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The Impact of Environmental Regulation on Collaborative Innovation Efficiency: Is the Porter Hypothesis Valid in Chengdu–Chongqing Urban Agglomeration?

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Abstract: Under the advocacy of sustainable and innovation-driven development, the potential impact of environmental regulation on collaborative innovation has become a controversial issue. This article uses panel data from 16 cities in the Chengdu–Chongqing urban agglomeration from 2011 to 2021 to analyze the impact of environmental regulation on collaborative innovation efficiency. First, this study uses the two-stage DEA model to analyze each city's industry–university–research collaborative innovation efficiency. Then, the impact of environmental regulation on collaborative innovation is analyzed using the Tobit model. The results show that in the temporal dimension, the collaborative innovation efficiency of each city shows an upward trend. This demonstrates the outstanding effectiveness of transforming knowledge into technology for economic development. In the spatial dimension, the collaborative innovation efficiency of this urban agglomeration shows a "high in the center and low in the surroundings" pattern. The Tobit regression model shows that environmental regulation significantly impacts collaborative innovation in the Chengdu–Chongqing urban agglomeration. Command-and-control environmental regulation policies have a threshold effect on collaborative innovation, verifying the Porter hypothesis that appropriate environmental regulation promotes innovative activities. The results provide an initial basis for formulating regional environmental policies to achieve a win–win situation for innovation and sustainability in underdeveloped regions.

Keywords: collaborative innovation; environmental regulation; two-stage DEA–Tobit model; urban agglomeration; the Porter hypothesis

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1. Introduction

Due to the rapid development of the new science and technology revolution, innovation has become a long-term driver of economic growth [1]. However, while innovation promotes regional economic development, it inevitably leads to environmental problems. The Global Sustainable Development Report 2023 suggests that transformational shifts rooted in science can achieve Sustainable Development Goals by 2030. The low-carbon green development path is an essential choice for future human development. Similar to many industrialized nations, China made economic profits at the cost of the environment in the early years [2]. China is still in accelerated industrialization, and the consumption of environmental resources is rising in the context of innovation-driven high-quality economic development. To achieve the goals of low-carbon and sustainable development, the Chinese Government has put forward the Beautiful China Initiative [3], which emphasizes the priority of an ecological civilization. At the same time, China has issued environmental regulatory regimes, such as the Overall Program for the Reform of the Ecological Civilization System and the Comprehensive List of Environmental Protection, to control environmental pollution caused by economic development. The innovation-driven development strategy has become essential for China to realize high-quality development [4]. Collaborative innovation (CI) has become critical to promoting regional development and building an innovative country. Environmental regulation (ER) inevitably conflicts with some innovative development goals. ER in each region may also have different impacts on CI. The famous theory for this effect is the Porter hypothesis. The Porter hypothesis argues that environmental policies promote technological innovation, reduce pollution, and promote economic development [5]. The verifiability of the Porter hypothesis has been debated in the academic field. On the one hand, many studies support the Porter hypothesis in that environmental policies force firms to innovate, which can lead to innovation compensation and promote economic development [2,6,7]. On the other hand, environmental policies increase production costs and reduce firms' investments in innovation [8]. However, some studies suggest there is no correlation [9]. The main reason for this difference is the heterogeneity of the study area. Many studies on China confirm the reliability of the Porter hypothesis [2,6]; most are based on analyses of provincial data, and fewer are based on data from urban agglomerations. Urban agglomerations are associations formed by the integration of several geographically concentrated cities. In China, urban agglomerations have become the main form of continuous regional economic growth. Building a collaborative innovation pattern of urban agglomeration to lead regional high-quality development is a new goal for China to move toward the ranks of innovative countries [10,11]. The development of urban agglomerations can provide a new solution to China's current urban diseases and realize the coordinated development of large, medium, and small cities [12].

The nineteen urban agglomerations in China have their functions. The Chengdu–Chongqing urban agglomeration (CCUA) is in the core of southwestern China, forming an emerging growth pole in China to balance regional development incoherence [13]. The unique and significant strategic position of the CCUA was highlighted in the Master Plan for the Chengdu–Chongqing Urban Agglomeration released by the State Council of the People's Republic of China on 20 October 2021 [14]. The government is building the CCUA into a science and technology innovation center with national influence to promote collaborative innovation [13]. However, the CCUA also faces the same problem: excessive economic development from innovation may cause high energy consumption, wasted resources, and excessive environmental burden [11]. Therefore, the Ecological Environmental Protection Plan for the Chengdu–Chongqing Economic Circle, released in February 2022, states that by 2025, severe environmental problems should be effectively managed. By 2035, the modern environmental governance system will be fully improved. There are differences in pollution control investments due to different economic scales between Chengdu and Chongqing, leading to differences in ecological and environmental governance capacity and intensity. This difference will affect the effectiveness of ER [15]. Based on policy, environmental protection is gradually rising to the same importance as quality economic development and impacting the effectiveness of CI of the urban agglomeration.

In this context, what is the performance of CI in the CCUA? What is the impact of ER on CI? Can it prove the win–win situation between ER and innovation advancement in the Porter hypothesis? Based on this, this study selects the Chengdu–Chongqing urban agglomeration located in southwest China as the research area and analyses the impact of ER on CI by constructing indexes. Firstly, this study decomposes the collaborative innovation efficiency (CIE) into the knowledge transformation-stage efficiency and the technological transformation-stage efficiency and constructs the evaluation indices of the CCUA's CIE using a two-stage dynamic DEA model. Then, a spatial–temporal comparison of urban agglomerations is carried out to explore the differences in CIE in different cities and the reasons for changes. Next, the entropy method measures the environmental regulation intensity. Finally, the impact of ER on CI is analyzed using the Tobit model. This research aims to establish a more reasonable evaluation index of CIE for urban agglomeration in western or underdeveloped regions of China and then be able to analyze the impact of ER on CIE in these regions. The purpose is to promote the rational flow and equitable distribution of regional innovation factors, thereby providing novel decision-making references for the authorities to formulate environmental regulation policies and innovation development policies.

2. Literature Review

This literature review is based on the Porter hypothesis. Reasonable environmental regulation can improve environmental quality through technological compensation and learning effects, stimulate enterprises' technological innovation, increase productivity, and offset the possible costs of ER. In the long term, it can improve technological innovation capacity [16]. This contrasts with the traditional view that "environmental regulation increases costs and thus reduces technological innovation" [17,18]. Existing research on ER and CI mainly focuses on three aspects: connotation, assessment, and influencing factors; therefore, this article summarizes the relevant literature based on three aspects. The first stage of the review addresses the concept, measurement methods, and analysis of influencing factors of CI; the second stage considers the concept, assessment of effects, and analysis of influencing factors of ER; and the third stage examines the correlation between ER and CI.

2.1. Research on Collaborative Innovation

CI is the driver of achieving industrial innovation and upgrading in a country or region [6]. Scholars have conducted in-depth research on CI, mainly focusing on three aspects.

First, as for the concept of CI, one theoretical foundation of CI is the synergy theory founded by Professor Haken of Germany. The central meaning is that economic and social development is jointly promoted through the interaction and coordination of various systems and elements within systems [19]. Schumpeter's theory of innovation further explores the role of innovation in economic development [20]. The combination of the two theories can form the theoretical basis of CI. Entering the 21st century, innovation has been recognized as a new product under the complex interaction of various innovation subjects and factors [21], involving collaborative cooperation between enterprises, universities, research institutes, and governments [22]. CI can perform well by reorganizing subjects and resources in the regional innovation system; therefore, this study analyzes CI in terms of subjects and resources.

Second, as for the measurement of CI, scholars usually adopt the DEA or coupled coordination degree model to evaluate regional collaborative innovation performance [23,24]. Evaluation models can be constructed from synergistic processes, including R&D cooperation, patent transfer, and technological innovation [25]. Models can also be constructed based on innovation processes and outcomes to evaluate the innovation process regarding participatory, synergistic, configurative, and sharing capabilities [26] and to evaluate collaborative innovation outcomes regarding resource input, achievement output, performance spillover, and environmental support [27]. The number of patents filed and papers published by regions and subjects are more common indicators scholars use to assess CI. Most studies show that CIE increases with economic growth and regional development. From the perspective of urban agglomerations, CI grows in different urban agglomerations but at different rates. There is variability in the efficiency of CI among cities within urban agglomerations [26].

Third, as for the influence factor of CI, various factors influence collaborative innovation performance, including internal and external factors [28]. Internal factors include inter-subjective cooperative relationships, cooperative strategy, and technical support. External factors include the market environment, institutional environment, cultural environment, and innovation policy. Firstly, inter-regional policy coordination impacts regional innovation [29]. Moreover, policy regulation in different regions produces different effects. Furthermore, the differences in innovation resources among innovation agents also significantly impact CI [30]. Therefore, collaborative innovation alliances can reduce transaction costs and achieve the transformation and application of knowledge and technology. In addition, the degree of synergy, innovation input, infrastructure level, and knowledge input level also affect regional collaborative innovation efficiency [31]. In recent years, research has gradually focused on the spillover and diffusion of knowledge and technology, the cross-domain flow of innovation factors, and the upgrading of high-tech industries [32,33]. These can affect CI in different regions in different ways.

Based on Section 2.1, this study proposes the first hypothesis:

Hypothesis 1. *Industry–university–research collaborative innovation efficiency will increase but with significant differences among cities in the Chengdu–Chongqing urban agglomeration.*

2.2. Research on Environmental Regulation

Countries are pursuing sustainable development and a low-carbon economy. However, many high-energy and high-emission industries still negatively impact the ecological environment. Therefore, scholars have focused on the ecological environment and green development, with studies focusing on the following three aspects.

The first aspect is the connotation of ER. Environmental resources are public property [34] and the government can protect environmental ownership through regulation. ER refers to the government's use of laws and regulations to constrain polluting behavior caused by social activities [35]. Because reducing pollution is not a natural behavior, regulatory systems are needed to curb polluting activities. According to the Environmental Kuznets Curve, economic growth is accompanied by increased pollution, and ER is becoming increasingly important [36]. ER should govern industry, businesses, and the people who use public resources. Local government is the leading implementer of environmental governance policies [37].

