land

Article

Study on the Efficiency, Evolutionary Trend, and Influencing Factors of Rural–Urban Integration Development in Sichuan and Chongqing Regions under the Background of Dual Carbon

Pan Jiang [1,2], Yirui Yang [1,*], Wei Ye [1], Liang Liu [1], Xinchen Gu [3,4], Haipeng Chen [5] and Yuhan Zhang [1,2]

1 School of Economics and Management, Southwest University of Science and Technology, Mianyang 621010, China; jiangpan@mails.swust.edu.cn (P.J.); yewei@mails.swust.edu.cn (W.Y.); liuliang@swust.edu.cn (L.L.); zhangyh@mails.swust.edu.cn (Y.Z.)
2 School of Environment and Resource, Southwest University of Science and Technology, Mianyang 621010, China
3 State Key Laboratory of Hydraulic Engineering Simulation and Safety, School of Civil Engineering, Tianjin University, Tianjin 300072, China; gxc@tju.edu.cn
4 State Key Laboratory of Simulation and Regulation of Water Cycle in River Basin, China Institute of Water Resources and Hydropower Research, Beijing 100044, China
5 College of Economics, Sichuan Agricultural University, Chengdu 611130, China; chenhaipeng@stu.xhu.edu.cn
* Correspondence: yyr201124@163.com

Citation: Jiang, P.; Yang, Y.; Ye, W.; Liu, L.; Gu, X.; Chen, H.; Zhang, Y. Study on the Efficiency, Evolutionary Trend, and Influencing Factors of Rural–Urban Integration Development in Sichuan and Chongqing Regions under the Background of Dual Carbon. *Land* **2024**, *13*, 696. https://doi.org/10.3390/land13050696

Academic Editor: Marko Scholze

Received: 15 April 2024
Revised: 11 May 2024
Accepted: 14 May 2024
Published: 15 May 2024

Abstract: Re-evaluating how urban and rural development can be integrated is a necessary step towards achieving the "dual-carbon" objective and facilitating a thorough transition towards a green and low-carbon economy and society. This study empirically investigates the geographical disparities, evolving patterns, and determinants of the effectiveness of urban–rural integration development in Sichuan and Chongqing. Results of the study indicate that (1) the effectiveness of urban–rural integration development in Sichuan and Chongqing is generally poor, and external environmental factors adversely affect the urban–rural integration of economically developed cities; (2) the urban–rural integration development efficiency in Sichuan and Chongqing does not show a more obvious polarization phenomenon, but the gap between the cities gradually widens; and (3) regarding influencing factors, market dynamics are favorable to overall urban–rural integration development in the Sichuan and Chongqing regions, while the development of the digital economy and the level of financial development can exacerbate the imbalance of regional urban–rural integration development. Based on this premise, pertinent policy suggestions are offered to facilitate the merger of urban and rural areas and foster efficient development in the regions of Sichuan and Chongqing.

Keywords: carbon emissions; Sichuan and Chongqing regions; integrated urban–rural development; three-stage DEA

1. Introduction

With the advancement of urbanization, rural labor and capital are constantly gathering in towns and cities. The phenomena of the hollowing out of rural areas and deterioration of the human environment are gradually emerging. Urban and rural development is increasingly unbalanced and uncoordinated. From the viewpoint of international trends [1,2], contradictions and conflicts that arise between rural and urban regions have emerged as a global phenomenon, and the increasing disparity between urban and rural areas poses formidable obstacles for countries globally in achieving the objective of sustainable development [3,4]. Thus, developed and developing nations are investigating this option to find an integrated urban–rural development strategy that works for their unique national circumstances. In Korea, the "New Rural Movement" was launched in 1970 to promote the reconstruction of villages. Other examples include Japan's "Integrated Village Construction Demonstration Project" and agricultural support policy, Europe's Common Agricultural

Policy, and the U.S. policy of building small towns to spur rural development. These are positive attempts to promote rural development. China has experienced the world's fastest urbanization process, and urban–rural inequality is obvious. Since the 21st century, with economic system reform measures implemented and deepened, China's urban–rural relationship has changed [5]. Several issues, such as the prominent urban–rural "dual structure" and the inadequate smooth flow of factors, have been partially addressed [6]. However, urban and rural construction requires a lot of energy and resource inputs and a massive carbon emission source. A low-carbon economy prioritizes reduced energy consumption, minimized pollution, and decreased emissions. However, the long-standing practice of promoting political success through crude urban and rural development is in direct opposition to the concept of a low-carbon economy. Focusing on this real-life contradiction, it is imperative to alter the development paradigm and policy implementation methodology to advance urban and rural development by prioritizing the efficient use of energy and the recycling of resources as the central focus. China is now focusing on urban–rural integration and reforming urban–rural connections as key ideas and strategies to implement the rural rehabilitation plan. The state council issued the Peak Carbon Action Program by 2030, which includes new guidelines for China's urban–rural integration with a focus on promoting green and low-carbon practices. Hence, the methods to advance the effective progress of urban–rural integration within a dual-carbon framework and stimulate rural revitalization through integrated urban–rural development are not only the primary concerns of the party and the state during the period of rapid transition, but also gaining more attention in the contemporary academic sphere.

Sichuan and Chongqing are the key development areas in the national western development plan. The urban and rural development of Sichuan and Chongqing has an important spillover effect on the healthy economic development of the western region. After the release of the "Outline of the Plan for the Construction of Chengdu-Chongqing Twin-city Economic Circle" in October, the development of Sichuan and Chongqing, with Chengdu and Chongqing at its core, has ushered in more opportunities and challenges. Since the implementation of the "Outline" since the landing of the Sichuan and Chongqing regions, the momentum of economic development has been strong, the industrial system, infrastructure, public services, etc., have continued to improve, and the innovation capacity has been significantly enhanced. It has become a synergistic drive for Western development on both an economic and social level. It has also been a drive for ecological civilization, reform, and innovation and the expansion of the opening vital important power sources. However, compared with the eastern region, where development started early and from a high base, and where the environment for development is good, urban and rural areas continue to be divided in the Sichuan–Chongqing region, with factors of production primarily flowing in one direction from urban to rural areas. Among urban and rural populations, income disparities are significant, as is the digital divide and unequal access to public services and infrastructure. The issue of environmental pollution caused by rapid development and the lack of green innovation technology is increasingly severe. Over CNY 20,000 of income gap existed between urban and rural residents in Chengdu City in 2021. At the level of pollution emission, per capita industrial wastewater emission in Yibin City has already exceeded 15 t/person. Therefore, the promotion of integrated urban–rural development not only needs to focus on the state and speed but also should take into account efficiency so as to ensure that the development is in a virtuous cycle.

Therefore, we establish a comprehensive evaluation framework for analyzing the efficiency of urban–rural integration development (EURI). Data from 19 cities in Sichuan and Chongqing from 2010 to 2021 were selected. The EURI is measured by using the three-stage DEA mode, the evolution trend of the EURI is identified through the kernel density method, and lastly, the factors influencing urban–rural integration are evaluated using the spatial Durbin model.

2. The Literature Review

Both urban and rural areas have a mutual influence and a symbiotic relationship that involves interaction [6]. Economically and socially speaking, the urban–rural relationship has a considerable effect on the cohesion of the whole country and has received significant attention from many researchers [7]. There has also been a change in the academic understanding of urban–rural relations, from symbiosis to separation and antagonism to coordination and integration. The integration of urban and rural areas represents a highly developed phase in the progression of urban–rural relationships, aiming to change regional development strategies' urban bias and promote equal development.

Engels first proposed and theorized "urban-rural integration" in Principles of Communism [8]. Dualistic structure theory [9], human–land relationship territorial system theory [10,11], regional spatial structure theory [12], spatial equilibrium theory [13], and other theories have been put forward. A variety of theoretical and empirical research has been conducted by scholars [14], focusing on the theoretical lineage of urban–rural integration, concept definition, connotation analysis, measurement and evaluation, influencing factors, etc. [15–18]. Results indicate that existing studies are primarily grounded in qualitative analysis [19–21] and quantitative research [22,23]. Academics both domestically and internationally have examined the implied meaning of urban–rural integrated development from sociology [24], economics [25], and ecology. Despite the differences in research focuses and perspectives, urban–rural integration is the process of merging and fostering the growth of urban and rural regions, as recognized by researchers.

A growing concern has arisen about how to measure urban–rural integrated development as its connotations and extension grow and deepen [8,26,27]. In addition to qualitative analysis, quantitative research has gradually replaced qualitative analysis as a method of measuring urban–rural integrated development. From the standpoint of quantitative research approaches, it is mainly divided into two categories: indicator method [28,29] and model method. The indicator method incorporates the principles of system theory and dual structure theory with the coupled coordination degree model [30], entropy weight method, and comprehensive index method [18,31] as the main focus, and the selection of indicators is also evolving from uni-dimensional to multi-dimensional [32–34]. After that, the use of spatial panel data imposed higher standards on research methods, and an increasing number of academics use data envelopment analysis to measure the EURI [35] to eliminate the limitations of the indicator system method in the assignment of variables, to make the efficiency results obtained from the measurement more truly and reliably reflect the degree of urban–rural integration and development. Simultaneously, with the help of the Tobit model [36], spatial Durbin model [37], and other methods, an in-depth analysis is conducted on the factors that influence the EURI. On the scale of research, existing studies are dominated by countries [38], urban agglomerations [39], and provinces [40] with a gradual focus from the meso-macro to the micro.

Previous studies have discussed the theoretical implications and measurement techniques for assessing urban–rural integration progress. However, there is a dearth of research that takes into account carbon emissions when assessing the effectiveness of urban–rural integration growth. Furthermore, the effects of external and stochastic factors are usually ignored in efficiency measurements. This study addresses these issues by using a three-stage DEA model to assess EURI in 19 cities in Sichuan and Chongqing from 2010 to 2021 and exploring its time-series dynamic evolution characteristics and spatial spillover effects based on the results of the measurements by comprehensively applying kernel density estimation and spatial Durbin model. Based on the study's conclusions, policy recommendations in line with the reality of the Sichuan and Chongqing regions are proposed.

3. Research Objects and Methods

3.1. Description of the Study Area

As shown in Figure 1, Sichuan Province and Chongqing Municipality are close to each other because of their proximity to each other and their similar cultural and living customs, so they often refer to the collective name of the two places as "Sichuan and Chongqing". The Sichuan–Chongqing region, sometimes called the "southwest hinterland" and "the land of abundance", has a population of over 120 million, making up 8.4% of the country's total population. It covers an area of over 560,000 square kilometers, accounting for 5.9% of the country's total area. The Sichuan–Chongqing region has the greatest growth potential in the western region and is a key component of the upper Yangtze River Economic Belt. It occupies an irreplaceable and significant position in the country's regional strategic layout.

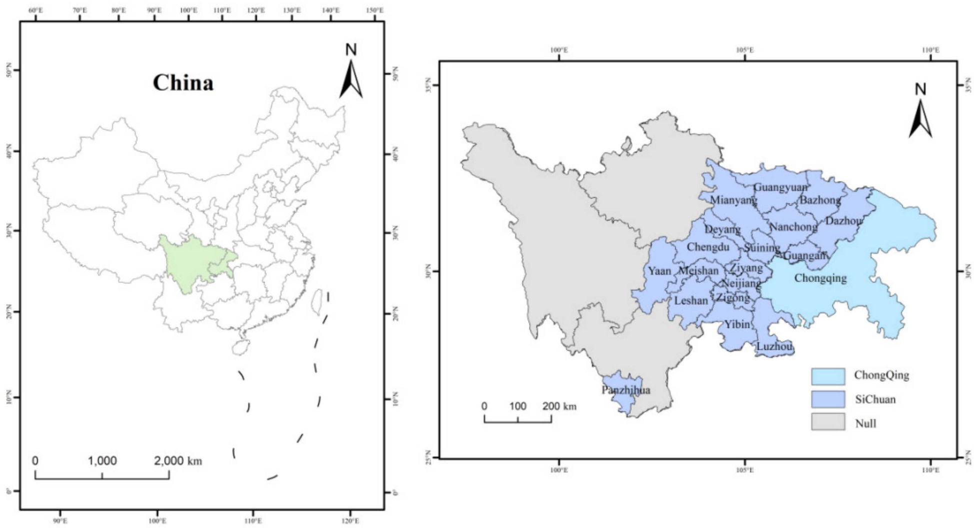

Figure 1. Location of Sichuan and Chongqing.

