obtained results will be the same as there will be big deviations in the real sales group. However, due to the particularity of panel data (individual effects), directly applying the IVQR method to the quantile regression model of panel data will lead to extremely complicated calculations, and may increase the bias of the estimate (bias) and reduce the validity of the estimate. Table 1 shows the estimated validity of different panel data models. With the in-depth study of the quantile regression model, the problem of endogeneity has received more and more attention.

2.2. Overview of Spillover Effects

2.2.1. Definition of Spatial Spillover.

"Overflow" is an imported word, and it is easy to misunderstand its meaning by literally interpreting its meaning. It is mistakenly believed that it is the overflow that has a positive impact on the surrounding area and affects the follow-up work of the text. In fact, spillover refers to the fact that when an economic subject conducts a certain social activity, it is easy to have a certain influence on similar subjects. Paul Krugman tried to introduce spatial factors to analyze the spillover effect, and explained the interaction between different subjects by considering the correlation between internal and external subjects in the system.

As for the research of spillover effect, the existing research is generally carried out from the perspective of economic spillover effect, knowledge spillover effect, and human capital spillover effect. First, Keeneth J. Arrow explained the impact of spillover effects on economic development with the help of externalities. Capital investment has spillover effects. Enterprises can promote production by accumulating experience through capital investment, and other enterprises can also promote production through experiential learning. Subsequently, Romer proposed that knowledge uniqueness has a spillover effect, so the knowledge produced by a firm can contribute to the overall production. Finally, Lucas believes that human capital has spillover effects, and a high-quality person promotes learning from each other in the surrounding people, thereby promoting the productivity of all people.

2.2.2. Theories Related to Spatial Spillover Effects.

The externality theory can well explain the spatial spillover effect. The first scholar who proposed the externality theory was Marshall. Economic externality generally refers to the fact that the economic subject's own activities will have an impact on other subjects. There are positive and negative externalities, and the economic interests of other subjects are lost as negative externalities. You will not receive external compensation or loss for your own actions. Albert Hirschman puts forward the theory of unbalanced growth.

TABLE 1: Validity of model estimation with different panel data.

Parameter	OLS		Equal-weight GMM-GLS		Optimal-weight GMM-GLS	
	Coefficient	T value	Coefficient	T value	Coefficient	T value
β	0.142	9.55***	0.243	5.28***	0.249	5.35***
β	0.898	51.94***	0.662	15.21***	0.653	15.01***
β	0.104	6.00***	0.361	7.07***	0.368	7.22***
C	−202	−20.54***	−3.11	−8.46***	−3.14	−8.48***
σ	—	—	0.0751	121.08***	0.0511	135.22***
σ	—	—	0.00067	483.54***	0.00076	50.19***
σ	—	—	0.00392	213.03***	0.00355	75.15***

The pole of economic growth is the precondition for economic development, and the huge impetus of economic progress will make economic growth focus on the pole of growth. He proposed the "trickle-down effect" and the "polarization effect," "trickle-down effect" refers to the promotion effect of developed areas on backward areas, and "polarization effect" refers to the unfavorable effect of developed areas on backward areas.

According to the theory of new economic geography, transportation cost, labor migration rate, and capital scale will affect the resource allocation and integration in the region, and determine whether wealth growth can be achieved in space. On the one hand, if labor migration and capital externalities are generated in the process of regional integration, the scale of industrial space agglomeration will continue to expand, and the distance between urban centers and peripheral areas will continue to increase, resulting in greater economic effects. This inference is also confirmed. On the other hand, if the mobility of labor and capital between regions is poor, the cost of hiring labor and traffic congestion in the urban center will increase, thereby weakening the agglomeration effect and expanding the scope of economic activities.

3. Methodology

3.1. Linear Regression Model for Panel Data.

The linear regression model considering panel data is as follows:

$$y_{it} = x_{it}^T \beta + \alpha_i + \varepsilon_{it}, \quad i = 1, \ldots, n, \ t = 1, \ldots, m_i, \quad (1)$$

where x_{it} is the p-dimensional explanation vector, $\{\alpha_i\}$ represents the individual effect, and $\{\varepsilon_{it}\}$ is the independent and identically distributed error term with a mean of 0 and a variance of $\sigma2$.

