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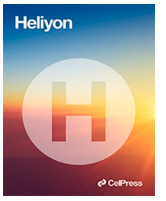

Research article

The impact of poverty alleviation policy on the industrial structure: Evidence from the Qinba Mountain contiguous poverty-stricken areas

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ABSTRACT

In 2015, the Chinese government issued the Decision on Poverty Alleviation(DPA), requiring poverty-stricken areas to develop local characteristic industries based on their resource endowments, to promote industrial structure diversification and industrial structure upgrading through industry-driven poverty alleviation. However, existing research lacks empirical analysis to evaluate it. Therefore, this paper takes poor counties in the Qinba Mountain contiguous poverty-stricken areas(QMCPA) as an example, using the difference in difference model and boundary effect model to evaluate whether DPA has promoted industrial structure upgrading and industrial structure diversification in poor counties. The results show that the DPA has promoted industrial structure upgrading and improved industrial structure diversification in the QMCPA. However, the effectiveness of it is not sufficient. Poor counties have failed to maintain the policy requirement of developing characteristic industries based on local natural resource endowments, leading to a decline in the degree of industrial structure diversification in the later period of the policy. This study indicates that local governments should strive to develop advantageous industries and form a division of labor and cooperation with neighboring areas, strengthen inter-regional cooperation and contact, and enhance anti-risk capabilities to avoid homogenized competition. Studying the changes in industrial structure in the QMCPA has important significance for the long-term stable development and poverty elimination of various poor areas.

1. Introduction

In 2015, the Chinese government issued the Decision on Poverty Alleviation (DPA), which explicitly required local governments of poor areas to formulate regional industrial goals based on the principles of industrial development in it. It means that poor county governments were no longer following the traditional path of industrial development with economic growth as the only goal [1,2], but using extending industrial chains and value chains as a means to promote industrial structure diversification and upgrading of contiguous poverty-stricken areas for economic growth and poverty alleviation [3,4]. Therefore, under the requirements of the DPA, local governments need to develop local industries based on their resource endowments, environmental capacity, industrial coverage

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and farmer preferences, and accurately select priority characteristic advantageous industries for development, so as to eventually achieve the development blueprint of "one county, one industry" and "one county, one policy" [5–7]. In China's poverty alleviation practice, most poverty alleviation funds are used to support industrial development, and the number of poor people lifted out of poverty by industry-driven is the largest [8]. As a guiding policy, DPA is a reasonable choice to transform poverty alleviation from "blood transfusion" to "hematopoiesis", and is the key pathway to help poor areas get rid of poverty [4]. The DPA aims to raise the income level of poor residents by developing agricultural and rural tourism industries and stimulating the inner driving force of poor residents to self-develop, guiding poor populations to participate in the development process of secondary and tertiary industries, and promoting the coordinated development of poor households and poor areas [9]. Therefore, under the guidance of the DPA, to promote industrial structure upgrading, local governments will actively guide production factors and resources to gradually shift to secondary and tertiary industries [10]. Meanwhile, cultivate the development of emerging industries, promote industrial agglomeration, improve industrial competitiveness, and thus enhance the diversification of regional industrial structure [11,12].

Many countries have tried to promote industrial development by elevating local economic levels to get rid of poverty [13–15]. For example, some African countries south of the Sahara have promoted cash crops to promote rural poverty alleviation [16], Thailand has made great efforts to promote local industrial development to boost economic growth and poverty reduction [17], Indonesia has encouraged labor-intensive industries such as textiles and palm oil production and promoted industrial development gradually towards capital-intensive and diversified development to reduce poverty [18]. However, the effects are not satisfactory, and the contradictions restricting the progress of poor areas still exist, and they even face the risk of returning to poverty [19–21]. This is mainly because the industrial development of poor areas is severely constrained by local resources, environment, socio-economic conditions and policies. In particular, the industrial structure is single, the industrial level is low, the proportion of the primary industry is high, and the secondary industry fails to form scale advantages [22]. Coupled with long-term deficiencies in institutional supply and weak fundamentals, problems such as natural resource outflows and talent outflows have occurred, making it difficult to optimize resource utilization, policy support and technological throughput and enhance anti-risk capabilities [23,24], and unable to transform from comparative advantages to industrial advantages. At the same time, the low rate of urbanization means that the whole area lacks core growth points, and the development of the tertiary industry is sluggish and stagnant, ultimately falling into the predicament of low-end development unintentionally [25,26], and unable to achieve industrial structure upgrading. In addition, some scholars point out that local officials may deviate from the goal and policy of industrial structural adjustment for their interests [27], leading to industrial development deviating from actual conditions [28]. For the Chinese government, poverty alleviation is the core goal of government departments. To fulfill the commitment to eliminating poverty by 2020, local governments at all levels will make poverty alleviation a top priority [29]. To ensure the improvement of the living standards of the poor population, the government will actively guide the poor population to participate in the entire industrial development chain and mobilize resources as much as possible to promote industrial development [30]. Therefore, whether poor areas in China can overcome many unfavorable factors and successfully realize industrial structure optimization and upgrading and diversification of development in contiguous poverty-stricken areas is worth attention [31].