Since the 21st century, economic growth as well as urbanization in Sichuan and Chongqing have entered the fast lane. From 2000 to 2021, the total population of Sichuan and Chongqing increased from 110.84 million to 115.84 million, an increase of 4.5 percentage points. The urban populations also doubled from 32.13 million to 70,998,300 during the same period. In terms of urbanization level, the urbanization rate of the Sichuan–Chongqing urban agglomeration increased from 28.99% in 2000 to 61.29% in 2021, an increase of more than 30 percentage points. However, compared with the national average over the same period, it lags behind by more than 3 percentage points, and the urbanization level is still low.

3.2. Choosing Indicators and Data Sources

3.2.1. Selection of Indicators for the Level of Integrated Urban–Rural Development

The degree of urban–rural integration in an area is intricately linked to the overall level of regional development. The presence of interwoven linkages and patterns of interaction between urban and rural regions is due to the varying stages of development and urbanization. The urban–rural integration index system developed by earlier researchers is cited in this work [29,41–43], combines the characteristics of its own research, and selects the relevant indicators from the five aspects of economic integration, demographic integration, social integration, spatial integration, and ecological integration. And the urban–rural integration development index system consisting of 5 first-level indicators and 12 second-level indicators is shown in Table 1. The composition and content of each dimension are as follows: (1) Economic integration is characterized by the urban–rural consumption structure and the urban–rural income structure, which serve as indicators of the region's economic development, the purchasing power of its residents, and the standards of living in terms of income and consumption. (2) Population integration: The population urbanization rate reflects the region's urbanization stage. At the same time, the number of students in compulsory education can measure the proportion of minors in the regional population structure. (3) Social integration: The allocation and investment in public goods by the government determine the distribution of public services and infrastructure, including educational equity, health security, and life support, in different regions. (4) Spatial integration: Transportation is crucial for the integration and development of urban and rural areas. The density of the highway road network indicates the level of ease and efficiency in facilitating two-way traffic between urban and rural areas. Urban spatial expansion is a measure of the extent and organization of urban space. It offers insights into the extent of regional development and the level of coordination in terms of land urbanization. (5) Ecological integration: The ecological environment serves as the fundamental and necessary basis for the existence, growth, and well-regulated functioning of other aspects of the urban and rural territorial system. It also serves as a crucial indicator of the sustainability of regional development. We have chosen key indicators for domestic waste management, air quality, and the level of greenery to assess the ecological environment and quality of life in the region.

Table 1. Evaluation indicators of the level of urban–rural integration development in Sichuan and Chongqing regions.

Subsystems	Indicators	Description or Calculation of Indicators	Weights	Causality
Economic integration	Rural and urban consumption structure	Regional total retail sales of consumer goods/regional average annual population (CNY/person)	0.110	+
	Rural and urban income structure	Per capita disposable income of permanent urban residents/per capita disposable income of permanent rural residents (%)	0.013	−
Population integration	Population urbanization level	Urban resident population/area average annual population (%)	0.060	+
	Number of pupils in compulsory education	Number of students enrolled in secondary and primary schools/average annual population of the region	0.033	+
Social integration	Social security services	Number of urban and rural residents enrolled in health insurance/area average annual population (%)	0.166	+
		Number of urban and rural residents insured by unemployment insurance/average annual population of the region (%)	0.247	+
	Configuration of educational services	Secondary school student–teacher ratio/ministry of education mandated student–teacher ratio standards	0.018	−
		Pupil–teacher ratio in primary schools/standard pupil–teacher ratio set by the ministry of education	0.019	−
	Urban and rural infrastructure	Urban and rural water penetration rate (%)	0.022	+
		Urban and rural gas penetration rate (%)	0.016	+
Spatial integration	Urban spatial expansion	Built-up area/total urban area (%)	0.168	+
	Density of road network	Road area per capita (square meters)	0.051	+
Ecological integration	Urban and rural domestic waste disposal	Non-hazardous treatment rate of domestic waste (%)	0.012	+
	Urban and rural air quality	$PM_{2.5}$ annual average concentration ($\mu g/m^3$)	0.046	−
	Level of urban and rural greening	Greening coverage of built-up areas (%)	0.020	+

This study utilizes the entropy weight approach to ascertain the weight of each indicator. The entropy weighting method provides objective weights, allowing for a more accurate reflection of the differences among various factors in the region. This method is more precise compared to subjective methods like the hierarchical analysis method.

3.2.2. Selection of Input–Output Indicators

At present, according to the basic theory of economics, the relevant economic output mainly depends on labor input, capital input, and land input; in addition to the above basic factors of production, the increasing significance of energy demand is evident in both urban and rural development. This study refers to the existing literature [35,44,45], which will be included in the energy input into the input indicators. The desired outputs are urban GDP and the level of urban–rural integrated development measured above. The goal of China's green transformation is to promote both social pollution reduction and carbon emission reduction. Therefore, this paper regards carbon emissions and pollutant emissions as undesirable outcomes that hinder China's overall progress in achieving its green transformation goals.

The urban–rural integrated development will be affected by environmental variables, and cities cannot control or change the external environment in the short term. Three aspects comprise the corresponding environmental variables: the social environment, the economic environment, and the institutional environment. A variable representing the economic environment is selected as GDP per capita [46]. Considering that GDP per capita reflects to some extent the regional economy's development, higher GDP per capita indicates a more favorable macroeconomic environment. The social environment variable selects industrial structure [47] because the industrial layout between urban and rural areas has an important influence on urban and rural development. At the same time, modifications and upgrades to industrial structures will also impact regional energy utilization and pollutant emissions. The institutional environment variable selects the general financial expenditure characterization [48], which indicates the regional government's support and regulation of urban–rural development because of the government's policies of assisting agriculture, and as a result of poverty alleviation, there has been some reduction in the urban–rural divide. Specific indicators and descriptive analysis are shown in Table 2.

Table 2. Input–output indicators of EURI in Sichuan and Chongqing regions.

Level 1 Indicators	Secondary Indicators	Description of Indicators	Data Sources
Input indicators	Labor inputs	Average annual number of practitioners	Municipal statistical yearbooks
	Land inputs	Built-up area	
	Capital inputs	Total investment in fixed assets	
	Energy inputs	Annual electricity consumption	
Output indicators	Expected outputs	Level of urban–rural integration and development GDP	
	Non-expected outputs	Total CO_2 emissions Pollutant emissions (entropy weighting synthesis)	
Environmental indicators	Economic environment	Per capita GDP	
	Institutional environment	Financial expenditure	
	Social environment	Value added of tertiary industry/value added of secondary industry	

3.2.3. Sources of Research Data

The research data for this study were extracted from the statistical yearbooks of 19 cities, including Sichuan Province and Chongqing Municipality, with areas such as Ganzi Aba and Liangshan Prefecture excluded due to data acquisition problems. Some of the data that are absent are supplemented with the official announcements of each municipality, and the data that remain are approximated through interpolation.

3.3. Research Methodology

3.3.1. Entropy Weighting Method

The entropy weight method is an evaluation method with objective assignment, and the weights of evaluation indicators depend on the degree of variability of the indicator values, which eliminates human factors and subjective evaluativeness to a certain extent, and the greater the degree of variability, the greater the weights, reflecting the relative importance between the indicators. Drawing on existing studies [43,49], this paper applies the entropy weight method to measure the urban–rural integration development of 19 cities in the Sichuan and Chongqing regions from 2010 to 2021. The following are the precise assessment steps.

(1) The following raw data matrix is created assuming the existence of assessment indicators and objects:

$$X = \begin{pmatrix} x_{11} & x_{12}\cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & x_{m2}\cdots & x_{mn} \end{pmatrix} = (X_1\, X_2 \cdots X_n) \tag{1}$$

$x_{ij}(i = 1, 2, \cdots, m; j = 1, 2, \cdots, n)$ represents the column vector data of every evaluation item in the j-th indicator, and $X_j(j = 1, 2, \cdots, n)$ represents the value of the i-th evaluation object in the j-th indication in Equation (1). As the original data of the selected evaluation indicators have different units and scales, they cannot be compared directly and need to be standardized for the original data. The polar deviation standardization technique is used in this article, and its formula is as follows:

$$\begin{aligned} \text{Positiveindicators: } x'_{ij} &= \frac{x_{ij} - min\{x_{ij}\}}{\underset{i}{max}\{x_{ij}\} - \underset{i}{min}\{x_{ij}\}} \\ \text{Negativeindicators: } x'_{ij} &= \frac{max\{x_{ij}\} - x_{ij}}{\underset{i}{max}\{x_{ij}\} - \underset{i}{min}\{x_{ij}\}} \end{aligned} \tag{2}$$

(2) Determine the ratio of the $i-th$ evaluation object's $j-th$ indication to the indicator y_{ij} in order to obtain the percentage matrix $Y = \left(y_{ij}\right)_{m\times n}$.

$$y_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{m} x'_{ij}} \qquad (j = 1, 2, \ldots, n) \tag{3}$$

(3) Calculate the information entropy e_j for the j-th indicator.

$$e_j = -K\sum_{i=1}^{m} y_{ij} ln\, y_{ij} \qquad (j = 1, 2, \ldots, n) \tag{4}$$

where $K = \frac{1}{\ln m}$ is a non-negative constant and $0 \le e_j \le 1$, and it is stipulated that $y_{ij}\ln\, y_{ij} = 0$ when $y_{ij} = 0$.

(4) Calculate the coefficient of variation for item j-th, d_j.

$$d_j = 1 - e_j \qquad (j = 1, 2, \ldots, n) \tag{5}$$

(5) Calculate the weight of the j-th indicator w_j.

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} = \frac{1 - e_j}{n - \sum_{j=1}^{n} e_j} d_j = 1 - e_j \ \ (j = 1, 2, \ldots, n) \tag{6}$$

(6) Calculate the level of urban–rural integration development U_i for the i-th evaluation object:

$$U_i = \sum_{j=1}^{n} y_{ij} w_j \ \ (i = 1, 2, \ldots, m) \tag{7}$$

3.3.2. Three-Stage DEA

The three-stage DEA method was proposed by Fried et al. The model firstly measures the efficiency of the research object initially in the first stage, then introduces the SFA regression model in the second stage to separate the effects of external environmental factors and random disturbances, and finally measures the real value of the EURI in the third stage. In this paper, the first stage of the three-stage DEA is improved into a super-efficient SBM-Global model based on non-expected output [50].

Phase I: Super-efficient SBM-Global model. An inventive non-radial, non-angle SBM model was put out by Tone [51]. The radial DEA model metric's input factor redundancy issue is well resolved by this model. In order to attain the aim of an efficient DMU without lowering output, this research chooses to use an input-oriented, super-efficient SBM model, concentrating on what modifications need to be made to each input.