3.1.1. Fixed-Effects Model.

In a fixed-effects model, the individual effect can be regarded as the intercept term for each group and thus can be estimated as a parameter. We make

$$y = \left(y_1^T, \ldots, y_n^T\right)^T,$$
$$X = \left(X_1, X_2, \ldots, X_n\right)^T, \quad (2)$$
$$\alpha = \left(\alpha_1, \alpha_2, \ldots, \alpha_n\right)^T,$$

and make

$$Z = \begin{pmatrix} 1_{m1} & 0_{m1} & \cdots & 0_{m1} \\ 0_{m2} & 1_{m2} & \cdots & 0_{m2} \\ \vdots & \vdots & \ddots & \vdots \\ 0_{mn} & 0_{mn} & \cdots & 1_{mn} \end{pmatrix}, \quad (3)$$

which is an indicative matrix of $(m1 + m2 + \ldots + mn) \times p$ dimensions; then, the model can be abbreviated as follows:

$$y = X\beta + Z\alpha + \varepsilon. \quad (4)$$

3.1.2. Random-Effects Model.

In the random-effects model, we regard the individual effect αi as a random term, so it can be combined with the error term ε_{it} as a whole. Let $e_{it} = \alpha_i + \varepsilon_{it}$, $e_i = (e_{i1}, e_{i2}, \ldots, e_{im_i})^T$, and the model transforms into the following:

$$y_i = X_i^T \beta + e_i, \quad i = 1, \ldots, n. \quad (5)$$

It should be noted that the covariance matrix of the vector e is not an independent structure, but

$$Z_i = \begin{pmatrix} \sigma_\varepsilon^2 + \sigma_\alpha^2 & \cdots & \sigma_\alpha^2 \\ \vdots & \ddots & \vdots \\ \sigma_\alpha^2 & \cdots & \sigma_\varepsilon^2 + \sigma_\alpha^2 \end{pmatrix} = \sigma_\varepsilon^2 I_{m_i} + \sigma_\alpha^2 1_{m_i} 1_{m_i}^T. \quad (6)$$

Among them, σ_α^2 represents the variance of the random effect α_i, and I_{mi} represents the mi-dimensional unit matrix.

3.1.3. Linear Models with Unknown Correlation Structure.

The fixed-effects model or the random-effects model above assumes that the individual effect can be extracted from other influencing factors, and is represented by a. However, in practical problems, the individual effect cannot be completely represented by a symbol. It reflects the correlation within the group, and this correlation is often unknown and complex. In order to describe this correlation, researchers proposed the following related structures (commonly referred to as job related structures) and conducted targeted research. We suppose that Ri is the correlation coefficient matrix of Yi (also known as the correlation structure matrix), the element on the diagonal is 1, and the element in the uth row and the Uth column is represented by R_{uv}. If no other restrictions are added, its estimates are available as follows:

$$\widehat{R}_{uv} = \frac{1}{N-p} \sum_{i=1}^{n} \widehat{r}_{iu} \widehat{r}_{iv}. \tag{7}$$

The structure of the work correlation matrix is generally assumed by the background and experience of the research problem. There are three commonly used assumptions: independent structure (independent), exchangeable structure (exchangeable), and first-order autocorrelation structure (AR-1). The work correlation matrix for the independent structure is the identity matrix, that is, it is assumed that there is no correlation within the group. The working correlation matrix of the interchangeable structure is as follows:

$$R(\delta) = \begin{pmatrix} 1 & \delta & \cdots & \delta \\ \delta & 1 & \cdots & \delta \\ \vdots & \vdots & \ddots & \vdots \\ \delta & \delta & \cdots & 1 \end{pmatrix}. \tag{8}$$

3.2. Complex Regression Models for Panel Data

3.2.1. Generalized Linear Model. The generalized linear models, first proposed by Nelder and Wedderburn, generalize traditional linear regression models by making wider assumptions about distributions and a nonlinear link function. It has a wide range of applications in the fields of actuarial science, social surveys, econometrics, biostatistics, and clinical medicine. The common logistic regression (logistic) and Poisson regression models belong to the generalized linear models. In the generalized linear model, the distribution of the explained variable y is extended to the exponential distribution family, and its probability distribution has the following form:

$$f(y \mid \theta, \phi) = \exp\{\phi^{-1}(y\theta - b(\beta)) + c(y, \phi)\}, \tag{9}$$

where θ is a natural parameter, and φ is a scale parameter.