Among China's 14 national-level contiguous poverty-stricken areas, the Qinba Mountain contiguous poverty-stricken areas (QMCPA) is the largest in scale and involves the most provinces. QMCPA is located at the junction of six provinces including Henan, Sichuan, Chongqing, Hubei, Gansu and Shaanxi, including 75 national-level poor counties, with complex causes of poverty [32]. Internally, there are large differences in natural environments, and the terrain is complex. The economic situation in QMCPA, especially the industrial structure, has obvious regional characteristics [33]. The degree of industrial diversification is low, and it is difficult to realize industrial structure upgrading [34]. One of the biggest features of the QMCPA is the poor basic conditions and weak carrying capacity of resources and environment, which inability to withstand more prosperous social and economic activities while maintaining regional environmental stability. In addition, the Qinba mountainous region is lagging behind in economic development, with a single industrial structure, a lack of large-scale industries, and a low cost of industrial restructuring [35]. This makes it possible to identify the impact of DPA on changes in the industrial structure of poor areas more easily compared with other economic policies.

In summary, to study the impact of the DPA on the industrial structure of the QMCPA, and verify whether each poor county follows the principles of DPA by developing industries based on local resource endowments, this paper will use county-level data and quantitative economic models to verify whether DPA can promote industrial structure upgrading and diversification, and further summarize the relevant experience of industrial development in poor areas and put forward policy suggestions. Current research on industrial poverty alleviation policies in poor areas focuses more on the path of poverty alleviation and its effects, especially its contribution to economic growth, and few studies focus on the changes in the industrial structure itself. In the context of China's comprehensive poverty alleviation, the study of industrial structure change in contiguous poor-stricken areas can help clarify the importance of industrial structure in the process of the poverty alleviation, which can provide reference experience for other poor areas in the world in the fight against poverty. At the same time, there is no research based on the micro level of poor counties, which makes the research on the industrial structure of poor counties relatively blank, so this paper starts from the county level of QMCA, which not only fills the gap in the relevant literature, but also provides references on how to achieve the optimization and upgrading of the industrial structure of the poor areas.

The structure of this paper is as follows: Section 2 is a literature review and research hypotheses; Section 3 is the methodology; Section 4 is empirical testing and result analysis; Section 5 is the conclusion.

2. Literature review and research hypotheses

2.1. Impact of DPA on industrial structure upgrading in QMCPA

Industrial structure refers to the proportion of the three sectors of regional industry in the economic structure, which has an irreplaceable role in economic development. After the issuance of the DPA, if local governments follow the policy requirements, with the progress of economic development and poverty alleviation tasks, the focus of industries should shift from labor-intensive industries to capital-intensive and technology-intensive industries [36]. However, some studies have shown that the degree of labor intensity of economic growth in poor areas will significantly improve the effect of poverty reduction [37,38]. Therefore, poor counties may ensure that their industries remain in the labor-intensive stage for the sake of economic growth, thereby negatively affecting industrial structure upgrading and falling into the low-end cycle of low-level repetitive production [26].

As such, there are two possible outcomes of industrial structural changes after the issuance of the DPA: falling into a low-cycle trap or promoting industrial structure upgrading. However, the DPA emphasized the importance of industrial development, which requires not only extending industrial chains to increase residents' income levels, but also playing a supporting role in talents to solve key technological difficulties in poor areas' industrial development, avoiding lagging industrial development due to imperfect education and talent levels [39]. Compared with the primary industry, the tertiary industry has a higher poverty reduction effect in rural areas [40]. Therefore, not all poor counties choose to remain in the low-production stage. To truly achieve poverty alleviation and ensure long-term development, poor counties will develop industries based on their resource endowments to effectively avoid the risk of falling into low-level production and gradually moving towards industrial structure upgrading. Therefore, this paper puts forward the hypothesis 1.