The specific form of the super-efficient SBM-Global model considering slack variables is as follows:

$$\min\rho = \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\overline{x}}{x_{ik}}}{\frac{1}{r_1+r_2}\left(\sum_{s=1}^{r_1}\frac{\overline{y^d}}{y_{sk}^d}+\sum_{q=1}^{r_1}\frac{\overline{y^u}}{y_{qk}^u}\right)}$$

$$\text{s.t.}\begin{cases} \overline{x} \geq \sum\limits_{j=1,\neq k}^{r_1} x_{ij}\lambda_j \ (i = 1,2,3,\ldots,m) \\ \overline{y^d} \leq \sum\limits_{j=1,\neq k}^{n} y_{sk}^d\lambda_j \ (s = 1,2,3,\ldots,r_1) \\ \overline{y^d} \geq \sum\limits_{j=1,\neq k}^{n} y_{qj}^b\lambda_j \ (q = 1,2,3,\ldots,r_2) \\ \lambda_j > 0 \ (j = 1,2,3,\ldots,n; j \neq 0) \\ \overline{x} \geq x_k \ (i = 1,2,3,\ldots,m) \\ \overline{y^d} \leq y_k^d \ (s = 1,2,3,\ldots,r_1) \\ \overline{y^u} \geq y_k^u \ (q = 1,2,3,\ldots,r_2) \end{cases} \quad (8)$$

where ρ denotes the efficiency of urban–rural integration development, and DMUs are fully efficient when $\rho \geq 1$ and the redundancy is 0; n is the number of decision-making units (DMUs); m, r_1, and r_2 are the number of inputs, desired outputs, and non-desired outputs, respectively, $s = \left(\overline{x}, \overline{y^d}, y^u\right)$ denotes the amount of inputs, desired outputs, and non-desired outputs redundancy, and λ denotes the vector of weights. When $\rho < 0.6$, DMU is inefficient; $0.6 \leq \rho < 0.8$ is moderately efficient; $0.8 \leq \rho < 1$ is good efficiency; and $\rho \geq 1$ is high efficiency.

Phase II: SFA regression. The input slack variable obtained in the first stage mainly consists of three parts: environmental factors, management inefficiency, and statistical noise, and the SFA regression model is used in the second stage to eliminate statistical noise and environmental influences. The following SFA regression model is constructed with each input slack as dependent variable and environmental variables as independent variables:

$$s_{ij} = f^j\left(z_i, \beta_j\right) + v_{ij} + u_{ij}(i = 1,2,\ldots,N; j = 1,2,\ldots,P) \quad (9)$$

It is defined as follows: s_{ij} is the input slack variable, z_i is the environmental variable, the coefficient of the environmental variable is β_j, $v_{ij} + u_{ij}$ are the mixed error terms, input slack is affected by random disturbances represented by v_{ij}, and $v_{ij} \sim N\left(0, \sigma^2{}_{iv}\right)$, and u_{ij} denotes managerial factors affecting the input slack variable, which obeys the semi-normal distribution, and $u_{ij} \sim N^+\left(\mu^j, \sigma^2{}_{ju}\right)$.

To exclude the influence of random and environmental elements from the efficiency assessment, the following adjustment formula is created based on the findings of the SFA regression:

$$\begin{aligned} X^A{}_{ni} = X_{ni} + [\max(f(Z_i:\beta_n)) - f(Z_i:\beta_n)] \\ +[\max(v_{ni}) - v_{ni}](i = 1,2,\ldots,I; n = 1,2,\ldots,N) \end{aligned} \quad (10)$$

where $X^A{}_{ni}$ and X_{ni} denote the inputs after and before adjustment, respectively, $\max(f(Z_i : \beta_n)) - f(Z_i : \beta_n)$ is the adjustment of the environmental factors, and $\max(v_{ni}) - v_{ni}$ denotes that all the decision-making units are adjusted to the same stochastic interference conditions.

Phase III: The above adjusted inputs and original outputs are again accounted for using the DEA model to obtain a more reliable efficiency of urban–rural integration development after removing environmental and random factors.

3.3.3. Kernel Density Estimation Method

Kernel density estimation is a crucial tool for analyzing the evolutionary pattern and distributional dynamics of certain variables. As is shown in the following equation, it is used to illustrate distributional dynamics and evolutionary patterns of integration development among rural and urban areas in Sichuan and Chongqing.

$$f(x) = \frac{1}{Nh}\sum_{i=1}^{N} K\left(\frac{X_i - x}{h}\right) \tag{11}$$

where $f(x)$ is the kernel density function of urban–rural integration development efficiency x; N is the number of cities in the observation area; X_i is the independently distributed observations; and x is the mean value of X_i, i.e., the mean value of the EURI measure of a certain region on the period i. This paper uses the Gaussian kernel density function as the kernel density function, and h is the bandwidth, and the smaller the bandwidth is, the more precise the estimation is.

3.3.4. Spatial Durbin Model

(1) Spatial weighting matrix setting

In this study, we sequentially constructed the geographic weight matrix w_{ij}^D between cities, the economic weight matrix w_{ij}^E between cities (districts), and the spatial nested weight matrix w_{ij}^O based on geographic distance and economic distance.

$$\begin{gathered} w_{ij}^D = \begin{cases} 0, (\text{When region i is not adjacent to region j}) \\ 1/d_{ij}^2, (\text{When region i is adjacent to region j}), \\ d_{ij} \text{ is the distance between the geographic centers of the two cities.} \end{cases} \\ w_{ij}^E = \begin{cases} 0, (\text{When region i is not adjacent to region j}) \\ 1/\left|\overline{Y_i} - \overline{Y_j}\right|, (\text{When region i is adjacent to region j}) \\ \overline{Y_i} \text{ and } \overline{Y_j} \text{ denote the GDP per capita of city(district) i and j.} \end{cases} \\ w_{ij}^O = w_{ij}^D \times w_{ij}^E \end{gathered} \tag{12}$$

(2) Spatial measurement modeling

Based on a spatial panel model, the influencing factors of EURI are analyzed.

$$\begin{gathered} EURI_{i,t} = \rho \cdot W \cdot EURI_{i,t} + \sum_{j=1}^{n} \beta_j X_{j,i,t} + D \cdot X_{i,t} \cdot \theta + \mu_i + \gamma_t + V_{i,t} \\ V_{i,t} = \lambda \cdot E \cdot V_{i,t} + \varepsilon_{i,t} \end{gathered} \tag{13}$$

where $EURI_{i,t}$ represents the EURI of the $i-th$ city for the year t; ρ is the coefficient of the spatial lag term of the EURI; W is the weight matrix; and $X_{j,i,t}$ is the explanatory variable. The explanatory variable's spatial lag is represented by $D \cdot X_{i,t} \cdot \theta$; μ_i and γ_t represent time and area fixed effects, respectively; $\lambda \cdot E \cdot V_{i,t}$ is the spatial lag of the perturbation term; λ is the appropriate coefficient; E is the perturbation term's spatial weight; and ε is the error term with zero mean and σ^2 variance.

When $\lambda = 0$ in the model, it is a spatial Durbin model (SDM).

When $\lambda = 0$ and $\theta = 0$ in the model, it is a spatial autoregressive model (SAR).

When ρ = 0 and θ = 0 in the model, it is a spatial error model (SEM).

4. Evaluation of EURI in Sichuan and Chongqing Urban Agglomerations

4.1. Phase I: Super-Efficient SBM-Global Model

The super-efficient SBM-Global model was used to measure and evaluate the EURI of 19 cities in the Sichuan–Chongqing cluster between 2010 and 2021, in accordance with the aforementioned index system. The exact findings are shown in Table 3.

Table 3. Results of Phase I measurements.

City	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Average Value	Arrange in Order
Chongqing	0.10	0.12	0.14	0.15	0.20	0.21	0.26	0.25	0.26	0.36	0.42	1.06	0.29	19
Chengdu	0.54	0.62	0.67	0.70	0.75	1.02	0.75	0.81	0.88	1.04	1.03	1.07	0.82	2
Zigong	0.46	0.53	0.56	0.59	0.64	0.67	0.79	1.01	1.01	1.01	0.77	1.14	0.76	5
Panzhihua	0.48	0.55	0.57	0.62	0.66	0.75	0.80	1.03	1.02	1.05	0.64	0.70	0.74	6
Luzhou	0.37	0.43	0.45	0.46	0.46	0.48	0.48	0.49	0.52	0.70	0.76	1.02	0.55	11
Deyang	0.42	0.50	0.58	0.60	0.66	0.74	1.01	1.01	1.02	1.03	0.88	1.04	0.79	3
Mianyang	0.30	0.38	0.42	0.43	0.46	0.48	0.53	0.61	0.61	0.79	0.94	1.08	0.59	10
Guangyuan	0.28	0.33	0.38	0.41	0.47	0.52	0.59	0.69	0.76	0.93	0.79	1.07	0.60	8
Suining	0.36	0.39	0.41	0.42	0.50	0.49	0.54	0.57	0.65	0.78	0.50	0.57	0.52	15
Neijiang	0.42	0.70	1.01	0.48	0.50	0.48	0.48	0.46	0.44	0.44	0.41	0.45	0.52	13
Leshan	0.33	0.40	0.40	0.41	0.44	0.47	0.52	0.56	0.58	0.69	0.66	1.06	0.54	12
Nanchong	0.32	0.36	0.39	0.41	0.44	0.47	0.49	0.50	0.50	0.57	0.78	1.02	0.52	14
Meishan	0.34	0.39	0.42	0.45	0.43	0.48	0.47	0.50	0.49	0.54	0.50	0.51	0.46	18
Yibin	0.37	0.42	0.42	0.41	0.45	0.45	0.45	0.50	0.44	0.55	0.53	0.66	0.47	17
Guang'an	0.40	0.51	0.55	0.44	0.48	0.52	0.53	0.48	0.46	0.53	0.55	0.70	0.51	16
Dazhou	0.41	0.42	0.58	0.47	0.50	0.49	0.53	0.52	0.54	0.79	0.85	1.05	0.60	9
Ya'an	0.39	0.51	0.56	0.64	0.64	0.67	0.77	1.00	0.77	0.86	0.82	1.10	0.73	7
Bazhong	0.54	0.56	1.00	0.57	0.62	0.77	1.01	0.64	0.64	1.04	1.01	1.07	0.79	4
Ziyang	0.58	1.00	1.00	1.02	1.01	1.05	0.71	1.01	1.04	0.75	0.77	1.12	0.92	1
Average value	0.39	0.48	0.55	0.51	0.54	0.59	0.62	0.67	0.66	0.76	0.72	0.92	0.62	

Table 3 analysis reveals that between 2010 and 2019, the average EURI of 19 Sichuan and Chongqing cities was 0.62, with the efficiency showing up but overall low, with small fluctuations in 2012–2014 and continuous rising trend from 2014 to 2021. This is primarily attributable to the ongoing optimization of the economic framework and the implementation of the "rural revitalization" strategy, both of which have been in progress since 2014 when the Chinese economy entered its "new normal". Comparing the EURI in each city, it is found that Bazhong Municipality has the highest efficiency mean value of 0.92, while Chongqing Municipality has the lowest efficiency mean value of only 0.29. In comparison to Ziyang Municipality, Bazhong Municipality, and other regions with a comparatively underdeveloped economy, the EURI is lower in Chongqing Municipality, Chengdu Municipality, Mianyang, Nanchong, and other cities with a relatively more developed economy. This suggests that the level of economic output in cities may not necessarily be positively correlated with the EURI. In contrast, sub-developed regions may have more balanced urban–rural industrial layouts, which makes the resource inputs corresponding to each input indicator more fully utilized in promoting urban–rural integrated development; whereas, cities with relatively more developed economies have more absolute resource wastage and higher total carbon emissions due to over-expansion of their cities and the rough development of urban and rural low- and medium-end industries, which leads to relatively lower input–output efficiency of their urban–rural integrated development.

4.2. Phase II: SFA Regression Analysis

Given that the efficiencies assessed in the initial phase fail to account for stochastic disturbances and external environmental factors, this section employs the SFA-like stochastic frontier model to estimate parameters and examine the distinct impacts of individual environmental variables on each input variable's slack variables. The specific findings are presented in Table 4.