The common probability distributions such as two-point distribution, binomial distribution, Poisson distribution, normal distribution, and gamma distribution are all exponential distributions. A generalized linear model for panel data is defined by the following three elements:

(1) Given the explanatory variable x_{it}, the conditional mean of the explained variable y_{it} is as follows:

$$\mu_{it} = E[y_{it} \mid x_{it}] = g(x_{it}^T \beta), \quad i = 1, \ldots, n, t = 1, \ldots, m_i, \tag{10}$$

where $g(\cdot) = h - 1(\cdot)$ is the known connection function.

(2) Given the explanatory variable x_{it}, the conditional variance of the explained variable Y_{it} is as follows:

$$\text{Var}(y_{it} \mid x_{it}) = \phi \nu(\mu_{it}), \quad i = 1, \ldots, n, t = 1, \ldots, m_i. \tag{11}$$

(3) Given the explanatory variable Xi, the conditional covariance matrix of the explanatory variable $y_i = (y_{i1}, \ldots, y_{im_i})^T$, where Ri depicts the intragroup correlation structure of the ith individual, and $A_i = \text{diag}(b\prime\prime(\theta_{it}))$.

For the generalized linear model of independent data, the maximum likelihood method can be used to estimate the parameters. The maximum likelihood method is a statistical method based on the maximum likelihood principle. The intuitive idea of the maximum likelihood principle is that there may be several results (such as A, B, and C) in a random test. If the result a appears in one test, it can be considered that a appears under the experimental conditions, that is, the probability of $P(A)$ is large. However, for the generalized linear model of panel data, the likelihood function is difficult to determine due to the addition of the intragroup correlation structure, so a new estimation method is required. Liang and Zeger proposed a pioneering estimation method, generalized estimating equation (GEE), which is similar to quasi-likelihood estimation and has become the most important and common method for solving the generalized linear models of panel data. The generalized estimating equation (GEE) is defined as follows:

$$U(\beta, \alpha) = \sum_{i=1}^{n} D_i^T V_i^{-1} S_i = 0. \tag{12}$$

3.2.2. Partial Linear Model. The partial linear models were first proposed by Engle et al. when they studied the relationship between electricity demand and climate change, and have the form

$$Y_i = X_i^T \beta + g(T_i) + \varepsilon_i, \quad i = 1, \ldots, n \tag{13}$$

where β is a $px1$-dimensional parameter vector, $g(\cdot)$ is an unknown benchmark function, ε_i is a random error term, and T can be a multidimensional random variable, but as the number of dimensions increases, the sample size required to estimate g will be very large, so the dimension of Ti is usually assumed to be 1. The partial linear models are a very important class of semiparametric models, which have greater adaptability and stronger explanatory power than the simple linear regression models or nonparametric models, and are widely used in medicine and econometrics. According to the needs of practical applications, many researchers have applied the partial linear models to analyze complex data such as measurement error data, censored data, and panel data and have achieved fruitful results.

We compared several different methods, namely, the quantile regression (QR) method, quantile regression method for panel data (FEQR), instrumental variable method for panel data quantile regression (IVFEQR), two-stage instrumental variable method for quantile regression (2S-IVFEQR1) models, and a two-stage (2S-IVFEQR2) method that improves the estimated fixed-effects part of the 2S-IVFEQR1 method, and when the fixed effects are known (ideal state), the two-stage instrumental variables approach (2S-IVFEQR3). The results are shown in Figure 3.
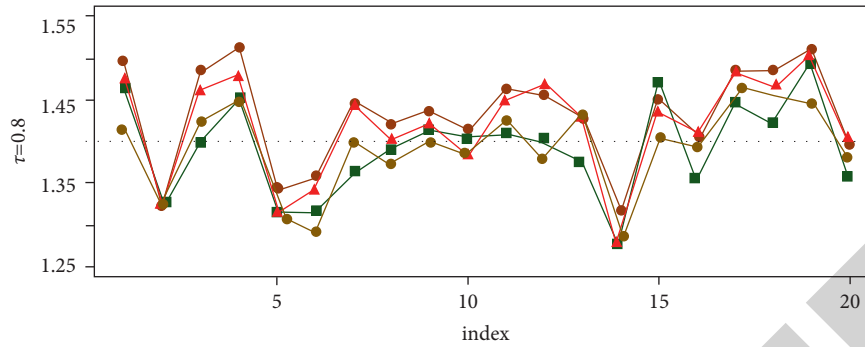
FIGURE 3: Comparison of the estimation results of several methods.