In recent years, the instruments of ER have been divided into three categories. The first type is the command-and-control type in the form of mandatory regulations [38]. This type of instrument is easy to implement but has high implementation costs. The second type is market regulation with economic incentives [39]. This type of tool has low implementation costs but ambiguous implementation effects. The third category is the voluntary implementation type associated with the subject's environmental perception or the acquisition of competitive advantage [40]. Such instruments have a low voluntariness standard, and their contribution to environmental protection is small and poorly measured. China mainly adopts command-and-control environmental regulatory instruments, supplemented by market-based and voluntary instruments [41]. The CCUA follows the first type of instrument. Regardless of the type of environmental regulation tool, the aim is to achieve the control of environmental pollution and regional sustainable development; therefore, it is necessary to take into account the region's advantages in terms of location, economic development, industrial structure, and resource endowment before selecting the tool and implementing the system [42].

The second aspect is the evaluation of environmental regulation effects. Some scholars have measured environmental regulatory effects through laws and regulations enacted by local governments. Examples include environmental law, administrative law, tort law, or industrial environmental regulatory standards [43]. However, laws or industrial standards are relatively stable within a certain period or a fixed industry, making it challenging to dynamically reflect changes in the intensity of ER. In addition, laws and regulations are not easy to quantify; therefore, more and more scholars choose to evaluate them from the perspective of pollutant emission or elimination. Scholars have constructed a comprehensive index-type indicator to measure the effect of ER by assigning different weights to each indicator, for example, the wastewater discharge compliance rate, sulfur dioxide removal rate, soot removal rate, dust removal rate, and solid waste comprehensive utilization rate [6]. Some scholars have also measured it from the perspective of pollution control investment. The amount of pollution treatment investment, the capital stock, and the number of people in the environmental protection system are also measurable indicators [35,44].

The third aspect is the impact of ER. ER affects a country or region's production efficiency [45], industrial structure [46], economic growth [47], and innovative activities [48]. However, according to relevant studies, ER's impacts are inconsistent across regions. Therefore, ERs do not necessarily improve production efficiency, promote industrial structure upgrading, stimulate economic growth, and incentivize innovative activities. China's environmental governance is an administrative regulation [37]. Such regulation can potentially increase compliance costs for firms and negatively affect productivity and economic growth [17]. However, it may also enhance environmental quality, curb the negative externalities of environmental pollution, and force firms to engage in technological innovation, thus potentially promoting economic growth [37].

2.3. Research on the Relationship between Environmental Regulation and Collaborative Innovation

According to the Porter hypothesis, environmental protection policies can generate innovation compensation effects and achieve a "win–win" situation for environmental protection and innovation upgrading [5]. In recent years, more and more research on the Porter hypothesis has produced different results; thus, the correlation between ER and CI is unclear. Existing research can be broadly categorized into the following two aspects.

The first aspect is the measurement of the relationship between ER and innovation. Most studies used DEA–Tobit, generalized linear, and geographic weighted regression models [2,7,49]. Minority studies also use vector autoregressive models and case studies [50,51]. The DEA–Tobit model is a common model for efficiency assessment and factor analysis. Shuai and Fan [2] used the DEA–Tobit model to analyze ER's impact on green economy efficiency in Chinese provinces; Huang, Xu et al. [6] have further analyzed the impact of ER on regional collaborative innovation in China's thirty provinces. Wu and Fu et al. [52] have narrowed the research scope and analyzed the impact of ER on green innovation efficiency in the Yangtze River Economic Belt with the DEA–Tobit model. There are differences in the results obtained due to differences in the study area, economic development, resource endowment, geographical location, and the selection of indicators.

The second aspect is the relationship between ER and CI. Most studies have focused on analyzing the relationship between ER and technological innovation or green innovation. This has three effect types: not significant, one-way, and dual. Regarding technological innovation, market-incentivized ER affects technological innovation, and command-and-control ER has no significant effect on technological innovation [51]. In technologically advanced countries, stricter environmental policies are more likely to promote short-term economic growth and innovation. However, in the long term, market-based environmental policies appear more favorable to productivity gains than non-market instruments [53]. Regarding green innovation, ER and green innovation might show a positive correlation [54] or an U-shaped relationship [7]. ER demonstrates a dual impact on regional innovation if considering factor allocation. The current-period ER policy is not conducive to improving regional innovation capacity. In contrast, the lagged-period ER favors enhance regional innovation capacity because the negative environmental cost effect is exceeded [55]. Based on the Porter hypothesis, studies have produced different results. Most Chinese-based research confirms the Porter. The results may be more plausible and generalizable if studies are conducted in specific industries or regions [2].

Based on Sections 2.1–2.3, this study proposes the second hypothesis:

Hypothesis 2. *The impact of environmental regulation on collaborative innovation in the Chengdu–Chongqing urban agglomeration is consistent with Porter hypothesis: Environmental regulation can improve environmental quality, promote technological innovation, and offset the costs incurred by environmental regulation.*

In summary, academics have conducted a wide range of studies on the applicability of the Porter hypothesis. Nevertheless, the conclusions are inconsistent due to differences in indicators, data, or models, as well as the economic development level, resource endowment, environmental regulation intensity, and how regulation is carried out in each region. First, fewer studies have analyzed data from the perspective of urban agglomeration data in western China or underdeveloped areas. Most have only analyzed provincial or developed region data. Second, few studies have specifically analyzed the influence of ER on CI, and most focus on the relationship between environmental protection and innovation. This study further remedies these two issues and verifies whether the Porter hypothesis is valid in the CCUA.

This study has three main contributions. First, it analyzes the innovation efficiency of ER from the perspective of urban agglomeration in western China (underdeveloped regions) to compensate for the inadequacy of previous national, provincial, or developed region studies. Second, ArcGIS 10.8 software is used to draw spatial distribution maps to compare the collaborative innovation performance of the CCUA on a geographical scale. This differs from previous studies in the literature that have used simple chart comparisons. Third, the Tobit model is used to analyze the impact, which avoids the bias that may arise from using the ordinary least squares (OLS) method for truncated data. At the same time, this study analyzes the heterogeneity of the impact of ER on CI. Analyzing the heterogeneity of the two stages of CI and the heterogeneity of the geographical distribution helps to identify the specific reasons for the differences and to make micro-level recommendations.

3. Method and Data

3.1. Study Area and Data Collection

This study selected the CCUA as the study area. The CCUA is located in the core of southwestern China, driving the western region's socio-economic development and the region's coordinated development. According to the Chengdu–Chongqing Urban Agglomeration Development Plan released in 2016, the division is classified by cities; the CCUA includes 16 cities. Therefore, this study focuses on the CCUA's 16 cities as the research object (Figure 1).

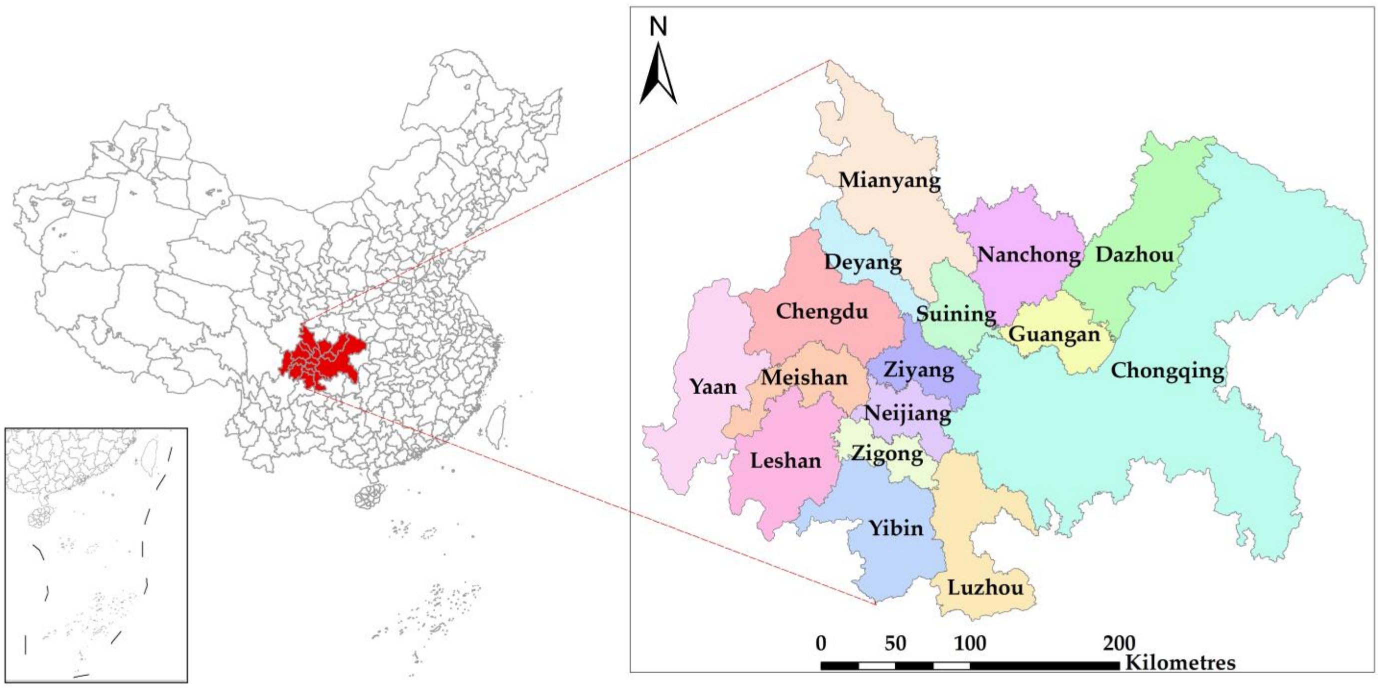

Figure 1. Study area.

This study uses the panel data of 16 cities in the CCUA from 2011 to 2021. During this period of 11 years, China has experienced three Five-Year Plans, each of which has profoundly impacted China's development. The world today is going through profound changes unseen in a century, and China's economy is in a period of transformation and upgrading [10]. As an essential growth pole for the high-quality development of the western economy, the CCUA, its ecological environment's current status, and its innovation-driven development's effectiveness have attracted the attention of scholars and decision-makers [13]. The CCUA is building the Western Science City. As a comprehensive science center, it has gathered several universities, research institutes, and leading science and technology enterprises with international influence. Increasing government financial investment has also laid a solid foundation for the transformation of knowledge achievements and technological achievements in this urban agglomeration.