Table 4. Results of the second-stage SFA regression model.

Input Slack Variables	Labor Input Slack Variables	Land Input Slack Variables	Capital Input Slack Variables	Energy Input Slack Variables
Constant term	36.95 ***	102.35 ***	8,501,899.20 ***	498,236.33 ***
Economic climate	−5.27 ***	−18.30 ***	−2,161,124.50 ***	9578.52 ***
Institutional environment	−5.64 ***	5.26	4,702,793.30 ***	−40,576.05 ***
Social environment	1.61 ***	−3.17	383,117.31 ***	−57,032.68 ***
Sigma-squared	1029.00 ***	5513.91 ***	56,401,398,000,000.00 ***	153,092,780,000.00 ***
Gamma	0.97 ***	0.81 ***	0.33 ***	0.85 ***
Log likelihood function	−743.85	−1157.60	−3898.32	−3105.43
Lr test of the one-sided error	116.81 ***	10.39 **	14.07 ***	130.55 ***

Note: **, and *** indicate the significance level, respectively, at 5%, and 1%.

While not all regressions of environmental variables with each slack value are significant, as shown in Table 4, the LR test values for each input slack variable are significant at the 1% and 5% levels, justifying the application of the SFA model in the analysis. With the exception of the capital input slack variable, which has a gamma value of 0.33, the gamma values of the input slack variables are all near one and significant at the 1% level. This indicates that the input slack variables are more significantly impacted by the management inefficiency in the mixed error term, thereby enhancing the explanatory power of the model. Three external environmental factors—economic, social, and institutional—have a major influence on the EURI based on the calculation of the SFA parameters. Therefore, it is reasonable and necessary to perform a second phase of adjustment.

Environment variables' regression coefficients reflect their effects on input slack as expressed by the direction of their coefficients. A positive regression coefficient indicates that environmental factors are not conducive to reducing input slack, i.e., as the amount of inputs increases, the more serious the waste problem becomes, and vice versa.

1. Influence of economic environment: GDP per capita is significant for all four input slack variables, with negative human slack variables for labor and capital inputs. However, the effect on the slack variable for energy inputs is positive. This is because the degree of regional economic development is partially reflected in the GDP per capita. When regional economic development is at a high level, the region can have more opportunities for planning, development, and investment using the amount of investment in fixed assets, thus facilitating the efficient use of capital and land. Additionally, the development and improvement of the economic climate can generate more employment opportunities and decrease labor waste. At present, the rate of urbanization in Sichuan and Chongqing is accelerating, and there is a certain degree of "city-building movement" in some of the cities. The immoderate increase in energy consumption caused by the continuous expansion of urban areas is not favorable to the efficient use of energy.
2. Influence of institutional environment: Both labor and energy redundancy are negatively affected by institutional factors. A majority of local general financial expenditures go towards innovation in science and technology, education, and social security and employment. Spending by the government may be used to preserve the environment, reduce emissions, and save energy. At the same time, through the government's influence and policy support, it can stimulate enterprises' enthusiasm to reduce the emissions of skills. However, the reduction in local financial expenditures is conducive to reducing the costly waste of fixed asset investment.
3. Influence of social environments: The initial stage of tertiary industry development in the cities of Sichuan and Chongqing necessitates significant labor and capital input,

leading to increased slack variables and waste. Compared with other industries, the tertiary sector consumes less energy. Therefore, it is more beneficial to grow the tertiary sector itself in order to reduce energy waste. However, industrial structure upgrading does not have a significant impact on land input.

4.3. Phase III: Recalculating Efficiency

Using the results of SFA parameter estimation, data rectification was applied to the original input variables. The value of EURI was then determined by reapplying the very effective SBM-Global model after removing random disturbances and outside environmental influences [52]. As shown in Table 5.

Table 5. Phase III results.

City	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Average Value	Arrange in Order
Chongqing	0.29	0.38	0.42	0.43	0.45	0.49	0.51	0.53	0.54	0.90	0.81	1.15	0.58	3
Chengdu	0.55	0.61	0.65	0.68	0.74	0.75	0.80	0.81	0.83	1.03	1.28	1.36	0.84	1
Zigong	0.27	0.30	0.35	0.39	0.44	0.48	0.53	0.70	0.71	0.91	0.61	1.07	0.56	5
Panzhihua	0.34	0.41	0.45	0.50	0.55	0.63	0.69	0.86	0.86	1.03	0.55	0.64	0.63	2
Luzhou	0.21	0.24	0.28	0.29	0.34	0.37	0.41	0.45	0.47	0.60	0.58	0.67	0.41	9
Deyang	0.27	0.31	0.35	0.39	0.43	0.48	0.52	0.59	0.59	0.68	0.62	1.01	0.52	6
Mianyang	0.28	0.33	0.38	0.39	0.45	0.50	0.55	0.62	0.66	0.75	0.87	1.07	0.57	4
Guangyuan	0.15	0.18	0.21	0.23	0.27	0.30	0.33	0.37	0.41	0.47	0.46	0.56	0.33	18
Suining	0.18	0.22	0.25	0.28	0.36	0.36	0.43	0.47	0.54	0.56	0.45	0.54	0.39	13
Neijiang	0.19	0.21	0.23	0.28	0.31	0.34	0.38	0.41	0.41	0.44	0.44	0.49	0.34	17
Leshan	0.22	0.26	0.30	0.33	0.40	0.44	0.48	0.53	0.52	0.58	0.55	0.78	0.45	7
Nanchong	0.20	0.23	0.26	0.28	0.32	0.34	0.37	0.41	0.44	0.48	0.59	0.75	0.39	12
Meishan	0.19	0.23	0.26	0.27	0.32	0.36	0.39	0.43	0.44	0.48	0.46	0.56	0.37	15
Yibin	0.23	0.27	0.30	0.33	0.37	0.41	0.45	0.48	0.52	0.58	0.56	0.62	0.43	8
Guang'an	0.16	0.19	0.21	0.24	0.28	0.31	0.34	0.37	0.37	0.40	0.40	0.46	0.31	19
Dazhou	0.20	0.23	0.25	0.28	0.32	0.35	0.37	0.42	0.43	0.54	0.62	0.75	0.40	10
Ya'an	0.19	0.22	0.24	0.26	0.30	0.33	0.37	0.40	0.42	0.46	0.47	1.02	0.39	11
Bazhong	0.11	0.13	0.15	0.17	0.21	0.23	0.25	0.29	0.30	0.58	0.68	1.05	0.35	16
Ziyang	0.18	0.21	0.25	0.27	0.31	0.34	0.31	0.35	0.40	0.38	0.52	1.08	0.38	14
Average value	0.23	0.27	0.30	0.33	0.38	0.41	0.45	0.50	0.52	0.62	0.61	0.82	0.45	

Comparing the levels of efficiency exhibited by the initial and third phases, as shown in Figure 2, it can be seen that adjusting the input term by constructing the SFA regression model not only eliminates random factors and environmental variables but also makes the efficiency value obtained from the measurement more realistic. The third stage of urban–rural integration efficiency in Sichuan and Chongqing showed an average value of 0.45 compared to the first stage, which is 27% lower compared with the first stage, indicating that ignoring random disturbances and external environmental factors results in an overestimation of the EURI in Sichuan and Chongqing to a certain extent.

At the same time, Chongqing and Chengdu's efficiency has increased, suggesting that external environmental factors have hindered the development of urban–rural integration in these two cities. This also reflects that cities with higher economic levels depend more on resources to sustain economic development. This has led to several issues, such as localized environmental contamination and a notable rise in energy use and carbon emissions in both urban and rural regions. On the contrary, the average value of EURI of other cities has decreased to some extent, among which Bazhong City, Ziyang City, and Ya'an City have shown the greatest decreases, indicating that the previously higher EURI of these cities was due to their better external environment, such as government policy support, reasonable industrial layout, and so on.

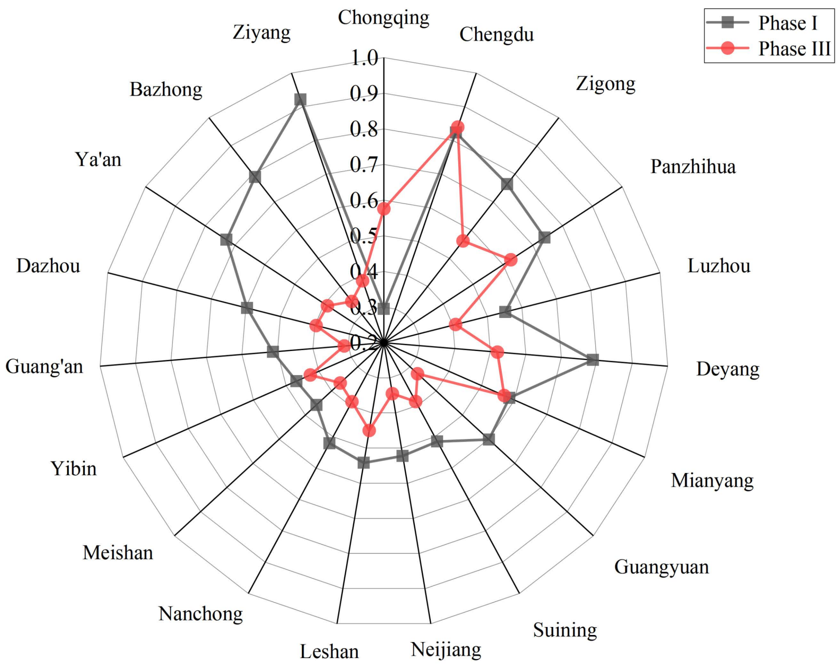

Figure 2. Radar chart of the EURI in Sichuan and Chongqing.

Studying the changing trend of EURI in the third stage, in Figure 3, it can be found that the EURI in Sichuan and Chongqing grew steadily, and the regional gap gradually widened in 2010–2017 and then entered a period of fluctuation in 2017–2021 with small fluctuations in the efficiency values of all cities. This transition can be attributed primarily to the rural revitalization initiative enforced by the government and the additional stringent carbon emission regulations.

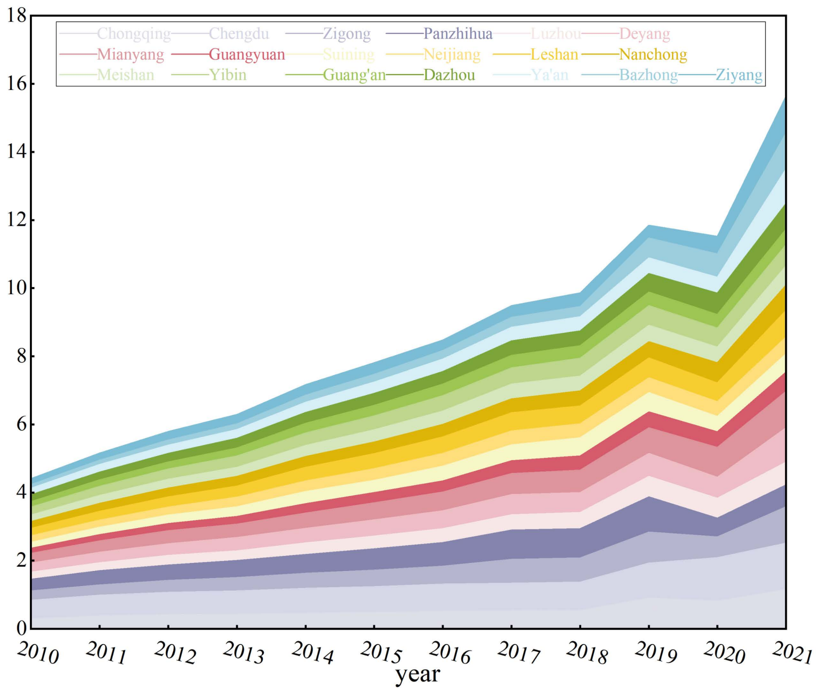

Figure 3. Changing trend of EURI in Sichuan and Chongqing.