4. Result Analysis and Discussion

4.1. Selection and Processing of Data

(1) The economic level of the park is the explained variable. This indicator reflects the overall level of the park's economic development. Based on the availability and representativeness of data, it is represented by the main business income of the industrial park in Guiyang.

(2) On the basis of referring to the existing relevant literature, according to the principles of comprehensiveness, objectivity, and availability of data, population urbanization, college agglomeration, and economic urbanization are selected as the core explanatory variables. The population urbanization rate is a commonly used indicator to measure population urbanization. It is represented by three methods: the proportion of permanent residents, the proportion of registered population, and the proportion of nonagricultural population. The population proportion method may underestimate the level of urbanization because it does not include the population without household registration in urban areas, and the nonagricultural population data of some prefecture-level cities are missing, so the nonagricultural population proportion method cannot be used, so the permanent resident population proportion method is selected to measure the population urbanization.

(3) Other control variables are as follows. Considering the significant heterogeneity, completeness, and availability of data in various regions of Guiyang City, combined with the previous theoretical analysis, this paper tries to control the relevant characteristic variables of various regions of Guiyang City, and the selected control variables mainly include the level of economic growth, education level, level of opening to the outside world, and level of government support, and the selection of these variables is explained as follows.

Finally, the definitions of variables selected in this paper are shown in Table 2.

4.2. Experimental Results and Analysis.

This paper uses the calculated spatial weight matrix to test the spatial correlation of the economic level of the parks in 14 districts of Guiyang and analyzes the spatial dependence of the park economy. Two indicators are used here, one is the global Moran'I index, and the other is the local Moran'I scatter plot. Table 3 shows the Moran'I index of the main business income of the municipal industrial park in Guiyang and the corresponding statistical test results. It is not difficult to find that at the 5% significance level, the values of the Moran'I index are all greater than 0. Therefore, it can be concluded that the economic space of parks in Hunan Province exhibits the characteristics of spatial dependence.

Next, we will further test the specific impact of each control variable on the economic level of the park, that is, to decompose the spatial effect of urbanization on the economic level of the park. The direct effect represents the direct effect of the independent variable in the model on its own dependent variable; the indirect effect, that is, the spatial spillover effect, represents the influence of the independent variable in the local area on the dependent variable in other areas; the total effect represents the total impact of the local independent variable on all regions in the province. Table 4 lists the total effect, direct effect, and indirect effect of the population urbanization of Guiyang on the park economy in the SDM model. The detailed spatial spillover of the park economy can be more intuitively presented.

It can be seen from Table 4 that the coefficients of lnurban, Intra, and lngov are positive, indicating that population urbanization, social urbanization, and the level of government support will have a positive effect on the park economy in the region. The coefficients of lnegdp, Instrr, Intech, and lnopen are negative, indicating that the park economy in this region will be negatively affected by the level of economic development, economic urbanization, education, and opening to the outside world.

Figure 4 presents the basic statistical information of the economic income of Guiyang Century Industrial Park. It can be seen from the figure that the yield rate does not obey the normal distribution, and the yield rate has the characteristics of the left-side thick tail. It is more reasonable to analyze this non-normal distribution with a quantile regression model. In order to avoid pseudoregression, the yield rate is tested by

TABLE 2: The variable definition table of the improved panel data measurement model.

Variable type	Specific indicators (variables)	Symbol	Definition
Explained variable core explanatory variables	Park economy	Park	Main business income of industrial park
	Population urbanization	Urban	Urban resident population as a percentage of total population
Other control variables' explained variable	Economic urbanization	Str	The output value of the tertiary industry accounts for the proportion of GDP
	Social urbanization	Tra	Regional passenger volume
Core explanatory variables	The level of economic development	Egdp	GDP per capita
	Education level	Edu	Education spending as a percentage of fiscal spending
	Level of opening	Open	The proportion of total foreign capital utilization in GDP
	Specific indicators (variables)	Gov	Local finance as a percentage of GDP

TABLE 3: The results of Moran's test on the main business income of the park in Guiyang.

year	Main business income		
	I	Z	P value
2010	0.036	2.87	0.007
2011	0.030	2.526	0.012
2012	0.023	2.365	0.018
2013	0.032	2.381	0.017
2014	0.031	2.182	0.029
2015	0.039	2.379	0.017
2016	0.039	2.398	0.016

TABLE 4: Decomposition of spillover effects between population urbanization in Guiyang.