The data in this study were obtained from the China Environmental Statistics Yearbook, China Science and Technology Statistics Yearbook, China Urban Statistics Yearbook, and statistical yearbooks of Chongqing, Sichuan, and various cities from 2012 to 2022. For a small amount of missing data, linear interpolation was used to complete the data.

3.2. The Two-Stage DEA Model

3.2.1. Model Construction

Among the efficiency evaluation tools, commonly used methods include the Delphi method and Fuzzy Hierarchical analysis, but subjectivity in prioritizing indicators can affect the evaluation results [2]. The DEA model is a mathematical planning-based efficiency analysis tool for analyzing the effectiveness of a decision-making unit (DMU) with multiple inputs and outputs, which can effectively avoid the problem of subjectivity. Cook established a two-stage network DEA model [56]. Liang and Y. Li have improved Cook's model [57,58], and more and more scholars have adopted this model for efficiency analysis [59]. In this study, focusing on the method of Liang and Li, the inputs of the second stage include the outputs of the first stage and the additional inputs of the second stage. The multiplication of the first stage's efficiency with the second stage's efficiency equals the total efficiency of the two stages. The process is shown in Figure 2.

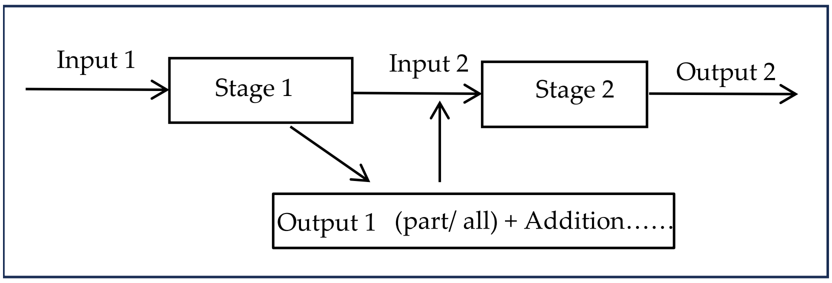

Figure 2. The two-stage dynamic DEA model.

Assume that there are n decision units and that the effective value of a decision unit is θ, specified as $0 \leq \theta \leq 1$, and the input and output variables are x and y. The coefficients are denoted by λ. Excesses of inputs are denoted by k^{+}, and deficiencies of outputs are denoted by k^{-}. If $\theta = 1$, the overall efficiency is effective; if $\theta < 1$, the decision unit is inefficient. This study uses the two-stage dynamic DEA model to divide the evaluation process into two sub-stages from the perspective of CIE, including the knowledge transformation stage and the technological transformation stage. This study uses an input–output model that can reflect the collaborative process of universities, research institutes, enterprises, and the government as the basis for model construction. In regional innovation systems constituted by the above subjects, knowledge can be transformed into new technologies and applied in production to enhance technological innovation [60]; this stage is expressed as knowledge transformation. Technological innovation can promote economic development and social progress [61]; this stage is expressed as technological transformation. This approach improves the accuracy of efficiency calculations and analyses the internal factors influencing efficiency in stages. The two-stage dynamic DEA model is based on Equation (1).

$$\begin{cases} \mathrm{Min}\left[\theta-\eta\left(k^{+}+k^{-}\right)\right] \\ \mathrm{s.t.} \sum_{j=1}^{n} \lambda_j x_j + k^{-} = \theta x_0 \\ \sum_{j=1}^{n} \lambda_j y_j - k^{+} = y_0 \\ \lambda_j \geq 0, j = 1,2,3,\cdots n \\ k^{+}, k^{-} \geq 0 \end{cases} \quad (1)$$

3.2.2. Variable Selection

This study constructs evaluation indexes of CIE from knowledge and technological transformation perspectives and conducts two-stage DEA analyses. The Western Science City in the CCUA is committed to building top universities, research institutes, and science and technology innovation centers with greater influence [7]. Talent factors, capital factors, technology factors, and financial support can have a noticeable impact on collaborative innovation. Based on this, this study also refers to the studies of Huang and Xu et al. [6] and Wang and Hu [32] to categorize the inputs and outputs of CIE. The selected indicators of CIE are shown in Table 1.

Table 1. Evaluation index of collaborative innovation efficiency.

Stage	Vector	Category	Indicator
Knowledge transformation stage	Inputs	Human resources	The number of full-time teachers in colleges and universities (TCUs) The number of students in colleges and universities (SCUs)
		Capital	Education expenditure of finance (EEF)
	Outputs	Science and technology	The number of scientific papers (SPs) The number of invention patents (IPs)
Technological transformation stage	Inputs	Science and technology	The number of scientific papers (SPs) The number of invention patents (IPs)
		Human resources	The number of employees in scientific research and technical services (ESTs)
		Capital	Science expenditure of finance (SEF)
	Outputs	GDP	GDP
		Innovation	Innovation index (II)

In the knowledge transformation stage, inputs consist of human resources of higher education, capital, and the transformation of scientific and technological achievements. Therefore, the input indicators include the number of teachers in colleges and universities (TCUs), students in colleges and universities (SCUs), and education expenditure of finance (EEF) [62]. The output indicators are the number of science papers (SPs) and invention patents (IPs). The FTCU, SCU, EEF, and IP values can be found directly in the statistical yearbook of each city. The SPs can be obtained by referring to the statistical methods of Lyu et al. [48], which include the number of Chinese and English scientific papers published annually in each city.

In the technological transformation stage, the output variables "science and technology—SPs and IPs" from the first stage become input indicators. In addition to technology-related human and capital, the contribution to economic development and effectiveness of environmental innovation are also considered. Therefore, the number of employees in scientific research and technical services (ESTs) and science expenditure of finance (SEF) are considered additional input variables [63,64]. The output indicators are the regional GDP (GDP) and the innovation index (II). The EST, SEF, and GDP are obtained in each city's statistical yearbook. The II can be calculated by referring to the "Report on the Innovativeness of Chinese Cities and Industries" published by the Centre for Industrial Development Research of Fudan University in 2017.

All indicators were normalized prior to the model analysis to avoid the effect of outliers. Linear mapping of the original data through min–max normalization maps the result from 0 to 1, in the 0–1 normalization method. Using the DEARUN 3.2 software, CIE and two-stage efficiency can be obtained so that annual averages and city averages can be calculated for comparing overall efficiency and temporal trends. Then, this study uses the Natural Breaks method to classify CIE into five levels and express it in geospatial visualization by using ArcGIS 10.8 software to carry out spatial distribution analysis [65].

3.3. The Tobit Model

3.3.1. Model Construction

Using the Tobit model, this study analyzed the impact of ER on CIE through two processes.

In the first process, the prevailing method measures ER through a composite index [66]. This study calculated environmental regulation intensity using the entropy method. "Entropy" is a measure of uncertain information. The entropy method can determine the weight coefficients of the metrics, which is more objective than the hierarchical analysis method of metrics, making the data evaluation more credible [67]. This objective weighting method avoids bias caused by human factors. The more information, the less uncertainty, and the less entropy; conversely, the less information, the more uncertainty, and the more entropy [68]. The smaller the entropy of the metrics, the greater the degree of dispersion and the greater the influence of the metrics on the comprehensive evaluation (i.e., the weight). The existing research on environmental regulation intensity has no direct indicators; therefore, the entropy weight method was used.

In the second process, the Tobit model was constructed to analyze the impact of environmental regulation intensity on CIE. The efficiency measured using the two-stage dynamic DEA model is between 0 and 1, and the data above one were truncated to 1 [6]. Therefore, the CIE of the two-stage DEA model are truncated data. Ordinary least squares (OLS) is a commonly used method to conduct regression analyses, but the dependent variable obtained is perhaps discrete [69]. As a result, the panel regression of OLS may be biased. The Tobit model can estimate linear regression models with missing or restricted dependent variables [70]; thus, using the Tobit model can effectively avoid the problems of OLS. As a result, this study used the panel Tobit regression model.

$$y_{ij} = \begin{cases} y^*_{ij} = \beta x_{ij} + \mu_{ij} \\ 0, \text{otherwise} \\ y^*_{ij}, 0 \le y^*_{ij} \le 1, i = 1, 2, 3, \cdots \end{cases} \quad (2)$$

The panel Tobit model is constructed as shown in Equation (2). i represents the year; j represents the city; y_{ij} is the CIE of the jth city in the ith year, between 0 and 1; β is a coefficient vector; x_{ij} represents the value of the influencing factors of the city's corresponding indicators in the ith year; μ_{ij} is a random disturbance term; and y^*_{ij} is the potential CIE.

3.3.2. Variable Selection

Since the model construction is divided into two processes, the variable selection also includes two aspects.

The first aspect is the determination of the variables of environmental regulation intensity in the entropy method. Most studies use environmental protection input and pollution output indicators to measure the effect of ER. In March 2023, the Ministry of

Ecology and Environment of the People's Republic of China issued the Implementation Plan for Setting and Allocating National Carbon Emission Trading Quotas in 2021 and 2022 to cope with climate change. As environmental pollutants and carbon emissions are highly homologous, synergizing to promote pollution reduction and carbon reduction has become an inevitable choice for the comprehensive green transformation of economic and social development in China's new development stage. This study, from the perspective of carbon emission and concerning the study of Huang and Xu et al. [6], has selected the urban domestic sewage treatment ratio (UDSTR), industrial solid waste comprehensive utilization ratio (ISWCUR), domestic waste harmless treatment ratio (DWHTR), volume of industrial sulfur dioxide removed (VISDR), industrial wastewater discharge reaches standard level (IWDRSL), and volume of industrial soot removed (VISR) indicators to measure the effect of ER. The corresponding indices are more relevant to carbon emissions than in previous studies. The larger (smaller) these indices are, the fewer (more) pollutants are emitted, and the more effective ER is. This can be seen in Table 2.

Table 2. Selection of indicators of environmental regulation.

	Indicator	Weight
Environmental Regulation (ER)	Urban domestic sewage treatment ratio (UDSTR)	0.054130137
	Industrial solid waste comprehensive utilization ratio (ISWCUR)	0.050324387
	Domestic waste harmless treatment ratio (DWHTR)	0.005603409
	The volume of industrial sulfur dioxide removed (VISDR)	0.163104783
	Industrial wastewater discharge reaches standard level (IWDRSL)	0.466230143
	The volume of industrial soot removed (VISR)	0.260607140

Note: Weight is calculated via the entropy method.