This paper compares and analyzes the EURI in 19 cities in the Sichuan and Chongqing regions from 2010 to 2021 using a violin plot, as shown in Figure 4. The violin plot consists of a box-and-line plot as well as a density plot, which can visualize the distribution density status of the data as well as the statistical characteristics. In Figure 4, the left side represents the scatter distribution of the data, on the right is a half violin in the form of a density distribution, the inner box of the half violin represents 25–75% of the data, the degree of width of the body of the violin indicates a probability density of EURI occurring at different levels, and the median's connecting line is shown by the red line. The long thin line in the middle of the graph for many of the cities in the figure indicates that these have higher variance in their EURI values and unstable efficiency values over the observation period. A comparison of the median EURI of cities reveals that relatively more developed cities such as Chongqing, Chengdu, and Mianyang have higher urban–rural integration development efficiencies than cities such as Bazhong, Ya'an, and Ziyang. This also shows that under a reasonable external environment, urban–rural integrated development can synergize with economic development.

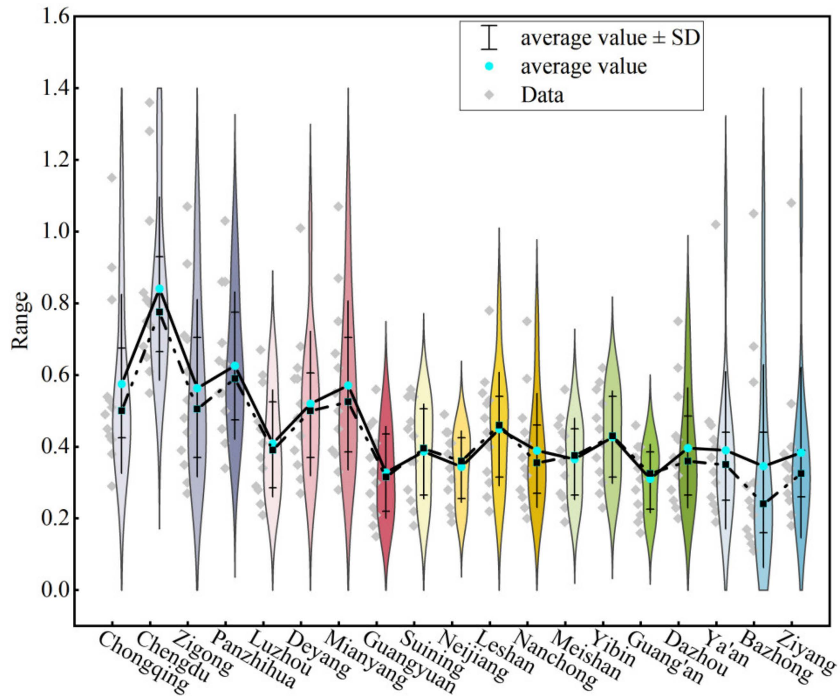

Figure 4. Violin of EURI in Sichuan and Chongqing regions.

4.4. Trend Analysis of the Evolution of EURI in Sichuan and Chongqing Regions

Calculated based on the third stage's efficiency results, the kernel density estimation method is used to analyze EURI in the Sichuan and Chongqing regions in 2010, 2014, 2018, and 2021 to further characterize the time-series dynamic evolution of the overall EURI in the region, as shown in Figure 5.

1. The displacement of the center of gravity towards the right is clearly discernible in the kernel density curve's position from 2010 to 2021. It shows that the EURI in the Sichuan and Chongqing regions during the study period is characterized by a large increase and then a small fluctuation;
2. The kernel density curve indicates that the kernel density map from 2010 to 2018 exhibits a unimodal distribution, and the density curve shape basically remains unchanged, only shifting to the right over time, which indicates that the gap between the EURI of the cities within the Sichuan–Chongqing region is relatively stable and that the EURI of the cities has steadily improved. In 2021, the peak is significantly lower and flatter, demonstrating the growing disparity between the region's growth and urban–rural integration;

3. Upon examination of both sides of the trailing kernel density curve, it is evident that there is a right trailing phenomenon present in all four curves. This phenomenon gradually emerges, indicating that the disparity between the level of urban–rural integration and development in the regions of Sichuan and Chongqing is progressively widening;
4. In view of the polarization phenomenon, it can be seen that a distribution curve shows a single-peak pattern without any tendency towards multipolarity or bipolarity.

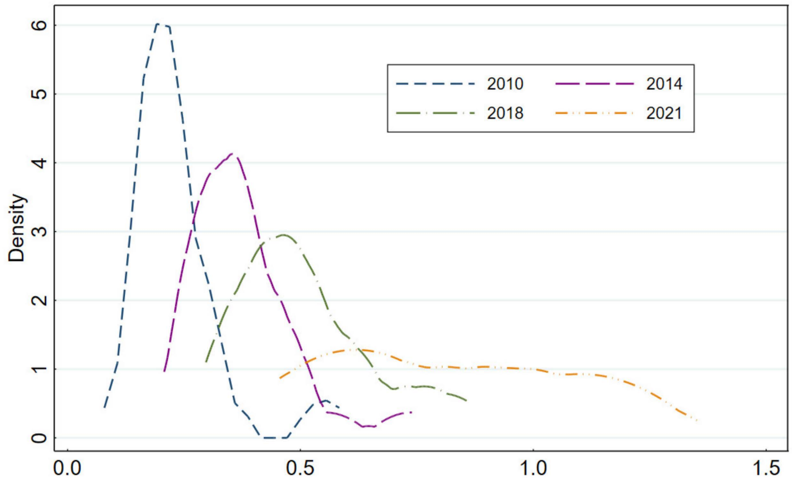

Figure 5. Kernel density map of the EURI in Sichuan and Chongqing regions.

Taken together, the distribution curve of EURI in the Sichuan and Chongqing regions shows the morphological characteristics of gradual rightward shift, decreasing height, expanding width, and showing right trailing tail, reflecting that the EURI in the region as a whole has steadily improved, but there exists a phenomenon that the absolute difference between cities has become larger and the gap has widened.

5. Analysis of Factors Affecting the EURI in Sichuan and Chongqing Regions

5.1. Spatial Autocorrelation Test for the EURI in Sichuan and Chongqing Regions

The pertinent characteristics of objects depend on and are impacted by distance, according to Tobler's first rule of geography. If the spatial correlation of things is not taken into account, it will bias the results. In this paper, based on the spatial nested weight matrix, STATA 16 software is used to calculate the global Moran's I statistics of the EURI in the Sichuan and Chongqing regions from 2010 to 2021. As shown in Table 6, from 2010 to 2019, the global Moran's I statistics are all greater than 0, and all of them are at 1% of the significance under the confidence interval, indicating that over the past ten years, there has been a clear positive correlation between urban–rural integration and economic growth in Sichuan and Chongqing, showing local clustering. After 2020, the Moran's I index displays a notable decline, with a z-value below 1.96 and deemed insignificant. There has been a clear decrease in the connection between the integration of urban and rural areas and the development in the regions of Chongqing and Sichuan. Significant differences in site circumstances and resources aggravate the economic and social development gap between regions and urban and rural areas. Radiation has a subtle effect on high-efficiency regions.

Table 6. Global correlation test for Moran's I index.

Year	Moran's I	z	*p*-Value *	Year	Moran's I	z	*p*-Value *
2010	0.472 ***	3.558	0.0000	2016	0.638 ***	3.908	0.0000
2011	0.505 ***	3.482	0.0000	2017	0.65 ***	3.856	0.0000
2012	0.51 ***	3.403	0.0000	2018	0.587 ***	3.492	0.0000
2013	0.56 ***	3.678	0.0000	2019	0.572 ***	3.357	0.0000
2014	0.57 ***	3.77	0.0000	2020	0.022	0.51	0.3050
2015	0.633 ***	3.942	0.0000	2021	−0.249	−1.013	0.1560

Note: *, and *** indicate the significance level, respectively, at 10%, and 1%.

5.2. Analysis of Spatial Spillover Effects on the EURI in Sichuan and Chongqing Regions

5.2.1. Selection of Impact Indicators

In order to examine the level of connection between cities in Sichuan and Chongqing and their neighboring cities and subsequently investigate the factors that affect the EURI, this study employs a spatial econometric model. EURI is used as the independent variable, and the factors influencing the EURI are analyzed in six different aspects. The precise indications and their respective meanings are outlined below.

1. Digital economy development (DE) [53]: In 2021, there were 284 million rural Internet users, and the rate of rural Internet penetration has been on the rise. This expansion provides a foundation for the development of the rural digital economy. While the Internet's expansion in rural areas facilitates urban–rural communication and resource sharing, it also creates a "digital divide" between urban and rural areas [54] due to insufficient rural infrastructure and low education levels of rural residents. This divide hinders the integration of urban and rural areas. Hence, this paper selects the metric of Internet users per 100 individuals as a means to gauge the digital economy.
2. Science and education support (SES) [55,56]: Investing in science and technology is crucial for promoting urbanization and improving the innovation capacity and level of integrated urban–rural development. Investing in education can enhance the development of skilled individuals, enhance the overall quality of the workforce, and contribute to the integration of urban and rural areas by providing support for talented individuals. This paper utilizes the ratio of science and education expenditure to fiscal expenditure as a specific indicator.
3. Financial development (Fin) [57]: The expansion of financial scale can broaden the credit channel and enhance the credit support surface, and through the revitalization of the market economy and other "main channel effects" to enhance the level of human capital investment and vocational skills in rural areas, this leads to a rise in the employment of workers in lower-level positions and creates more opportunities for generating income. Thus, this paper chooses the aggregate of financial institutions' deposits and loans as a ratio to the Gross Domestic Product (GDP) as a specific measure.
4. Business environment (BE) [58]: An optimal business environment can facilitate the unrestricted movement of rural labor between urban and rural regions and entice rural inhabitants to relocate and engage in urban living and employment, so that rural residents' incomes increase wage incomes in addition to the original purely agricultural business incomes. Therefore, this initiative fosters the growth of both urban and rural economies, enhancing the level of integration and development between urban and rural areas. The variables measuring the regional business environment in this paper are the number of private and self-employed workers in towns and cities.
5. Population quality (PQ): Enhancing population quality promotes the accumulation of human capital in both urban and rural areas and, thus, this will reduce the disparity in income between urban and rural regions and facilitate the integration of urban and rural areas. However, urbanization has exacerbated the migration of rural labor, which hinders the modernization of rural areas. In this paper, the number of college

students is used to measure the high human capital stock of urban agglomerations, and the high human capital stock is used to represent population quality.

6. Market dynamics (MD): Investment in agriculture by enterprises can activate various production factors in rural areas, thus promoting local agricultural development and urban–rural integration. The variable measuring regional market vitality in this paper is the number of industrial enterprises.

5.2.2. Spatial Measurement Model Selection

The study used the LM test, Wald test, LR test, and Hausman test for model selection to ascertain the appropriate model type. The specific outcomes of these tests are shown in Table 7.

Table 7. Results of LM test and LR test.