H1. The DPA will promote industrial structure upgrading in the QMCPA.

2.2. Impact of DPA on industrial structure diversification in QMCPA

The DPA pointed out that local governments need to develop characteristic industries suited to local resource endowments, raise the income level of poor populations, and promote regional economic growth. Therefore, governments in the QMCPA need to not only ensure industrial structure upgrading but also guarantee the improvement of inter-regional diversification of industrial structures, form a virtuous cycle of industrial chains, and avoid the phenomenon of vicious competition between localities due to industrial homogenization. They should also cooperate to achieve division of labor and cooperation between regions, jointly build local advantageous brands to enhance market share and ensure long-term development of poor areas [12].

Therefore, after verifying the impact of industrial structure upgrading in QMCPA, this paper further considers the changes in industrial structure diversity within contiguous poverty-stricken areas. Compared with industrial structure upgrading being implemented in each specific poor county, industrial structure diversification pays more attention to the degree of industrial specialization and division of labor cooperation within the region. In the past economic development process, local protectionism has led to fragmented policies such as trade barriers and differentiated enterprise treatment [41]. The restrictions on trade and the flow of production factors made it difficult for QMCPA across provincial boundaries to achieve specialized development. This also triggered the phenomenon of imitation of high-tax profit industries in adjacent areas, further reducing the diversification of regional industrial structures. However, the DPA clearly proposes to promote diversified upgrading of industrial structures in contiguous poverty-stricken areas through extending industrial and value chains. Therefore, governments in poor areas need to fully leverage local comparative advantages, comprehensively consider natural endowments and production factors, and select characteristic industries that can serve as pillars of poverty alleviation. This forces local governments to no longer focus solely on similar industries that generate high taxes, but must consider diversification of industrial structures according to policy requirements, develop characteristic poverty alleviation industries, and strengthen support for agriculture and traditional handicrafts based on resource endowments in poor counties. Characteristic industrial development plans should be formulated to support the construction of characteristic agricultural bases and rational and orderly exploitation of poor area resources to ultimately achieve an industrial development pattern of "one county, one industry" and "one region, one characteristic industry" [26].

In addition, the terrain of the QMCPA is complex with diverse internal environments. Different places will face different choices, and factors such as altitude and slope will also affect local industrial selection [42]. Therefore, if local governments in QMCPA advocate alleviating poverty through characteristic industries as advocated in the DPA, the diversification of industrial structures will gradually improve based on the different characteristic industries selected by different local governments. Based on the above analysis, this paper puts forward the hypothesis 2.

H2. The implementation of the DPA has improved the level of industrial structure diversification in the QMCPA.

3. Methodology

3.1. Empirical model construction

Quantitative economic models play an irreplaceable role in the field of public policy analysis [43]. They can help quantify policy impacts, quantitatively evaluate the correlation between policy objectives and indicators, and examine changes before and after a policy is implemented to determine policy effects [44]. The implementation of a public policy impacts some social groups, while others

may not be impacted or impacted to a much lesser degree. Therefore, the execution of a policy can be analogous to conducting a "treatment" on natural experimental objects in a natural science experiment, where external events that cause changes to individuals' or cities' environments in society are called natural or quasi-experiments.

If a public policy can be considered a natural experiment, then the effects of the policy can be understood by comparing the "treatment group" of social groups impacted by the policy and the "control group" of social groups not impacted. The DID model has been widely used in policy evaluation research and is a primary method for causal inference [45]. Scholars use the DID model to examine the impacts of various public policies such as welfare and environmental policies to provide a basis for their continuous improvement [46–49].

Although some scholars argue that DID cannot completely resolve the endogeneity issue of policies, the DID model calculates the size of the impact on the treatment group by computing the difference in average values between the treatment and control groups before and after the exogenous event (i.e. policy implementation). If the model controls for time trends and regional effects, it indicates that unobservable natural changes unaffected by the policy have been excluded, and the coefficient of the core explanatory variable interaction term represents the net effect of the policy. If the coefficient is positive, it means the policy promoted the increase of the variable of concern; if negative, it means the policy resulted in a decrease.