The second aspect is the determination of the variables in the Tobit model.

Explained variables: Collaborative innovation efficiency (CIE) was selected as the explained variable in the total effects model. Knowledge transformation-stage efficiency (KE) and technological transformation-stage efficiency (TE) were each selected as explanatory variables in the two-stage decomposition.

Explanatory variable: Environmental Regulation (ER).

Control variables: The performance of regional CIE is related to each region's physical capital, economic development, and financial input. This study refers to the research of Huang and Xu et al. [6]. It utilized fixed asset investment (FAI), regional economic level (GDP), and science and education expenditure of finance (SEEF) indicators as control variables. The selected indicators are shown in Table 3.

Table 3. Indicator selection of the factors affecting the collaborative innovation efficiency.

Index Category	Index Name
Explained variables	Collaborative innovation efficiency (CIE) Knowledge transformation-stage efficiency (KE) Technological transformation-stage efficiency (TE)
Explanatory variable	Environmental regulation (ER)
Control variables	Fixed asset investment (FAI) Economic level (GDP) Science and education expenditure of finance (SEEF)

Thus, Equation (3) of the Tobit model was derived.

$$Y_{ij}^{k} = \alpha_0 + \alpha_1 ER + \alpha_2 ER^2 + \alpha_3 \ln FAI_{ij} + \alpha_4 \ln GDP_{ij} + \alpha_5 \ln SEEF_{ij} + \varepsilon_{ij} \quad (3)$$

Here, i represents the year; j represents the city; α is the regression coefficient of each variable; ε is a random interference term; and Y is the explained variable. When $k = 1, 2, 3$, it represents CIE, knowledge transformation efficiency, and technological transformation efficiency, respectively. The explanatory variable is environmental regulation (ER). According to the Porter hypothesis and related studies, the relationship between ER and innovation may show a U shape. The quadratic term may fit the data better; therefore, ER^2 is one of the explanatory variables. The other control variables are fixed asset investment (FAI), regional economic level (GDP), and science and education expenditure in finance (SEEF). To make the model more stable, the variables are taken to be logarithmic. Table 4 shows the descriptive statistics of the variables.

Table 4. Descriptive statistics of variables.

Variable	Sample Size	Mean	Median	Standard Deviation	Min	Max
CIE	176	0.6819	0.6857	0.0913	0.4946	0.9506
KE	176	0.8205	0.8300	0.1018	0.5300	1.0000
TE	176	0.8345	0.8083	0.0844	0.6224	1.0000
ER	176	0.1084	0.0716	0.1487	0.0152	0.9252
ER^2	176	0.0337	0.0052	0.1185	0.0002	0.8561
LNGAI	176	16.4457	16.2689	0.9769	14.8573	19.0518
LNGDP	176	16.6619	16.4305	0.9062	15.0686	19.4465
LNSEEF	176	13.2642	13.0434	0.8829	11.5469	15.9989

4. Results and Discussion

This section begins with analyzing CIE and making a spatial–temporal comparison, followed by an analysis of the regression results of the panel Tobit model.

4.1. Results of the Two-Stage DEA Model

This study evaluated the CIE of the CCUA and the two-stage efficiency from 2011 to 2021. Based on this, it compared the spatial–temporal differences in 16 cities.

4.1.1. Overall Efficiency Analysis

The DEA model can obtain the efficiency of collaborative innovation in each city in each period. By analyzing the average CIE of each period during the study time, Figure 3 was obtained. To make the results more accurate, an analysis of variance (ANOVA) was conducted in this study. Table 5 shows that the differences in CIE ($p < 0.01$), knowledge transformation efficiency ($p < 0.01$), and technological transformation efficiency ($p < 0.01$) among different cities are statistically significant. There are significant differences in CIE among the cities in the CCUA. The city efficiency is between 0.55 and 0.85. The efficiency of Chengdu, Chongqing, Yibin, and Ziyang is above 0.75. The efficiency of Dazhou, Suining, and Guang'an is between 0.7 and 0.75. The efficiency of Neijiang and Meishan is between 0.65 and 0.7. The efficiency of Zigong, Luzhou, Mianyang, and Leshan is between 0.6 and 0.65. The efficiency of Deyang, Nanchong, and Ya'an is between 0.55 and 0.6. There is a significant gap between Chengdu, with the highest efficiency value, and Deyang, with the lowest. The 2022 China Urban Statistical Yearbook shows that Chengdu has 65 regular higher education institutions. Chengdu is a center of education and research in southwest China, and several high-quality universities and research institutes are located here [71], indicating that the knowledge transformation is effective. The number of patent authorizations in Chengdu is 88,414, transforming technological achievements more effectively as the government's financial investment continues to increase. The 2022 China Urban Statistical Yearbook shows that Deyang has 13 regular higher education institutions, and most are vocational colleges. Therefore, the knowledge transformation efficiency is weak in the short term, which negatively impacts CI. The number of patent authorizations in Deyang is 6743, which is 7.6% of that of Chengdu. Deyang has a substantial accumulation of innovation resources but a relative lack of output capacity and low innovation performance in a short period [72]. Therefore, there is a gap between the two cities.

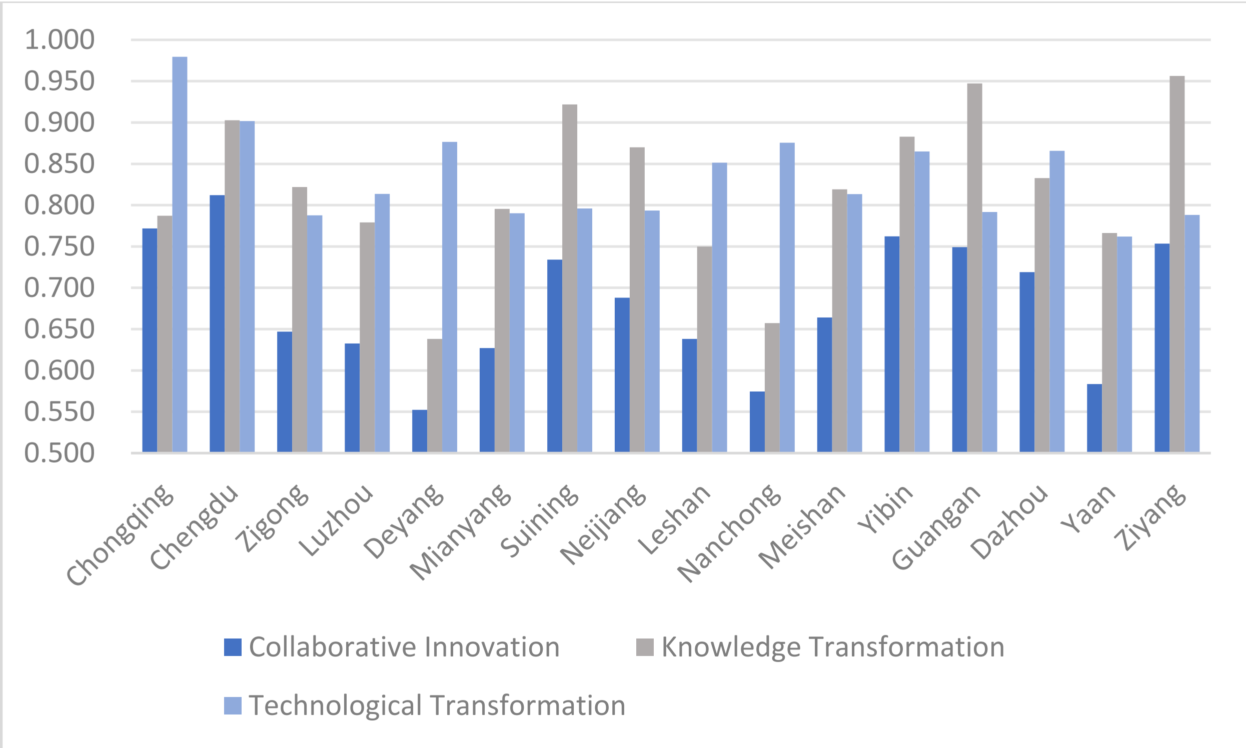

Figure 3. Average collaborative innovation efficiency and its stages of 16 cities in the CCUA.

Table 5. Results of the ANOVA for three efficiencies.

ANOVA—Collaborative innovation efficiency						
Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F-value	*p*-value	F crit
Between Group	1.013878	15	0.067592	24.30412	0.0000	1.72930841
Within Group	0.444974	160	0.002781			
Total	1.458851	175				
ANOVA—Knowledge transformation efficiency						
Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F-value	*p*-value	F crit
Between Group	1.42189	15	0.094793	38.63534	0.0000	1.72930841
Within Group	0.392564	160	0.002454			
Total	1.814454	175				
ANOVA—Technological transformation efficiency						
Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F-value	*p*-value	F crit
Between Group	0.534873	15	0.035658	8.020298	0.0000	1.72930841
Within Group	0.711359	160	0.004446			
Total	1.246232	175				

There is a wide gap in knowledge transformation-stage efficiency among the cities in the CCUA. The efficiency of each city is between 0.6 and 1; most are concentrated between 0.75 and 1. This result indicates that the CCUA has a better effect on knowledge transformation, but there is still room for upward growth. Universities and local governments also strongly support the region's high economic development, but more attention needs to be paid to the balanced distribution of knowledge resources.

There is little difference in technological transformation-stage efficiency among the cities in the CCUA, and the development is relatively balanced. The efficiency of each city is between 0.75 and 1, and most are concentrated between 0.8 and 1. These results indicate that the CCUA has a better effect on technological transformation, but there is still room for upward growth. This trend indicates that the urban agglomeration has a high transformation rate of technological innovation, which is consistent with the critical positioning of the Chengdu–Chongqing region to build a "scientific and technological innovation center with national influence". In recent years, technological innovation has been effective in promoting economic development.

4.1.2. Temporal Dynamics Analysis

By comparing the dynamic development of each year, this study further analyzed the CIE and the two-stage efficiency. Figure 4 shows the averages for each city over the study period.