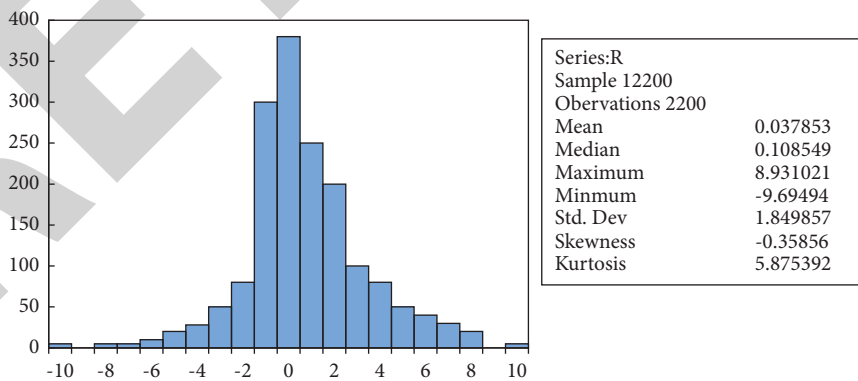| Variable	Direct effect	Indirect effect	Total effect
Inurban	4.159*** (1.434)	5.238*** (3.371)	9.397*** (2.913)
Instrr	−3.273*** (1.018)	2.014 (1.304)	−1.260 (0.769)
Intra	0.761 (0.646)	−5.905*** (1.307)	−5.144** (1.268)
Inegdp	−2.030* (1.099)	3.284*** (1.104)	1.255*** (0.462)
Intech	−0.620 (0.458)	−0.206 (0.466)	−0.826*** (0.102)
Inopen	−0.354*** (0.100)	−0.250 (0.178)	−0.604*** (0.121)
Ingov	1.179 (0.915)	−1.735* (0.976)	−0.555 (0.502)

FIGURE 4: Economic income of Guiyang industrial park.

five methods. This sequence is stable and can be used in regression analysis.

In order to compare the regression results of different methods, the traditional quantile regression method is used to obtain the estimation of the slope parameter and its 95% confidence interval under different quantile levels (91 levels in total), and as shown in Figure 5, the abscissa in the figure represents the quantile level, from 0.05 to 0.95, and the ordinate represents the estimated value of the slope parameter.

It can also be seen from Figure 5 that the parameter estimates under different quantile levels are different. The
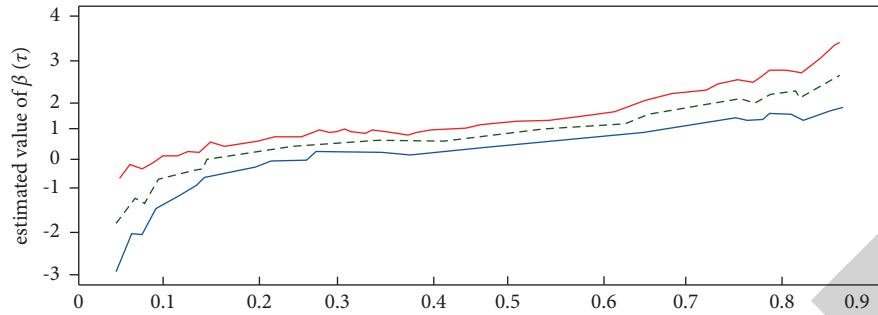
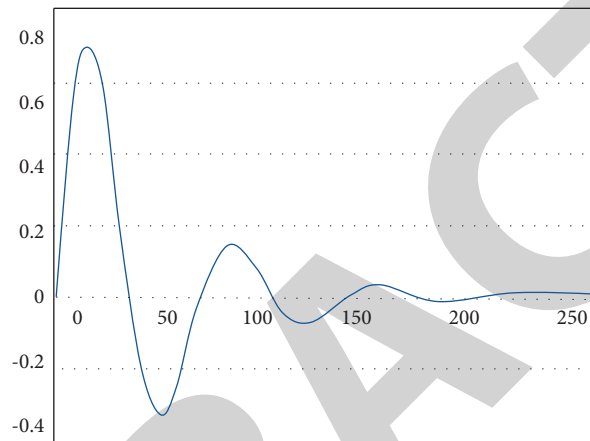FIGURE 5: Quantile regression slope parameter estimates.