Many studies have used DID models to evaluate policy effect and determine if they achieved the expected results [50–53]. Therefore, this paper selects the DID model to examine the policy effects of DPA and determine if it promoted industrial structure upgrading. Industrial structure upgrading is generally measured by combining rationalization and advancement of industrial structure [54,55]. Given data availability, we choose the industrial structural advancement index as an alternative variable and use a DID model to test whether the DPA affected industrial structure upgrading in the QMCPA. The quantitative economic model is as follows.

$$inh_{it} = cons + \beta_1 Policy_t * Poverty_i + \beta_2 X_{it} + \delta_t + \gamma_i + \varepsilon_{it} \tag{1}$$

The dependent variable inh_{it} refers to the industrial structural advancement index; the independent variable $Policy_t * Poverty_i$ indicates whether the region has implemented the DPA, β_1 is the impact coefficient of x on the dependent variable inh, representing the degree of influence of DPA implementation on industrial structure upgrading, which is also the core focus of this paper; X_{it} represents other control variables, representing the degree of influence of control variables on industrial structure upgrading; δ_t is the time fixed effect, γ_i is the regional fixed effect, and ε_{it} is the error term.

In measuring the level of industrial structure diversification in the QMCPA, we selected industrial structure deviation as an alternative indicator of industrial structure diversification based on Young's paper [56]. The deviation is calculated at the county, city and provincial levels respectively.

By observing the changes in industrial structure deviation in the QMCPA from 2011 to 2019 through these three dimensions, it can be determined whether there are differences in industrial structure between counties, cities and provinces, thereby validating the changes in diversification of industrial structures in poor areas are real and effective, brought about by DPA.

It is worth noting that changes in industrial structure diversification require more precise identification to avoid temporal randomness and misjudging existing industrial structure differences as policy-driven. Many studies note that inter-provincial boundary effects lead to significant differences in industrial development and structure, economic growth rate, and factor mobility between adjacent inter-provincial prefecture-level cities [57,58]. If there was no policy intervention, industrial structures would naturally distribute spatially, but administrative changes alter the original distribution pattern while institutional factors of each province would effectively intervene in the industrial layout, appearing natural. Especially under local government competition, through specialized division of labor and cooperation, regions move towards inter-regional coordination and mutual cooperation, further enlarging differences in inter-provincial industrial structures.

Therefore, if the province is solely taken as the smallest research unit for QMCPA, it would be difficult to distinguish whether industrial structure diversification is driven by DPA or administrative division. To further validate that inter-provincial industrial structure trends still exist after excluding inter-provincial heterogeneity, this paper will use boundary effect models and the construction of virtual provinces to test [41].

First, quantitative economic models are utilized to prove whether actual differences in industrial structure diversification exist between provinces, thereby weakening the trend of industrial structure diversification in QMCPA. Taking the industrial structure differences of cross-provincial boundary poor counties as the dependent variable, the least squares dummy variable (LSDV) model is estimated to test whether the industrial structure differences between cross-provincial boundary poor counties and non-cross-provincial boundary poor counties are significant [59,60].

To avoid the influence of too few observations on research results, boundary counties are defined as counties located on or adjacent to provincial boundaries. The following quantitative economic model is established:

$$Diff_{ijt} = cons + \alpha * cross - province_{ij} + \varphi_{ij} + \theta_t + \varepsilon_{ijt} \tag{2}$$

The dependent variable $Diff_{ijt}$ represents the difference in industrial structure between two poor counties paired according to the principle of spatial proximity; $cross - province_{ij}$ represents whether the two paired poor counties are cross-provincial, and this variable does not vary over time; φ_{ij} is the regional fixed effect at the provincial boundary junction line, θ_t is the time fixed effect, and ε_{ijt} is the error term.

After empirical model verification, the sample counties are sorted alphabetically and then divided into 6 virtual provinces. The calculation results of industrial structure differences constructed along this path show no significant differences from randomly shuffled calculation results.

If competition between different provincial governments leads to differences in industrial structures, randomly constructing virtual provinces to reintegrate poor counties from different original provinces into new "administrative regions" effectively eliminates provincial effects, with no heterogeneity between virtual provinces.

If similar trends in industrial structural changes are observed in the virtual provinces, it would be sufficient to explain that the level of industrial structure diversification within the QMCPA underwent significant changes after the implementation of the DPA.

By constructing virtual provinces in this way, the inter-provincial heterogeneities are removed to the greatest extent while still retaining the characteristics of original contiguous geographical connections within the QMCPA. This provides an effective means to accurately verify the independent impact of policy implementation on industrial structure diversification.