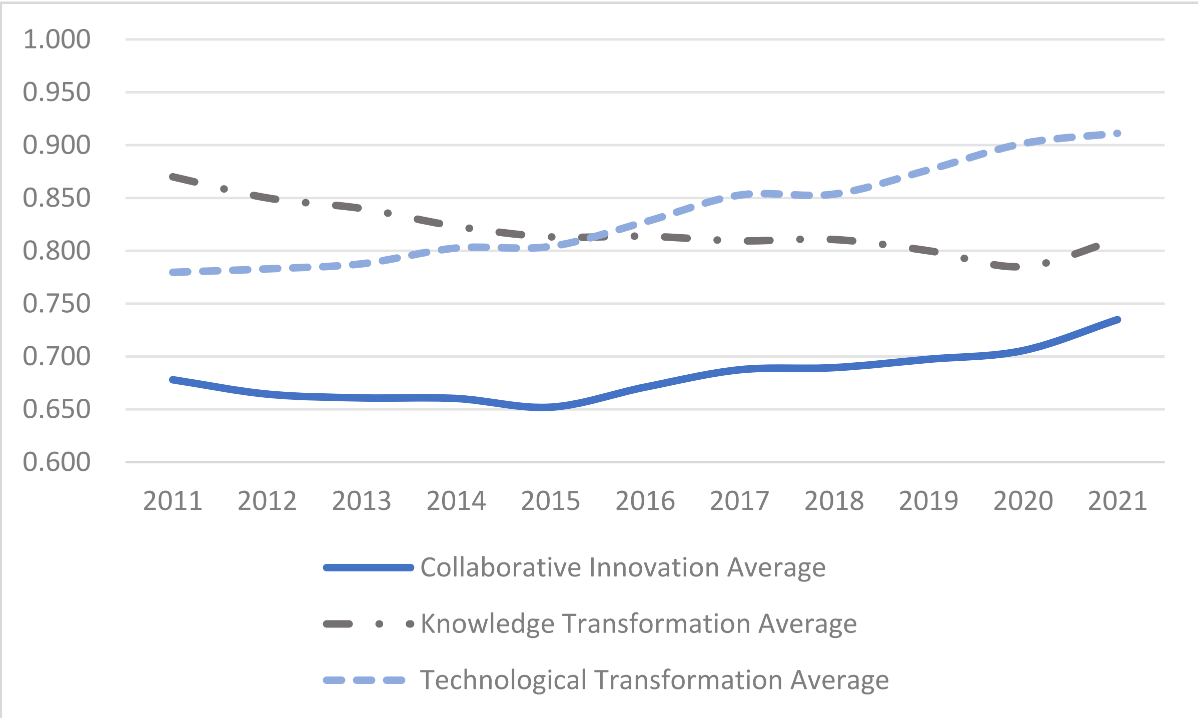

Figure 4. Annual collaborative innovation efficiency and its stages of the CCUA from 2011 to 2021.

The CIE shows an oscillating upward trend from 2011 to 2021. The first wave of minor increases from 2015 to 2017 indicates that the Chengdu–Chongqing Urban Agglomeration Development Plan (CCUADP) has begun to bear fruit. The CCUADP proposed that the CCUA would build a series of industrial zones with output values of CNY 100 billion and CNY 10 billion and promote the independent innovation capacity of the Chongqing Economic and Technological Development Zone and the Chengdu Economic and Technological Development Zone. Based on this, the CCUA established an industry–university–research innovation alliance, breaking down regional administrative barriers and forming the foundation for CI. The second wave of minor increases from 2018 to 2021 indicates that the effectiveness of the construction of the Western Science City, built with Chengdu and Chongqing at its core, is gradually coming to the fore. In July 2020, the People's Government of Sichuan and Chongqing issued the "Advancement Program for Building Regional Development Functional Platforms in Adjacent Regions of Sichuan and Chongqing", which demanded that adjacent regions of Sichuan and Chongqing cooperate to build "9+1" regional (cities included in this study) development functional platforms. This policy opens channels for innovative resource flows, effectively promotes exchanges and cooperation among adjacent cities in the CCUA, and contributes to the transformation of CI's knowledge and technology.

From the outcomes of CI, the CCUA set up the National Technology Innovation Center for the Sichuan–Xizang Railway, the National Technology Innovation Center for High-end Aviation Equipment, the National Technology Innovation Center for Hogs, and the China Earthquake Science Experimental Ground, which are national scientific and technological infrastructures. Since establishing the Chengdu–Chongqing Comprehensive Science Center, 11 national key laboratories have been reorganized, and 114 key R&D projects were implemented before July 2023. The amount of growth in 11 years proves Hypothesis 1, that industry–university–research CIE will increase.

Knowledge transformation efficiency shows a slow downward trend from 2011 to 2021. There are two reasons to explain this. First, most cities in the CCUA have a knowledge transformation innovation efficiency higher than 0.75, which is a high starting point, so there is less room for increase. Second, Sichuan and Chongqing have abundant universities and educational resources, but the transformation rate of results is low. According to the 2022 China Urban Statistical Yearbook, Sichuan and Chongqing have 208 colleges and universities. Still, there are only 80 undergraduate colleges and universities, and even fewer high-quality undergraduate colleges and universities, with most undergraduate colleges and universities are concentrated in the core cities of Chengdu and Chongqing. As a result, the transformation rate of educational resources in this urban agglomeration is low, and the transformation efficiency of knowledge in non-core cities is low.

Conversely, technological transformation efficiency shows a continuous increase from 2011 to 2021. This result indicates that the transformation of technological inputs in these cities is improving. Influenced and radiated by the Western (Chengdu) Science City and the Western (Chongqing) Science City, the cities in the CCUA, relying on their own industrial and policy advantages, have made significant progress in the transformation of scientific and technological achievements with the support of financial and technological funds [71]. However, the efficiency has not yet reached a value of 1, indicating that there is still room for most cities to rise in terms of science and technology fueling economic development. This further reflects that the development strategy of establishing the CCUA as a national urban agglomeration is still a short period, and the government's support for the innovation capacity of high-tech industries still needs to be improved.

Taken together, Hypothesis 1 is valid, and the CIE of the CCUA is increasing yearly. The knowledge transformation stage has a negative impact on CI, and the technological transformation stage positively impacts CI. The negative impact of the knowledge transformation stage was particularly significant between 2011 and 2015. During these five years, the technological transformation stage continued to increase steadily. Still, it did not lead to an increase in CIE in the urban agglomerations because the negative impact of the knowledge transformation stage outweighed the positive impact of the technological transformation stage. After 2015, the positive impact of the technological transformation stage far exceeds the negative impact of the technological transformation stage, causing CI to rise steadily. This fully illustrates that the transformation of scientific and technological achievements significantly affects regional economic development [47,73].

4.1.3. Spatial Distribution Analysis

Based on each city's CIE average from 2011 to 2021 (Table 6), the sixteen cities in the CCUA are divided into five categories. The details are presented in Table 7.

Table 6. The average of each city's collaborative innovation efficiency from 2011 to 2021.

City	Collaborative Innovation Efficiency	Knowledge Transformation Efficiency	Technological Transformation Efficiency
Chongqing	0.772	0.787	0.980
Chengdu	0.812	0.903	0.902
Zigong	0.647	0.822	0.788
Luzhou	0.633	0.779	0.814
Deyang	0.552	0.638	0.877
Mianyang	0.627	0.795	0.790
Suining	0.734	0.922	0.796
Neijiang	0.688	0.870	0.793
Leshan	0.638	0.750	0.851
Nanchong	0.575	0.657	0.876
Meishan	0.664	0.819	0.813
Yibin	0.762	0.883	0.865
Guang'an	0.749	0.947	0.792
Dazhou	0.719	0.833	0.866
Ya'an	0.583	0.766	0.762
Ziyang	0.754	0.956	0.788

Table 7. Classification of collaborative innovation efficiency cities in the CCUA.

Category	Number	City
Category I	1	Chengdu
Category II	6	Chongqing, Guang'an, Ziyang, Suining, Yibin, Dazhou
Category III	2	Neijiang, Meishan
Category IV	4	Mianyang, Leshan, Zigong, Luzhou
Category V	3	Ya'an, Deyang, Nanchong

Chengdu, Chongqing, Guang'an, Ziyang, Suining, Yibin, and Dazhou have outstanding performance in CIE and are in Category I and Category II. Chengdu and Chongqing have several high-level educational institutions and the Western Science City, which provide an advantage in knowledge and technological transformation. The high CIE of Ziyang, Suining, and Guang'an is because the three cities have fewer inputs and fewer outputs for knowledge transformation and technological transformation. Therefore, it does not represent the solid collaborative innovation capacity of the three cities. Ziyang, Suining, and Guang'an are relatively backward areas in the urban agglomeration, and they have small-scale economies with insufficient aggregate effects. Based on data from the China Urban Statistical Yearbook, since 2016, the GDP of Suining, Guang'an, and Ziyan ranked 13th, 14th, and 15th among the CCUA's 16 cities. Yibin's fiscal spending on education and science is higher than comparable cities. Relying on the construction of university cities and science and technology cities, Yibin has promoted the integration of industry–university–research, which has facilitated the rapid transformation of knowledge and technology. Dazhou is close to Chongqing, favoring the flow of innovation factors. Dazhou has focused on building the Dazhou High-Tech Zone in recent years as its Eastern Economic Development Zone is the core area for high-tech research and development.

Ya'an, Deyang, and Nanchong have the worst performances in CI and are in the fifth category, which indicates that the ability of knowledge transformation and technological transformation in this category is weak and does not have a more obvious promotion effect on economic development. Ya'an is an impoverished area on the edge of the CCUA, with both science and education levels lagging. Deyang has many students and teachers in colleges and universities; therefore, its educational expenditure is high. Based on data from the China Urban Statistical Yearbook, since 2013, the number of students and teachers in universities and colleges in Deyang have ranked third or fourth among the CCUA's

16 cities. However, the number of papers and patents in Deyang have ranked eighth or ninth. Fewer papers and patents on scientific and technological achievements result in lower knowledge transformation efficiency, dragging CI in the city down. Nanchong invests more in education and science but produces fewer knowledge outputs, leading to less CI.