Tests	Categorization		Statistic	*p*-Value
LM test	Spatial error model (SEM)	Lagrange multipliers	22.74	0.000
		Lagrange multipliers (robust)	2.554	0.110
	Spatial lag model (SAR)	Lagrange multipliers	25.196	0.000
		Lagrange multipliers (robust)	5.01	0.025
Wald test	Spatial error model (SEM)		19.31	0.002
	Spatial lag model (SAR)		22.67	0.000
LR test	Spatial lag model (SAR) vs. spatial Durbin model (SDM)		38.82	0.000
	Spatial error model (SEM) vs. spatial Durbin model (SDM)		43.16	0.000
Hausman test	SDM		33.35	0.000
Joint significance tests	Likelihood ratio test (assumption: ind nested in both)		171	0.000
	Likelihood ratio test (assumption: time nested in both)		154.51	0.000

The applicability of spatial measures can be examined using the LM test, in which both LM_Error and LM_Lag statistics (i.e., non-robust forms of the statistic) are significant with a *p*-value of 0.000, which rejects the original hypothesis of "no spatial autocorrelation" and suggests that spatial measures should be used in the model analysis. Further robust LM diagnosis was performed. The Robust LM_Error and Robust LM-Lag statistics were calculated, and the Robust LM_Lag was 5.01, which was significant at the 5% level, whereas the Robust LM_Error statistic was not significant, indicating that the spatial lag model is more applicable than the spatial error model.

The Wald test and LR test are used for the spatial Durbin model to determine whether it will degenerate into the spatial lag model (SAR) and spatial error model (SEM). In the Wald test, the *p*-values are all at a 1% significance level, rejecting the original hypothesis that can be simplified, i.e., the spatial Durbin model (SDM) cannot be degraded into the spatial lag model (SAR) and the spatial error model (SEM). Therefore, SDM was selected for this paper's study. The LR test is consistent with the results of the Wald test, which significantly rejects the original hypothesis that SDM will degenerate into SAR or SEM, thus further justifying the selection of SDM for the study.

The Hausman's test yields a statistic of 33.35 and a *p*-value of 0.000, indicating statistical significance at a 1% level. Therefore, it is recommended to choose fixed effects for the research at this stage. After conducting additional joint significance tests on the spatial fixed model, time fixed model, and double-fixed effect model, it was determined that the ind-both value is 171 and the time-both value is 154.51. Both values passed the significance test at the 1% level, indicating that the double-fixed effect model is the preferable choice. In summary, the spatial Durbin model with double-fixed effects is the optimal model, which should be chosen to empirically analyze the factors affecting the EURI.

5.2.3. Base Regression Analysis

Table 8 shows the effects of digital economic development (DE), science and education support (SES), financial development (Fin), marketing environment (BE), population quality (PQ), and market dynamics (MD) on the EURI based on SDM.

Table 8. Baseline regression results.

Variable	Ratio	Variable	Ratio
DE	4.14×10^{-10} *** (3.23)	W*DE	-9.64×10^{-10} *** (−5.43)
SES	0.675 ** (2.30)	W*SES	−0.162 (−0.38)
Fin	−0.00806 (−0.23)	W*Fin	−0.168 *** (−3.31)
BE	0.0214 * (1.80)	W*BE	0.0187 (1.12)
PQ	−0.0000291 (−0.76)	W*PQ	−0.0000264 (−0.40)
MD	−0.0000476 * (−1.83)	W*Com	0.000103 (1.51)
Rho	−0.26092 *** (−3.69)	sigma2	0.0044461 *** (10.58)
Log-L	290.75200	n	228

t statistics in parentheses. Note: *, **, and *** indicate the significance level, respectively, at 10%, 5%, and 1%.

Table 8 clearly demonstrates the following: (1) The spatial autoregressive coefficient Rho of the explanatory variable urban–rural integration and development efficiency is −0.26092, and it is significant at the 1% level, indicating a significant negative spatial spillover effect of the EURI, which may be due to the fact that the regions with high efficiency have gained more resources for development and, therefore, have produced a siphoning effect, bringing negative spillover utility to the neighboring regions. (2) The coefficient for digital economic development (DE) is strongly positive, with statistical significance at the 1% level, suggesting a substantial positive influence of ongoing digital economy growth on the EURI. (3) The correlation between science and education support (SES) and urban–rural integration development is statistically significant at the 5% level. This suggests that investing in science, technology, and education has a positive impact on the development of urban–rural integration. (4) The insignificance of the coefficient of financial development (Fin) suggests that financial development is insufficient to make a substantial contribution to the development of urban–rural integration. (5) The coefficient of the business environment (BE) is positively and significantly correlated at the 10% level, suggesting that the business environment factor has a beneficial effect on the EURI. (6) The population quality (PQ) coefficient exhibits a negative value, however, it lacks statistical significance. This suggests that the unequal distribution of educational resources in rural regions impacts the progress of urban–rural integration, but its influence is not statistically significant. (7) The market dynamism (Com) exhibits a substantial negative impact at the 10% significance level. This is likely due to the fact that an increase in the number of industrial firms leads to higher consumption of fossil energy and carbon emissions in urban areas [59], consequently impairing the efficiency of urban integration. (8) The findings of the spatial weighting coefficients indicate that the progress of digital economy and financial development in neighboring regions significantly impact the effectiveness of urban–rural integration in the region. However, the weighting coefficients of other variables lack significance, indicating that the neighboring regions' factors have minimal impact on the region.

5.2.4. Decomposition of Spatial Effects

Because of the presence of the "feedback effect" in the spatial Durbin model, it is not methodologically sound to directly utilize the regression coefficients to elucidate the economic significance of the variables. Therefore, it becomes imperative to decompose the spatial spillover effect. This paper utilizes the research conducted by Lesage & Pace [60] and employs the partial differential method to break down the spatial spillover effect into its direct and indirect components. The direct effect measures the extent to which the independent variables of a region impact its explanatory variables. The indirect effect measures the extent to which the explanatory variables of neighboring regions impact the region's explanatory variables. The total effect is the combined influence of both the direct and indirect effects, representing the impact of a specific independent variable across all cities on the region's explanatory variables. The decomposition results are shown in Table 9. The spillover effects of the development of the digital economy, financial development, and market dynamics are clearly evident. The analysis provided is as follows.

Table 9. Direct, indirect, and total effects of the double-fixed spatial Durbin model.

Variables	Direct Effects	Indirect Effects	Total Effects
DE	5.28×10^{-10} *** (4.02)	-9.61×10^{-10} *** (−5.76)	-4.33×10^{-10} ** (−2.42)
SES	0.696 ** (2.37)	−0.312 (−0.90)	0.384 (0.99)
Fin	0.0114 (0.33)	−0.146 *** (−3.30)	−0.135 *** (−2.87)
BE	0.0197 * (1.67)	0.0120 (0.83)	0.0318 * (1.90)
PQ	−0.0000265 (−0.70)	−0.0000170 (−0.30)	−0.0000435 (−0.69)
MD	−0.0000580 ** (−2.09)	0.000110 * (1.73)	0.0000516 (0.86)

t statistics in parentheses. Note: *, **, and *** indicate the significance level, respectively, at 10%, 5%, and 1%.

1. The direct and indirect effects of digital economy development on EURI are significant. However, the indirect and total effects are negative. This local digital economy development is detrimental to the EURI of neighboring cities. And because the positive direct effect cannot offset the negative indirect effect, it exacerbates the differences in the overall EURI in the study area. This may be because regions with a high level of digital economy development attract population, resource, and product spillovers from neighboring cities, creating a "Matthew effect". In addition, there is an inverted "U"-shaped nonlinear relationship between the level of digital economy development and urban–rural integration, and the siphoning effect and digital divide between urban and rural areas also inhibit the improvement of EURI.
2. The impact of science and education support: As far as the whole region is concerned, science and education expenditures do not show obvious spatial spillover effects, which may be because science and education expenditures are essentially investments in the future, which tend to have a delayed effect, and the effectiveness of the effect needs to be revealed after a longer time cycle. This also indicates that in Sichuan and Chongqing, the "competition effect" between urban development and the surrounding cities is greater than the "synergy effect", and the cities mainly focus on developing their regions. It is unlikely that there will be any active spillovers of scientific and technological inputs as well as educational support.
3. The level of financial development has a significantly negative impact on both indirect and total effects, while the direct effect is not significant. This suggests that increased financial development will negatively impact the process of integrating neighboring cities, with a stronger negative effect as the level of financial development rises. This may be due to the inconsistency of financial development in Sichuan and Chongqing,

and the expansion of financial services to improve the rural living environment still needs to reflect production promotion. Financial institutions are more biased towards cities in allocating financial resources, and this unbalanced financial development will exacerbate the urban–rural gap, which is not conducive to urban–rural integrated development [61,62].

4. The direct impact of market dynamics is strongly negative, while the indirect impact is strongly positive. However, the overall impact is not statistically significant, suggesting that market dynamics hampers the efficiency of urban–rural integration and development in this region. On the other hand, it has a positive spatial spillover effect on the surrounding areas. The surge in the number of industrial enterprises in the neighboring cities can stimulate the progress of industrialization in the region and create additional job prospects for both urban and rural inhabitants. This, in turn, can help bridge the gap between urban and rural areas and facilitate the advancement of urban–rural integration.
5. None of the effects on population quality are significant. This could be attributed to the fact that Sichuan and Chongqing are situated in the western region of China, which serves as the primary source of population outflow. The mobile population of Chengdu has reached 8,459,600 in 2020. The large-scale outflow of the population hurts the overall human resource status of the rural resident population [63,64]. Furthermore, the western region has a comparatively lower level of educational achievement. This is due to the influence of employment pressure, which causes college students in Sichuan and Chongqing to relocate to neighboring regions with higher levels of economic development. Consequently, there is a more severe brain drain, resulting in the demographic factors in Sichuan and Chongqing having an insignificant impact on urban–rural integration development.

In general, the immediate impacts of the factors that influence the results align with the direction and significance of the coefficients shown in Table 8. This further demonstrates the reliability and strength of the empirical findings. Market dynamics plays a crucial role in promoting urban–rural integration development, with a notable positive spillover effect. Conversely, the impact of digital economy development and financial development level on spatial spillover effects is notably negative. The spillover effects of science and education support, business environment, and population quality were ineffective.

6. Discussion

6.1. Spatio-Temporal Evolution of EURI and Its Influencing Factors

It was found that excluding external environmental disturbances, the mean value of EURI in Sichuan and Chongqing nearly doubled to 0.45 from 2010 to 2021. Nevertheless, the overall efficiency level remains subpar, leaving ample opportunity for enhancement, consistent with the findings of related studies at the national and provincial levels [65]. Divergent social and institutional contexts, along with disparities in economic progress, have resulted in distinct patterns of urban–rural integration across various cities [66]. The more economically developed cities, such as Chongqing and Chengdu, have high energy consumption and concentrated carbon emissions in order to maintain a sustained high level of economic growth, coupled with their relatively sloppy development patterns of urban and rural middle- and low-end industries, thus creating a certain inhibition to the efficient progress of urban–rural integration. In contrast, the development of urban–rural integration in more economically backward cities, such as Bazhong and Ziyang, benefits more from the government's pro-poor policies and rational industrial layout. The above results are similar to those of studies on urban sprawl in China and spatial and temporal differences in China's urbanization development [35,67]. In terms of the evolution of the EURI, there is an obvious spatial non-equilibrium in Sichuan and Chongqing during the study period, and the regional differences are gradually expanding, but there is no bifurcation phenomenon yet. This coincides with the findings of Xu Xue, Ren Xiaohong, and other scholars [65,68].

In order for urban–rural integration to occur, various socioeconomic factors must be collaboratively influenced. Various academics have divergent perspectives about the elements that impact the process of urban–rural integration. The research findings indicate that the expansion of the digital economy in Sichuan and Chongqing is beneficial for attracting the influx of human resources, capital, and other factors from the neighboring areas, resulting in the "Matthew effect", which adversely affects the EURI in the neighboring areas. Similar results were obtained by Luo Run and other scholars [62,69]. The influence of financial development on the process of urban–rural integration in Sichuan and Chongqing is not substantial because of the delayed start of financial development in these areas and the need for a higher degree. Xu Yueli and other scholars highlighted that the impact of financial development on urban–rural integration is contingent upon the level of regional development [70]. The impact of inclusive finance on reducing the income disparity between urban and rural areas and fostering the integration and development of urban and rural areas is particularly pronounced in the eastern region [71]. Additionally, science and education support, marketing environment, and population quality did not produce effective spillover effects in Sichuan and Chongqing. In the related research on the east–central region and city clusters, scholars such as Wang Kaiyong [72,73] highlighted that the rate of population growth would impact the urban–rural land use scenario. Additionally, he emphasized that the migration of individuals between urban and rural regions in the east–central region has the potential to greatly contribute to the revitalization of rural communities [27,72]. At the same time, population growth and policy guidance play crucial roles in promoting urbanization and urban–rural development [74]. This suggests choosing appropriate paths for integrated urban–rural development according to different regional characteristics [29].