FIGURE 6: Impulse response function of industrial park structure in Guiyang.

TABLE 5: Regression results of university aggregation on the economic level of industrial park in Guiyang city.

	NF	SF	TF	STF
CSN	0.129*** (6.481)	−0.005 (−0.164)	0.094*** (5.397)	0.052* (1.657)
LAB	−0.009 (−0.351)	0.046 (1.503)	0.004 (0.164)	0.110*** (3.233)
KCS	0.787*** (38.901)	0.435*** (17.320)	0.645*** (31.084)	0.358*** (13.256)
OP	0.066*** (6.945)	−0.008 (−0.654)	0.113*** (12.037)	0.011 (0.987)
IS	−0.00003 (−0.001)	−0.100** (−1.982)	−0.011 (−0.359)	−0.146*** (−2.923)
MARK	0.344*** (9.509)	−1.799** (−5.272)	1.513*** (5.262)	−0.314 (−0.370)
W* dep.var	−0.039*** (−5.629)	0.342*** (10.766)	−0.049* (−1.657)	0.131*** (3.071)
R^2	0.842	0.945	0.893	0.954
Log L	−13.451	235.571	29.571	282.589

higher the quantile level, the larger the estimated parameter value. When the correlation between the economic level of Guiyang industrial parks, college agglomeration, and population urbanization is positive, the greater the quantile level, and the stronger the correlation between the economic level of Guiyang industrial parks, college agglomeration, and population urbanization. This may be because he higher the yield, the heavier the bullish sentiment of investors, and the greater the impact on the trading volume. The more obvious this two-way impact is, the stronger the correlation is.

The structure of the industrial park in Guiyang is analyzed using the impulse response function, and the results are shown in Figure 6. The horizontal axis represents the number of variable responses, and the vertical axis represents the magnitude of the variable responses. Figure shows under the condition of the second-order lag, the industrial

structure response to GDP, in the early industrial upgrading on the impact of GDP, and the secondary industry development impulse response to GDP that the development of GDP has a positive impact on industrial development; after 150 period, the function gradually tends to 0, because the subsequent pulse influence relationship tends to 0, indicating that the model is stable.

Table 5 shows the regression results of the agglomeration of colleges and universities in Guiyang on the economic level of the industrial park. It can be seen from the table that the estimated coefficient of agglomeration of colleges and universities in Guiyang is 0.052, and it is significantly positive at the level of 10%, indicating that the degree of college agglomeration increases by 1% for every 1% increase. Through the lag effect of spatial economic growth in Guiyang, that is, the overflow of urban

spatial economic growth, the economic growth of Guiyang is 0.052 percentage points, that is, the direct output elasticity value of college agglomeration is 0.052. The estimated coefficient of the spatial autoregression coefficient is 0.131, and through the 1% significance test, it can be seen that the spillover effect of economic growth is 0.131, and then, the spillover effect of college agglomeration is calculated to be 0.008. This means that the economic growth rate will increase by 0.008 percentage points for every 1 percentage point increase in the degree of university aggregation in Guiyang, which indicates the positive externality of the degree of university aggregation.

5. Conclusions

The purpose of this study is to use the improved panel data econometric model theory and incorporate spatial effects to deeply explore the role of population urbanization and college agglomeration in Guiyang on the economy of Guiyang's industrial parks. According to the analysis results of the above paper, the following conclusions are drawn: the agglomeration of colleges and universities has a spatial spillover effect on the economic growth of industrial parks in Guiyang, and its output effect is 0.06, which means that every 1% increase in the degree of agglomeration of colleges and universities will lead to the economic growth of industrial parks in Guiyang. The direct output elasticity of college agglomeration is 0.052, while the output elasticity of the spillover effect is 0.008. In addition, the positive spatial spillover effect of the labor force and physical capital is significant, which has a significant promoting effect on economic growth, and the industrial structure and marketization level have a negative spatial spillover effect on economic growth.

Data Availability

The labeled dataset used to support the findings of this study is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

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