Based on Table 6, Figure 5 was plotted. It shows the breakpoints of spatial differences in CIE and two-stage efficiency for each city. Regarding regional spatial differences, the CIE of the urban agglomeration is balanced, but there are variations among cities. This proves that Hypothesis 1 is valid. Significant differences exist in CIE among cities in this urban agglomeration. It roughly shows higher values for Chengdu, Chongqing, and their intermediate cities, with the remaining cities' efficiency values gradually decreasing. The urban agglomeration's higher knowledge transformation efficiency region is in the northwest, with Chengdu, Ziyang, Suining, Neijiang, and Guang'an having higher efficiency values. The remaining cities around the northwest have progressively lower efficiency values. The highest technological transformation efficiency in the urban agglomeration is found in Chongqing in the southeastern part of the urban agglomeration. At the same time, the rest of the cities with high-efficiency values are dispersed in different parts of the urban agglomeration.

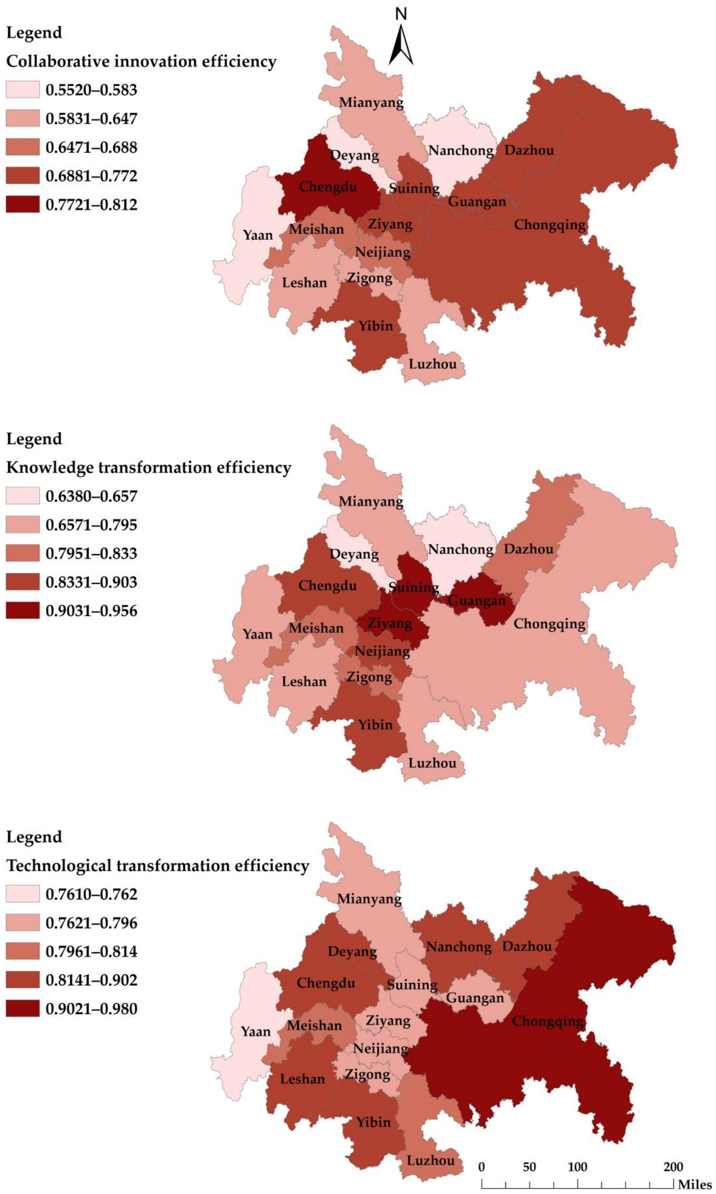

Figure 5. Spatial distribution of collaborative innovation efficiency in the CCUA from 2011 to 2021.

In summary, combining the results of the two-stage analysis, cities with higher knowledge transformation efficiency and technological transformation efficiency constitute several cities with higher CIE, i.e., Chengdu, Chongqing, and Yibin. The knowledge transformation effect is relatively low, and the technological transformation effect is relatively high, confirming the negative impact of knowledge transformation on CI and the positive impact of technological transformation on CI.

4.2. Results of the Panel Tobit Model

Using the Stata 17.0 software, this study applied the Tobit model to analyze the impact of ER on the CIE of 16 cities in the CCUA.

4.2.1. Model Selection

Fixed effects Tobit models do not usually produce consistent, unbiased estimates, and random effects models are better [74]. However, based on multiple circumstances, this study began with selecting the different models. Since the Tobit model is mainly the pooled Tobit model or the random Tobit model, the Breusch–Pagan Lagrange multiplier (LM) test was performed. The chibar^2 value was 272.21, and the p-value was 0.0000. The hypothesis of "no random effects" was rejected, implying that the random effects model was preferred over the fixed effects model. Therefore, the random Tobit model was chosen.

4.2.2. Regression Results

The regression results of the three efficiencies using the random effects Tobit model are shown in Table 8.

Table 8. Tobit regression results of influencing factors.

CIE	Coefficient	Std. Err.	z	$p > z$	[95% Conf. Interval]	
ER	−0.5343932	0.2434281	−2.2	0.0280	−1.011503	−0.057283
ER^2	0.5600783	0.1961016	2.86	0.0040	0.1757262	0.9444305
LNFAI	−0.0291481	0.01567	−1.86	0.0630	−0.0598608	0.0015645
LNGDP	0.2143501	0.0356376	6.01	0.0000	0.1445016	0.2841986
LNSEEF	−0.1095134	0.029577	−3.7	0.0000	−0.1674832	−0.0515436
_cons	−0.9186117	0.2322074	−3.96	0.0000	−1.37373	−0.4634936

LR test of sigma_u = 0: chibar^2(01) = 163.80 Prob $\geq$ chibar^2 = 0.000.

The Tobit regression analysis revealed the following:

As the core explanatory variable, the coefficient of ER is −0.53439 with a p-value of 0.0280, which passes the 5% test. This means the negative effect of ER on CIE is significant. The coefficient of ER^2 is 0.5600783 with a p-value of 0.0040, which passes the 1% test. This indicates that ER^2 has a significant positive effect on CIE. According to the regression results, the influence of ER on CIE is in a U shape. However, existing studies point out that it is not rigorous enough to judge the U shape only by the significance of the quadratic term coefficients. This study refers to Lind and Mehlum et al. [75] to test the existence of a U shape between ER and CIE through the U test. The results are shown in Table 9. According to the results of the U test, first, the extreme point is 0.47707, which is in the range of value of the independent variable (0.0152–0.9252). The overall test of the presence of a U shape shows that the p-value is significant at a 5% level, rejecting the null hypothesis that the curve is monotonic or an inverted U shape, meaning that the curve exhibits a U shape. Second, the slopes on both sides of the curve are consistent with a U shape. When the independent variable is on the lower bound, the slope of the curve is significantly negative (−0.5173668, p = 0.0155). When the independent variable is on the upper bound, the slope of the curve is significantly positive (0.5019757, p = 0.0008). This study further plotted the U-shaped relationship. Figure 6 shows that with the growth of ER, CIE first decreases and then increases. Growing environmental regulation may increase innovation costs and reduce innovation efficiency. However, once reaching the threshold minimum, stricter environmental regulation promotes innovative activity, realizing "innovation compensation", increasing productive efficiency, and promoting economic growth. This is consistent with the Porter hypothesis. The Porter hypothesis suggests that the adoption of innovative technologies is the primary way in which ER has an impact on the economy [16]. This result validates Hypothesis 2; that is, the impact of ER on CIE is consistent with the Porter hypothesis in the CCUA.

Table 9. Results of the U test.

	Lower Bound	Upper Bound
Extreme point	0.47707	
Interval	0.0152	0.9252
Overall test of the presence of a U shape	*t*-value	2.18
	p > t	0.0155
Slope	−0.5173668	0.5019757
t-value	−2.175422	3.200778
p > |t|	0.015466	0.0008131

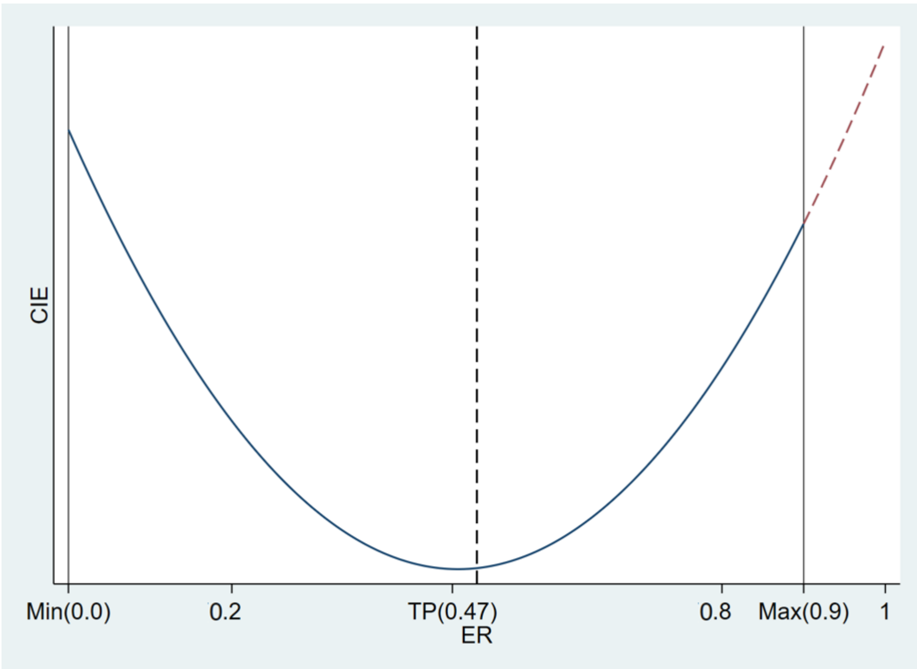

Figure 6. The U-shaped association between ER and CIE.