6.2. Advantages and Limitations

This research uses a three-stage DEA model to quantify the EURI. It considers the influence of carbon emissions, which is an unfavorable measure of productivity, and may provide a more precise representation of the present condition of urban–rural integration growth. The study's findings serve as a useful complement to other similar investigations. In addition, this study's evaluation of EURI, the research framework, and the method of identifying influencing factors can provide a comparison and reference for similar studies at other provincial, municipal, and county levels. Nevertheless, due to the accessibility and comprehensiveness of the data, this research did not examine the impact of other variables, such as agricultural disasters, population movement, and topography, on EURI. In addition to the fact that the policies of closure and control that were implemented during the spread of COVID-19 had a significant influence on the growth of urban industrial enterprises, the lives of residents living in rural areas, the governance of rural areas, and the ecological environment, these impacts, such as the negative impact on the non-farm incomes of rural residents, only became part of the indicators of the urban–rural integration and development index (EURI) in this study and were not fully reflected in the process of our empirical analyses. Therefore, the mechanism of the COVID-19 epidemic and other factors influencing EURI can be analyzed in the future with a more micro perspective.

7. Conclusions and Recommendations

In this paper, the three-stage DEA method and the spatial Durbin model are combined to examine the EURI in 19 cities in the Sichuan and Chongqing regions from 2010 to 2021, and the following conclusions are drawn:

1. The average value of EURI in the Sichuan and Chongqing regions from 2010 to 2021 is 0.45, which is low and there is much room for improvement and optimization;
2. The EURI in Sichuan and Chongqing is greatly influenced by external environmental conditions, and when the external environmental conditions are the same, the EURI decreases in most areas, which indicates that the EURI is generally overestimated.

The higher EURI in less economically developed regions is mainly due to external policies such as rural revitalization and precision poverty alleviation;
3. In terms of the evolution, the EURI in the Sichuan and Chongqing regions shows an upward trend, but the regional differences gradually widen;
4. From the perspective of the influencing factors of the EURI, the development of the digital economy, the support of science and education, and the business environment have significant positive facilitating effects, the market dynamics has a significant negative inhibiting effect, and the financial development and the quality of the population do not have a significant effect. An analysis of the efficiency spillover effects of urban–rural integration and development shows that differences in the level of digital economy development and financial development within regions exacerbate the polarization of urban–rural integration and development. The increase in market dynamics, on the other hand, is conducive to the overall coordinated development of the region.

Based on the above findings, this paper offers the following policy implications:

1. To address the generally ineffective outcomes of urban–rural integrated development, the government must establish a well-planned urban–rural development strategy. This strategy should focus on enhancing the exchange of resources such as skilled individuals, financial capital, technology, and funding between urban and rural areas with the aim of reducing the disparity in development between the two.
2. The government needs to optimize industrial planning and reduce excessive attention to economic benefits. Bazhong City, Ziyang City, and other cities with poor economic foundations should pay more attention to the optimization of internal management, not blindly invest funds, and grasp great protection, not to engage in great development, but to achieve the integrated development of urban and rural areas.
3. The Sichuan and Chongqing regions should establish economic ties based on unique historical origins, build regional integration mechanisms, avoid the negative effects of direct vicious competition in the region, emphasize the radiation function of high-value efficiency zones, and form benign interactions between regions.

Author Contributions: Conceptualization, P.J. and L.L.; methodology, L.L.; validation, Y.Y., P.J. and W.Y. formal analysis, H.C.; investigation, X.G.; resources, L.L.; data curation, W.Y.; writing—original draft preparation, P.J. and Y.Y.; writing—review and editing, L.L. and W.Y.; visualization, Y.Z.; supervision, L.L.; project administration, P.J. and L.L.; funding acquisition, L.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Open Fund of Sichuan Research Center for Urban–Rural Integration (No. SCCXRH2023YB06), the Open Fund of Sichuan Province Cyclic Economy Research Center (No. XHJJ-2217), and the Chinese Academy of Engineering Strategic Research and Consultancy Projects (No. 2024-XZ-71).

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Acknowledgments: The authors would like to thank the reviewers and the editor whose suggestions greatly improved the manuscript.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Sen, K.; Sumner, A.; Yusuf, A. Double Dividends and Mixed Blessings: Structural Transformation, Income Inequality and Employment Dynamics. *J. Dev. Stud.* **2020**, *56*, 1638–1642. [CrossRef]
2. Yin, X.; Chen, J.; Li, J. Rural Innovation System: Revitalize the Countryside for a Sustainable Development. *J. Rural Stud.* **2022**, *93*, 471–478. [CrossRef]
3. Bennett, K.J.; Yuen, M.; Blanco-Silva, F. Geographic Differences in Recovery after the Great Recession. *J. Rural Stud.* **2018**, *59*, 111–117. [CrossRef]

4. Ma, C.; Jiang, Y.; Qi, K. Investigating the Urban–Rural Integrated Town Development Strategy on the Basis of the Study of Rural Forms in Nantong, China. *Front. Archit. Res.* **2021**, *10*, 190–201. [CrossRef]
5. Kong, X.Z.; Zhang, X.R. From Urban-Rural Integration to Rural Revitalization: The Path and Development Trend of the Evolution of China's Urban-Rural Relationship since the 18th National People's Congress. *Teach. Res.* **2018**, *52*, 5–14.
6. Zonneveld, W.; Stead, D. European Territorial Cooperation and the Concept of Urban—Rural Relationships. *Plan. Pract. Res.* **2007**, *22*, 439–453. [CrossRef]
7. Jezierska-Thöle, A.; Gwiaździńska-Goraj, M.; Dudzińska, M. Environmental, Social, and Economic Aspects of the Green Economy in Polish Rural Areas—A Spatial Analysis. *Energies* **2022**, *15*, 3332. [CrossRef]
8. Zhou, D.; Qi, J.L.; Zhong, W.Y. Review of Urban-Rural Integration Evaluation Research: Connotation Identification, Theoretical Cognition and System Reconstruction. *J. Nat. Resour.* **2021**, *36*, 2634–2651.
9. Wei, X.S. Research on Rural Development Path with Chinese Characteristics from Dual Structure to Urban-Rural Integration. *Agric. Econ.* **2019**, *2*, 26–28.
10. He, R.W. Rural-Urban Integration and Rural Revitalization: Theoretical Discussion, Mechanism Explanation and Path of Realization. *Geogr. Res.* **2018**, *37*, 2127–2140.
11. Lu, D.D.; Guo, L.X. The Research Core of Geography—Territorial System of Human-Earth Relations—On Academician Wu Chuanjun's Geographic Thought and Academic Contributions. *Acta Geogr. Sin.* **1998**, *53*, 3–11.
12. Cao, Z.; Li, Y.R.; Chen, Y.F. Exploring the Path of Rural Transformation and Sustainable Development in the Context of Urban-Rural Integration. *Acta Geogr. Sin.* **2019**, *74*, 2560–2571.
13. Yan, S.H.; Bai, G.Q. New Exploration of the Connotation of Coordinated Regional Economic Development. *Hubei Soc. Sci.* **2009**, *3*, 95–98.
14. Abrhám, J. Rural Development and Regional Disparities of the New EU Member States. *Agric. Econ. (Zeměd. Ekon.)* **2011**, *57*, 288–296. [CrossRef]
15. Smith, N.R. Rural Perspectives on Asia's Urban-Rural Relations—Mobilizing for Development: The Modernization of Rural East Asia. By Kristen E. Looney. Ithaca, N.Y.: Cornell University Press, 2020. Xv, 213 Pp. ISBN: 9781501748844 (Cloth).—More than Rural: Textures of Thailand's Agrarian Transformation. By Jonathan Rigg. Honolulu: University of Hawai'i Press, 2019. Xx, 300 Pp. ISBN: 9780824876593 (Cloth). *J. Asian Stud.* **2021**, *80*, 540–543. [CrossRef]
16. Gorriz-Mifsud, E.; Secco, L.; Da Re, R.; Pisani, E.; Bonet, J.A. Structural Social Capital and Local-Level Forest Governance: Do They Inter-Relate? A Mushroom Permit Case in Catalonia. *J. Environ. Manag.* **2017**, *188*, 364–378. [CrossRef]
17. Guo, D.; Jiang, K.; Xu, C.; Yang, X. Industrial Clustering, Income and Inequality in Rural China. *World Dev.* **2022**, *154*, 105878. [CrossRef]
18. Ma, L.; Liu, S.; Fang, F.; Che, X.; Chen, M. Evaluation of Urban-Rural Difference and Integration Based on Quality of Life. *Sustain. Cities Soc.* **2020**, *54*, 101877. [CrossRef]
19. Baier, N.; Pieper, J.; Schweikart, J.; Busse, R.; Vogt, V. Capturing Modelled and Perceived Spatial Access to Ambulatory Health Care Services in Rural and Urban Areas in Germany. *Soc. Sci. Med.* **2020**, *265*, 113328. [CrossRef] [PubMed]
20. Zarifa, D.; Seward, B.; Milian, R.P. Location, Location, Location: Examining the Rural-Urban Skills Gap in Canada. *J. Rural Stud.* **2019**, *72*, 252–263. [CrossRef]
21. Seale, E. Coping Strategies of Urban and Rural Welfare Organisations and the Regulation of the Poor. *New Political Econ.* **2013**, *18*, 141–170. [CrossRef]
22. Wang, Y.M.; Liu, G.; Shi, J.C.; Cai, M. Provincial and Regional Differences in the Level of Urban-Rural Integration in China. *China Popul. Resour. Environ.* **2012**, *22*, 137–142.
23. Xu, S.; Wu, Q.Q. Analysis of the Characteristics of Spatial and Temporal Differentiation of the Level of Urban-Rural Integration in China and the Factors Affecting It. *Stat. Decis.* **2023**, *39*, 114–119.
24. Shan, B.; Liu, J.; Liu, Y.; Wang, H.; Wang, A. How Is Construction Land Transition Related to Rural Transformation? Evidence from a Plain County in China Based on the Grey Correlation Model. *Land* **2022**, *11*, 641. [CrossRef]
25. Dou, H.; Ma, L.; Li, H.; Bo, J.; Fang, F. Impact Evaluation and Driving Type Identification of Human Factors on Rural Human Settlement Environment: Taking Gansu Province, China as an Example. *Open Geosci.* **2020**, *12*, 1324–1337. [CrossRef]
26. Cui, S.Q.; Zhou, G.H.; Dai, L.Y.; Wu, G.H.; He, Y.H. Progress and Prospects of Research on Urban-Rural Integration Development Based on Geographic Perspectives. *Econ. Geogr.* **2022**, *42*, 104–113. [CrossRef]
27. Yan, J.; Chen, H.; Xia, F. Toward Improved Land Elements for Urban–Rural Integration: A Cell Concept of an Urban–Rural Mixed Community. *Habitat Int.* **2018**, *77*, 110–120. [CrossRef]
28. Brauer, R.; Dymitrow, M. Quality of Life in Rural Areas: A Topic for the Rural Development Policy? *Bull. Geogr. Socio-Econ. Ser.* **2014**, *25*, 25–54. [CrossRef]
29. Yang, Y.; Bao, W.; Wang, Y.; Liu, Y. Measurement of Urban-Rural Integration Level and Its Spatial Differentiation in China in the New Century. *Habitat Int.* **2021**, *117*, 102420. [CrossRef]
30. Zhang, H.P.; He, R.W.; Li, G.Q.; Wang, J. Spatio-Temporal Evolution of Coupled Coordination Degree of Rural-Urban Integration System in Metropolitan Areas and Its Influencing Factors—A Case Study of the Capital Ring Region. *Econ. Geogr.* **2020**, *40*, 56–67. [CrossRef]
31. Liu, Y.; Lu, S.; Chen, Y. Spatio-Temporal Change of Urban–Rural Equalized Development Patterns in China and Its Driving Factors. *J. Rural Stud.* **2013**, *32*, 320–330. [CrossRef]