There are two potential reasons for the Tobit regression results. The first reason may be that the CCUA's environmental regulatory policies positively offset the cost of innovation only afte r a reasonable value has been reached. This reasonable value is the threshold value. This process produces different effects with differences in cities and time. Different cities with different intensities of environmental policies and different timings of regulatory effects will have different effects on collaborative innovation. Therefore, the "innovation compensation" effect of the Porter hypothesis could emerge after the "threshold effect" of ER on CIE in the CCUA. The second reason lies in the instruments of ER. China's environmental regulation approach is based chiefly on command-and-control policies, with low environmental regulation standards and a lack of cost-effectiveness or even feasibility of some policies. The government's economic incentives and information disclosure policies also have limitations [41]. Voluntary environmental disclosure usually comes at the cost of weaker tax contributions, leading to fiscal constraints for governments [76] (p. 452). The ER in Sichuan and Chongqing are of the command-and-control type, with lower market incentives and lower voluntary implementation [77]. In this situation, the ER in the CCUA raises the cost of business, although it significantly facilitates the transformation of knowledge resources into technology. However, enterprises need to spend a lot of money on pollution control, which takes up resources that could be used for R&D and innovation in the short term. This implies that more flexible and diverse environmental regulatory instruments can mobilize enterprises to innovate effectively and, consequently, to realize the "innovation compensation" effect of the Porter hypothesis more speedily.

Next, the control variables were analyzed. Fixed asset investment (FAI) significantly negatively affects CIE. The economic development of the CCUA is mainly driven by investment, but it is still in the initial stage [78]. This indicates that initial investment-driven urban construction inhibits urban innovation performance in the sample period. Regional economic development (GDP) significantly positively affects CIE. In recent years, the GDP of the CCUA has steadily increased, ranking high in the country and growing faster than the national average [11]. The CCUA remains the economic development leader in southwest China. Therefore, the higher economic level can provide funding for science and technology innovation and CI. The science and education expenditure of finance (SEEF) significantly negatively impacts CIE. Regions with backward tertiary industries may show inefficient uses of fiscal expenditures [79], affecting innovation effectiveness. The Chengdu–Chongqing region used to be the core area of third-line construction. In recent years, it has undertaken many manufacturing-based industrial transfers; therefore, the development of the tertiary industry has lagged behind relative to the secondary industry [80]. Therefore, the financial expenditure on science and education of the CCUA has not provided full play to the original impetus of collaborative innovation and technological transformation.

4.2.3. Robustness Tests

To further verify the reliability of the findings, this study conducts a robustness test in two dimensions: replacing explanatory variables and replacing the research models.

1. Replacement of the explanatory variables

Based on the previous analyses, this study refers to the study of Qing-qing and Jun et al. [81] to lag the explanatory variables to verify the robustness of the model. Considering that there may be a delay in the impact of ER on CI, a one-phase lag term and a two-phase lag term of ER were adopted as the replaced explanatory variables to evaluate the robustness of the model. The estimation results after replacing the explanatory variables are shown in Table 10. It is not difficult to find that after replacing the explanatory variables, ER with one and two lags still has a significant negative effect on CIE, and ER^2 still has a significant positive effect on CIE. This is consistent with the previous findings. The significance and impact of control variables are consistent with the results of random Tobit regression.

2. Replacement of research models

To further validate the robustness of the model, this study used different models to test whether the model's results are consistent. The selected models include fixed effects OLS estimation and random effects GLS estimation.

Table 11 shows the comparison results of fixed effects OLS estimation, random effects GLS estimation, and random effects Tobit estimation. Based on the comparison results, the fixed effects model and the random effects model show the negative effect of ER on CIE, and ER^2 shows a significant positive effect on CIE. The significance and impact of the control variables are also consistent with the previous findings using the random effects Tobit model. However, the significance of using the random effects Tobit model is better than the other two, and the model fit is the best. Therefore, conclusions based on this model will be more robust.

Table 10. Comparison of explanatory variable replacement.

Variables	(1) CIE Random_Tobit	(2) CIE Lag1−Random_Tobit	(3) CIE Lag2−Random_Tobit
ER	−0.534 ** (0.243)		
ER^2	0.560 *** (0.196)		
LNFAI	−0.0291 * (0.0157)	−0.0404 ** (0.0160)	−0.0431 ** (0.0171)
LNGDP	0.214 *** (0.0356)	0.225 *** (0.0397)	0.241 *** (0.0426)
LNSEEF	−0.110 *** (0.0296)	−0.0968 ** (0.0387)	−0.0964 ** (0.0423)
Lag1.ER		−0.470 * (0.263)	
Lag2.ER			−0.528 * (0.291)
Lag1.ER^2		0.580 ** (0.229)	
Lag2.ER^2			0.694 ** (0.272)
_cons	−0.919 *** (0.232)	−1.085 *** (0.247)	−1.313 *** (0.275)
N	176	160	144

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11. Comparison of model replacement.

Models	(4) Fixed_Ols	(5) Random_Gls	(6) Random_Tobit
ER	−0.585 (0.343)	−0.462 (0.302)	−0.534 ** (0.243)
ER^2	0.581 ** (0.240)	0.520 *** (0.178)	0.560 *** (0.196)
LNFAI	−0.0374 (0.0450)	−0.0204 (0.0385)	−0.0291 * (0.0157)
LNGDP	0.248 ** (0.0945)	0.177 ** (0.0781)	0.214 *** (0.0356)
LNSEEF	−0.127 ** (0.0545)	−0.0893 (0.0570)	−0.110 *** (0.0296)
_cons	−1.106 (0.814)	−0.721 (0.610)	−0.919 *** (0.232)
N	176	176	176

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2.4. Endogeneity Test

Although the model passes the robustness test, the regression results obtained from the random Tobit model may be affected by endogeneity, resulting in biased and inconsistent regression results. Endogeneity mainly comes from reverse causation and omitted variables. First, we consider reverse causation: innovative activities can affect environmental sustainability and stimulate governments to take action to protect the environment. Second, we consider omitted variables; some unobservable individual micro-variables related to ER may also affect CI activities. The instrumental variables method can solve the endogeneity problem. The selection of instrumental variables must fulfill the conditions of correlation and exogeneity. Correlation means that the instrumental variable and the endogenous variable must be related. Exogeneity means that the instrumental variables affect the explained variables only through the endogenous variables. In this study, starting from the micro dimension, referring to the studies of [47,73], the number of practitioners in water conservation, environment, and public facility management (PWEPM) was selected as the instrumental variable of ER. The correlation of the instrumental variable was fulfilled because a city with more environmental practitioners can reflect that the government is more stringent in ER. At the same time, environmental practitioners' behaviors do not directly affect the subject's innovative activities. Therefore, the exogeneity of instrumental variables was also fulfilled.

The first-stage regression shows that the coefficient of PWEPM on the effect of ER is 0.018897 with a standard error of 0.0026695 and a *p*-value of 0.000, which is significantly positive at 1% level, indicating a strong correlation between the instrumental variable and the explanatory variable. The F statistic is 1071.83 > 10, and there are no weak instrumental variables, indicating that the selected instrumental variables are valid. The results of the Tobit with endogenous regressors show that ER significantly negatively affects CIE and ER^2 significantly positively affects CIE, which is consistent with the U shape of the Porter hypothesis. This shows consistency with the previous findings after overcoming endogeneity. The results of the instrumental variables regression are provided in Table 12.

Table 12. The results of the endogenous analysis.

	First-Stage Regression	**Tobit with Endogenous Regressors**
ER		−1.083742 ** (0.4854951)
ER^2	1.045021 *** (0.0231158)	1.169474 ** (0.5196073)
IV(PWEPM)	0.018897 *** (0.0026695)	

Standard errors in parentheses; ** $p < 0.05$, *** $p < 0.01$.

4.2.5. Heterogeneity Test

For more comprehensive results, this study considers heterogeneity. On the one hand, according to the previous analysis, CI is divided into two stages. Therefore, there would be differences in the impact of ER on different stages of CI. On the other hand, there are differences in the development of different cities in the CCUA. Therefore, there are also regional differences in the impact of ER on CI. This study focuses on two heterogeneity tests: one is the heterogeneity test based on the two-stage CI, and the other is the regional heterogeneity test based on the geographic locations of "East, Central, and West".

1. Heterogeneity test for two-stage collaborative innovation

Table 13 shows the influence of ER on two-stage collaborative innovation. In the knowledge transformation efficiency stage, only FAI is significant, and the other variables are insignificant. In the technological transformation efficiency stage, all variables are significant. Regarding the core variables, ER and ER^2 positively affect knowledge transformation efficiency but are statistically insignificant. ER has a significant negative effect on technological transformation efficiency, and ER^2 has a significant positive effect on technological transformation. Therefore, in this urban agglomeration, there is heterogeneity in the effect of ER on two-stage collaborative innovation, and the effect of ER on innovation in the technological transformation stage is more significant than its effect on innovation in the knowledge transformation stage. This indicates that in this urban agglomeration, stricter governmental environmental regulations affect CI mainly through the transformation of technological innovations rather than the transformation of knowledge innovations.

Table 13. Impact of environmental regulation on different stages of collaborative innovation.

Variables	Explained Variables		
	CIE	KE	TE
Explanatory variable			
ER	−0.534 **	0.0211	−0.739 ***
	(0.243)	(0.251)	(0.242)
ER^2	0.560 ***	0.304	0.530 **
	(0.196)	(0.201)	(0.245)
Control variables			
LNFAI	−0.0291 *	−0.0566 ***	0.0345 *
	(0.0157)	(0.0155)	(0.0180)
LNGDP	0.214 ***	0.0341	0.228 ***
	(0.0356)	(0.0340)	(0.0454)
LNSEEF	−0.110 ***	−0.0231	−0.129 ***
	(0.0296)	(0.0291)	(0.0328)
_cons	−0.919 ***	1.479 ***	−1.765 ***
	(0.232)	(0.227)	(0.298)
N	176	176	176

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

2. Heterogeneity test of different regions

This study divides the CCUA into three regions by geographic location. Eastern cities include Chongqing, Luzhou, Guang'an, and Dazhou. Central cities include Zigong, Suining, Neijiang, Nanchong, Yibin, and Ziyang. Western cities include Chengdu, Deyang, Leshan, Meishan, Mianyang, and Ya'an. Table 14 shows the impact in the eastern, central, and western regions. There are obvious differences in impact in each region. Eastern cities show a significant negative effect of ER on CIE, and ER^2 has a significant positive effect on CIE. Central cities show a positive effect of ER on CIE and a negative effect of ER^2 on CIE. Western cities show a negative effect of ER on CIE and a positive effect of ER^2 on CIE. However, in terms of statistical significance, the impacts of both central and western cities are not significant, and only the impact and significance of ER on CIE in the eastern region are consistent with the findings of the CCUA, which is U-shaped. Therefore, in this urban agglomeration, there is heterogeneity in the effect of ER on CI in cities with different locations, and the effect in eastern cities is significantly higher than that in central and western cities. This indicates that the CCUA is mainly attributed to the influence of eastern cities. Therefore, central–western cities need to strengthen their links with eastern cities to allow for a more balanced development of the environment and innovation in the CCUA.