32. Zhou, J.N.; Zou, W.; Qin, F.C. A Multidimensional Review of China's Rural-Urban Integration under the Concept of Equalization and Its Influencing Factors. *Geogr. Res.* **2020**, *39*, 1836–1851.
33. Gao, B.; Kong, L.C. Analysis of Regional Differences in the Integration of Urban and Rural Development in China. *Hebei Acad. J.* **2017**, *37*, 101–108.
34. Wu, X.; Cui, P. A Study of the Time–Space Evolution Characteristics of Urban–Rural Integration Development in a Mountainous Area Based on ESDA-GIS: The Case of the Qinling-Daba Mountains in China. *Sustainability* **2016**, *8*, 1085. [CrossRef]
35. Shi, J.; Duan, K.; Wu, G.; Li, J.; Xu, K. Efficiency of Urban-Rural Integration Development in the Yangtze River Delta Under the Background of Carbon Emission Constraint. *Econ. Geogr.* **2021**, *41*, 57–67. [CrossRef]
36. Wang, D.C.; Zhao, H. Research on the Evaluation of the Efficiency of China's Urban-Rural Integration Development and Its Influencing Factors. *Res. Financ. Econ. Issues* **2022**, *10*, 101–109. [CrossRef]
37. Yin, Q.M.; Wang, X. Does the Digital Economy Promote Rural-Urban Integration in China—A Test Based on Mediated Effects Modeling and Spatial Durbin Modeling. *J. Technol. Econ.* **2022**, *41*, 114–127.
38. Tang, C.L.; Ma, Y.R. Measuring the Level of Urban-Rural Integration in Chinese Provinces Based on Intuitionistic Fuzzy. *Econ. Geogr.* **2016**, *36*, 52–59. [CrossRef]
39. Zhang, X.L.; Chou, F.D.; Zhu, C.G. Evolution of Urban-Rural Integration Development Level in Huaihai Economic Zone under the Perspective of Spatio-Temporal Interaction. *J. Nat. Resour.* **2020**, *35*, 1867–1880.
40. Liu, M.H.; Lu, F. Rural-Urban Factor Mismatch and Rural-Urban Integrated Development: An Empirical Study Based on Chinese Provincial Panel Data. *J. Agrotech. Econ.* **2019**, *2*, 33–46. [CrossRef]
41. Tian, Y.; Qian, J.; Wang, L. Village Classification in Metropolitan Suburbs from the Perspective of Urban-Rural Integration and Improvement Strategies: A Case Study of Wuhan, Central China. *Land Use Policy* **2021**, *111*, 105748. [CrossRef]
42. Pan, W.; Wang, J.; Li, Y.; Chen, S.; Lu, Z. Spatial Pattern of Urban-Rural Integration in China and the Impact of Geography. *Geogr. Sustain.* **2023**, *4*, 404–413. [CrossRef]
43. Zheng, Y.; Long, H. Evaluation of the Measurement of China's Urban-Rural Integration Development and Its Spatio-Temporal Pattern. *Acta Geogr. Sin.* **2023**, *78*, 1869–1887.
44. Lyu, L.; Kan, D. Measurement and analysis of the development effciency of urban-rural integration—A case study of central china. *Chin. J. Agric. Resour. Reg. Plan.* **2021**, *42*, 176–183.
45. Lu, X.; Shi, P.; Deng, Z.; Li, X.; Hu, Y. Calculation of Green Production Efficiency of Tourism in the Yangtze River Economic Belt and Analysis of Its Spatial and Temporal Evolution. *China Popul. Resour. Environ.* **2019**, *29*, 19–30.
46. Xiao, R.; Chen, Z.; Qian, L. China's High-Tech Manufacturing Industries' Innovation Efficiency: Technology Heterogeneity Perspective. *J. Manag. Sci.* **2018**, *31*, 48–68.
47. Zhao, X.; Shang, Y.; Song, M. Industrial Structure Distortion and Urban Ecological Efficiency from the Perspective of Green Entrepreneurial Ecosystems. *Socio-Econ. Plan. Sci.* **2020**, *72*, 100757. [CrossRef]
48. Chen, Y.; Miao, J.; Zhu, Z. Measuring Green Total Factor Productivity of China's Agricultural Sector: A Three-Stage SBM-DEA Model with Non-Point Source Pollution and CO_2 Emissions. *J. Clean. Prod.* **2021**, *318*, 128543. [CrossRef]
49. Zhang, A.; Zhou, J.; Zhang, L.; Wang, Q. Measurement, Restrictive Factors and Development Path of Urban-Rural Integration Coordinated Development in Yellow River Basin. *J. Stat. Inf.* **2022**, *37*, 34–43.
50. Gai, M.; Zhu, J.M.; Sun, C.Z.; Sun, K. Spatio-Temporal Evolution of Marine Economic Efficiency in China's Coastal Areas and Analysis of Influencing Factors. *Resour. Sci.* **2018**, *40*, 1966–1979.
51. Tone, K. A Slacks-Based Measure of Super-Efficiency in Data Envelopment Analysis. *Eur. J. Oper. Res.* **2002**, *143*, 32–41. [CrossRef]
52. Liu, L.; Yang, Y.; Liu, S.; Gong, X.; Zhao, Y.; Jin, R.; Duan, H.; Jiang, P. A Comparative Study of Green Growth Efficiency in Yangtze River Economic Belt and Yellow River Basin between 2010 and 2020. *Ecol. Indic.* **2023**, *150*, 110214. [CrossRef]
53. Wang, Y.; Peng, Q.; Jin, C.; Ren, J.; Fu, Y.; Yue, X. Whether the Digital Economy Will Successfully Encourage the Integration of Urban and Rural Development: A Case Study in China. *Chin. J. Popul. Resour. Environ.* **2023**, *21*, 13–25. [CrossRef]
54. Peng, Z.; Dan, T. Digital Dividend or Digital Divide? Digital Economy and Urban-Rural Income Inequality in China. *Telecommun. Policy* **2023**, *47*, 102616. [CrossRef]
55. Guo, L.X.; Liu, Y.F.; Feng, J.M.; He, S. Spatio-Temporal Patterns of New Urbanization and Integrated Urban-Rural Development in Chinese Provinces and Their Influencing Factors. *J. Earth Sci. Environ.* **2023**, *45*, 781–795. [CrossRef]
56. Luo, W.L.; Wang, W.L.; Lin, Z.; Zhou, W.J. Spatio-Temporal Evolution and Driving Factors of Urban-Rural Integration in China. *Prog. Geogr.* **2023**, *42*, 629–643. [CrossRef]
57. Fan, S.; Jiang, M.; Sun, D.; Zhang, S. Does Financial Development Matter the Accomplishment of Rural Revitalization? Evidence from China. *Int. Rev. Econ. Finance.* **2023**, *88*, 620–633. [CrossRef]
58. Tiwasing, P.; Gorton, M.; Phillipson, J.; Maioli, S. Rural Businesses and Levelling up: A Rural-Urban Analysis of Business Innovation and Exporting in England's North and Midlands. *J. Rural Stud.* **2023**, *100*, 103007. [CrossRef]
59. Qi, H.B.; Shen, X.Y.; Long, F.; Liu, M.J.; Gao, X.W. Spatial and Temporal Patterns and Influencing Factors of Carbon Emissions in Zhejiang Province's Counties. *Resour. Environ. Yangtze Basin* **2023**, *32*, 821–831.
60. LeSage, J.; Pace, R.K. *Introduction to Spatial Econometrics*; Chapman and Hall/CRC: New York, NY, USA, 2009; ISBN 978-0-429-13808-9.
61. Zhang, K.; Liu, L. The Practical Exploration, Cognitive Thinking, and Countermeasures for the Revitalization of Urban-Rural Integrated Villages. *Acad. J. Zhongzhou* **2024**, *1*, 45–53.

62. Sun, Y.; Lei, N.; Liu, X. Can Digital Economy Promote Urban-Rural Integration and Development: Empirical Evidence from 268 Cities in China. *South China Financ.* **2023**, *1*, 38–53.
63. Chang, M.; Li, F.; Liu, J. Effect of Population Urbanization on the Income Structure of Farmers: An Empirical Analysis Based on Chinese Provincial Panels. *J. China Agric. Univ.* **2024**, *29*, 228–239.
64. Yang, S.; Du, H.; Yang, X. Land Transfer and Rural Household Income Gap: An Empirical Exploration from the Perspective of Household Development. *J. Huazhong Agric. Univ.* **2024**, *1*, 178–191. [CrossRef]
65. Xu, X.; Wang, Y. Evaluation of Urban-Rural Integration Development and Analysis of Spatial Differences in the Yellow River Basin Based on the Dual Logic Perspective. *J. Desert Res.* **2024**, *6*, 1–13.
66. Liu, W.; Wu, M.; Zhang, J. Study on the Impact of Polycentric Spatial Structure on Urban-Rural Integration and Development. *J. Manag.* **2024**, *1*, 1–18.
67. Huo, L. Spatial and Temporal Evolution Analysis of the Coupling and Coordinated Development of Urban Expansion and Rural Revitalization in China. *J. Tech. Econ. Manag.* **2024**, *2*, 129–136.
68. Ren, X.; Pan, Y.; Nie, J.; Shen, J. High-Quality Integration Level and Spatio-Temporal Characteristics of the Chengdu-Chongqing Twin-City Economic Circle. *Resour. Dev. Mark.* **2024**, *40*, 1–19.
69. Luo, R.; You, W.; Zhou, N.; Li, Z. Impact of Digital Economy on New-Type Urbanization in the Yangtze River Delta: Simultaneous Discussion on the Moderating Effect of Digital Divide. *Geogr. Geo-Inf. Sci.* **2024**, *40*, 114–124+133.
70. Xu, Y.; Ji, X. Impact of Digital Inclusive Finance on the Integration of Urban and Rural Capital Factors in Counties: Based on the Perspective of New Binary Transformation. *J. Quant. Technol. Econ.* **2024**, *41*, 193–212.
71. Wang, L.; Wang, X. Impact of Inclusive Finance on Economic Growth and Urban-Rural Income Gap. *Stat. Decis.* **2024**, *40*, 145–150. [CrossRef]
72. Wang, K.; Deng, Y. Whether New Urbanization Can Break through the "Hu Huanyong Line"—Another Discussion on the Geographic Connotation of the "Hu Huanyong Line". *Geogr. Res.* **2016**, *35*, 825–835.
73. Wang, K.; Chen, Y.; Ding, J. The Demand Forecast and Impact of Population Growth on Urban-Rural Construction Land after Implementing the Universal Two-Child Policy. *China Land Sci.* **2016**, *30*, 37–47.
74. He, Y.; Zhou, G.; Tang, C.; Fan, S.; Guo, X. The Spatial Organization Pattern of Urban-Rural Integration in Urban Agglomerations in China: An Agglomeration-Diffusion Analysis of the Population and Firms. *Habitat Int.* **2019**, *87*, 54–65. [CrossRef]