Table 14. Impact of environmental regulation on collaborative innovation in different regions.

Variables	Total UR	Different Regions		
		EAST	CENTRAL	WEST
Explanatory variable				
ER	−0.534 **	−0.497 ***	2.414	−1.421
	(0.243)	(0.162)	(5.690)	(−0.57)
ER^2	0.560 ***	0.570 ***	−30.62	2.249
	(0.196)	(0.130)	(39.45)	(0.17)
Control variables				
LNFAI	−0.0291 *	−0.0219	−0.0263	−0.122 ***
	(0.0157)	(0.0211)	(0.0180)	(−3.54)
LNGDP	0.214 ***	0.139 ***	0.241 ***	0.394 ***
	(0.0356)	(0.0312)	(0.0398)	(5.11)
LNSEEF	−0.110 ***	−0.0543	−0.0649 *	−0.211 **
	(0.0296)	(0.0430)	(0.0343)	(−3.10)
_cons	−0.919 ***	−0.491 *	−1.993 ***	−1.075 **
	(0.232)	(0.253)	(0.304)	(−2.64)
N	176	44	66	66

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.3. Discussion

The empirical results confirm Hypothesis 1 and Hypothesis 2. International studies on the impact of ER on CI are broadly classified into three categories: the first is the innovation compensation theory, which argues that ER can incentivize firms to innovate and thus reduce costs [5]. Albrizio and Kozluk et al. [53] have found that strict environmental policies in technologically advanced countries can promote short-term productivity growth in industries. The second is "the following the cost theory", which argues that ERs can increase the cost of firms and discourage innovation [8,68]. The third is the uncertainty theory, which argues that the relationship between ER and innovation is uncertain [9].

Chinese studies are also consistent with these three theories. Huang and Xu et al. [6], as well as Zhao and Sun et al. [82] have empirically analyzed the positive impact. This is consistent with the first category. Yawei and Changqi et al. [55] have found that ERs in Beijing, Inner Mongolia, and Heilongjiang have a small hindering effect on innovation capacity. Still, ERs in Hainan, Yunnan, and Guangxi, which have better ecological environments, impede innovation. This is in line with the second type of theory. Pan and Ai et al. [51] have found that market-incentivized ER significantly impacted innovation. In contrast, by analyzing provincial data in China, command-and-control ER had an insignificant impact on innovation. Shuai and Fan et al. [2] have discovered that ER positively promoted green economic efficiency in eastern China but negatively impacted mid-western China. This conforms to the third category theory.

With China's promotion of a coordinated regional development strategy, studies have gradually considered the impact of ER on regional collaborative innovation. However, the generalizability and heterogeneity of the research findings need to be discussed in depth. Through regression analyses, this study confirms that upon reaching the threshold, at the macro level of the CCUA, the Porter hypothesis can be realized as "innovation compensation" in line with the first theory. This finding is consistent with international and Chinese provincial studies, as well as with the findings of studies that adopt command-and-control ER [51], suggesting that this study has some generalizability. The results confirm the Porter hypothesis of a win–win situation between environment and innovation and emphasize the importance of studying regions and policy regimes. Environmental regulation and collaborative innovation take more time to be effective in regional development. Developed countries or regions take less time because of their factor endowments. China should take "advantage of backwardness" in environmental management compared with other Western industrial countries and make environmental development itself the "lead" for innovation through the adoption of more advanced and cleaner technologies and diversified incentive-based environmental regulations [83]. This will facilitate the appropriate allocation of innovation resources within urban agglomerations.

By analyzing heterogeneity, it was determined that the results are not entirely consistent with the Porter Hypothesis at the micro-level of cities. Still, they are consistent with the third theory and the results of relevant sub-regional studies in China [2,55]. First, the differences in impacts and significance across the two transformation stages of the CIE illustrate the diversity of this study. In the CCUA, the utility of high-quality higher education and research institutes for science and technology development has not been sufficiently highlighted, which is closely related to the geographic location of the urban agglomeration and its education policies. This urban agglomeration is inland and mountainous in the west, while China's educational resources are tilted toward the eastern and coastal open areas. Although China has been improving the equitable distribution of education resources in recent years, it will take longer for the effects to be felt in this urban agglomeration. In the CCUA, the impact of environmental regulations on technological innovation transformation is significant, suggesting that using environmental regulations to force technological innovation is effective. The Western (Chongqing) Science City and the Western (Chengdu) Science City can take advantage of the industry–university–research collaborative innovation efficiency. Second, differences in the impact relationships and significance of cities located in different geographic locations in the CCUA also illustrate the diversity and comparability of this study. It is expected that the results of this study will be enlightening for related studies based on cities, micro, individual, or non-developed regions. At a deeper level, preferential policies for urban conglomerates or "innovation zones" are more conducive to accelerated innovation and economic development [76] (p. 452) but can cause some districts to become high-pollution districts. In particular, tax incentives may have a more detrimental effect on voluntary corporate disclosure, thereby increasing pollution [76] (p. 591). China continuously contributes to regional sustainable development. The China (Chongqing) pilot Free Trade Zone and China (Sichuan) pilot Free Trade Zone, established in 2016, can take advantage of the heterogeneity of cities within urban agglomeration. These "innovation zones" have enacted more environmental regimes to promote in-depth environmental governance and relieve the government's fiscal constraints due to preferential policies such as tax incentives. Enterprises in the CCUA will be subject to stricter regulatory rules to ensure more transparent disclosure of environmental information. Such regional heterogeneous development policies will reduce resource consumption and favor the economic and ecosystemic sustainability of the regional environment.

5. Conclusions and Suggestions

5.1. Conclusions

This study analyzed the impact of ER on CI based on the panel data of 16 cities in the CCUA from 2011 to 2021. Firstly, this study used the two-stage dynamic DEA model to divide the CIE into knowledge transformation-stage efficiency and technological transformation-stage efficiency. Then, the changes and causes were analyzed regarding overall efficiency, temporal dynamics, and spatial distribution. The overall efficiency was analyzed according to the average of the study period. The results showed that the difference in CIE among the cities in the CCUA is noticeable, and that the knowledge transformation stage efficiency gap is significant. However, the technological transformation stage efficiency gap is small, with more balanced development. The temporal dynamics were analyzed based on each city's average efficiency. The results revealed that the CIE of the CCUA shows an oscillating upward trend between 2011 and 2021, whereas knowledge transformation efficiency shows a slow downward trend. Moreover, technological transformation efficiency shows a continuous upward trend. The Natural Breaks method of ArcGIS 10.8 software was used to analyze the spatial distribution. The results showed that the spatial distribution of CIE in the CCUA is more balanced, showing higher values in Chengdu, Chongqing, and their intermediate cities. The region with a higher knowledge transformation efficiency is in the northwest. The region with a higher technological transformation efficiency is more dispersed. Overall, it was determined that knowledge transformation stage innovation has a negative impact on CIE, and technological transformation stage innovation has a positive impact on CIE.

The random effects Tobit model revealed that the impact of ER on CI exhibits a threshold effect in the CCUA consistent with the Porter hypothesis. There was a significant negative impact between ER and CIE and a significant positive impact between ER^2 and CIE. The possible reason is that China's command-and-control ER policy increases the cost of pollution control for enterprises and crowds out the resources for innovation. However, upon reaching the threshold, the costs will be offset, resulting in a win–win situation for both the environment and innovation. Therefore, ER for collaborative innovation produces better economic, social, and sustainable development outcomes. Fixed asset investment (FAI) and science and education expenditure of finance (SEEF) were found to have a significantly negative effect on CIE. Untimely information disclosure, investment-driven city construction, and inefficient utilization of financial expenditures are the main reasons for the negative impact. Regional economic development (GDP) was found to have a significantly positive effect on CIE and technological transformation efficiency, indicating that economic growth is the driving force and guarantee of innovation.

5.2. Suggestions

Based on the results of this study, it is recommended to enhance industry–university–research cooperation and smooth the flow of collaborative innovation factors in the CCUA. According to the two-stage DEA model results, the CIE is not high, and the knowledge transformation efficiency of most cities shows a downward trend. Therefore, exploring the cooperative mechanism of CI across administrative boundaries is necessary to provide full play to the core and radiation role of Chengdu and Chongqing as megacities, to promote industry–university–research cooperation, and to make the innovation collaboration among cross-city research institutes, universities, and enterprises within the urban agglomeration smoother. At the same time, exploring the cooperative mechanism of CI will provide full play to the functions of vocational colleges and higher education institutions in marginal cities with lower innovation efficiency, innovative education and teaching reforms, and talent training models. Combining the human resources of universities and the technological resources of enterprises will better assist the high-quality development of the economy.

The next recommendation is the improvement in environmental regulatory policies and the adoption of incentivized and differentiated policies to stimulate innovation in urban agglomerations. According to the results of the Tobit model, command-and-control environmental policies increase the cost of pollution control and crowd out innovation resources in the short term. Therefore, incentives in the form of emission reduction subsidies or moderately higher pollution taxes can be adopted to complement the administrative command regulation policy. At the same time, differentiated environmental regulation policies should be formulated for different businesses and different cities. For example, incentivized abatement subsidies should be adopted for polluters more affected by ER. In contrast, stricter administrative controls should be adopted for polluters less affected by ER [37]. Moreover, governments need to focus on the balance of policy implementation. Different environmental regulatory policies for cities in the east, center, and west would be more targeted and more effective. Policy effects may be more easily realized in the short term.

The final recommendation is to press the responsibility of each city's government into service and develop a stricter and more effective monitoring mechanism. According to the results of the Tobit model, fixed-asset investment and fiscal spending on science and education have a negative impact on CI. Therefore, the government needs to promote the construction of innovation-driven cities, strengthen the supervision and assessment of local environmental protection officials, and provide information disclosure in a timely manner. At the same time, it should optimize the structure and direction of financial expenditure and strengthen the assessment and supervision of the efficiency of the financial expenditure of each city's government. The government also needs to build a favorable climate of innovation support to amplify the positive impact of high-quality economic development on collaborative innovation.

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