3.2. Indicator construction

3.2.1. Dependent and independent variables

According to the method proposed by Young, industrial structure diversification is measured by industrial structure deviation [56, 61]. The lower the industrial structure deviation, the more similar the regional industrial structures. Industrial structure deviation includes absolute deviation and weighted deviation. The calculation method for absolute deviation of industrial structure is as follows:

$$E = \sum_{i}^{n} \sum_{j}^{m} \left| S_{ij} - \overline{S}_j \right| \tag{3}$$

where S_{ij} refers to the proportion of the output of industry j in region i, $\overline{S}_j$ refers to the proportion of industry j in total output. The weight deviation is calculated as follows:

$$E = I * \sum_{i}^{n} \sum_{j}^{m} w_i \left| S_{ij} - \overline{S}_j \right| \tag{4}$$

where I is the number of regions, w_i is the share of the output of region i in the total output, and S_{ij} and $\overline{S}_j$ are defined in the same with absolute deviation.

The dependent variable in the boundary effect model of this paper is the difference in local industrial structures between neighboring counties. This paper adopts the "industrial division of labor index" proposed by Krugman to calculate the difference in industrial structures between two poor counties [62]. The calculation method is as follows:

$$Diff_{ijt} = \sum_{k=1}^{m} \left| X_{ik} - X_{jk} \right| \tag{5}$$

where $Diff_{ijt}$ is the difference in industrial structure between two poor counties i and j in period t. The higher the value of $Diff_{ijt}$, the greater the difference in industrial structure between the two poor counties. X_{ik} is the share of the kth industry in county i, and X_{jk} is the share of the kth industry in county j.

The dependent variable in the DID model is the industrial structure upgrading index. The connotation of industrial structure upgrading includes progress in industrial proportional relationships and rationalization of production factor allocation between industries.

However, due to data availability constraints, this paper has to give up industrial structural rationalization and chooses the industrial structure upgrading index as the dependent variable. The industrial structure upgrading index involves the evolution of proportional relationships between industries. The higher the value, the higher the level of regional industrial structure upgrading. Referring to existing studies, this paper uses the spatial vector method to calculate it as follows:

Take the proportion of the industrial added value of the three industries in GDP as a component in the spatial vector, thus forming a set of 3-dimensional vectors $X_0 = (x_{1,0}, x_{2,0}, x_{3,0})$, and then calculate the angles $\theta_1, \theta_2, \theta_3$ between X_0 and the vectors $X_1 = (1,0,0), X_2 = (0,1,0), X_3 = (0,0,1)$ of the industries arranged from low to high levels:

$$\theta_j = \arccos\left(\frac{\sum_{i=1}^{3} \left(x_{i,j} \cdot x_{i,0} \right)}{\left(\sum_{i=1}^{3} \left(x_{i,j}^2 \right)^{\frac{1}{2}} \cdot \sum_{i=1}^{3} \left(x_{i,0}^2 \right)^{\frac{1}{2}} \right)} \right), j = 1, 2, 3 \tag{6}$$

$$inh = \sum_{k=1}^{3} \sum_{j=1}^{k} \theta_j \tag{7}$$

3.2.2. Control variables

In addition to DPA, many other factors can affect industrial structure upgrading in poor areas. Therefore, this study selects control variables from three aspects:1) Economic development: GDP growth rate, per capita income, and the number of industrial enterprises; 2) Fiscal: fiscal decentralization; 3) Population: population density, and human capital level.

1. GDP growth rate (SGDP)

As an indicator of economic growth, the GDP growth rate is also used in studies related to industrial structure. The relationship between industrial structure upgrading and economic growth is not stable, with a negative direct effect and a positive indirect effect [63]. It is necessary to include the GDP growth rate as a control variable in the regression to ensure accuracy.

2 Per capita income (AveGDP)

Although regional GDP is often used to measure the economic situation of an area, per capita regional GDP is one of the important indicators to measure local development level, which can better represent the level of economic growth than regional GDP alone. Generally, the better the economic development of an area, the more reasonable the industrial structure and the stronger the speed and ability of industrial transformation and upgrading [63,64]. Therefore, this paper uses the per capita GDP of each poor county to represent the level of per capita income within the poor county.

3. Number of industrial enterprises (Firm)

Poverty alleviation is closely related to industrial development [5]. The more industrial enterprises, the higher the degree of industrial agglomeration, and the greater the scale effect, thereby driving the development of local industrial structure [37]. Therefore, including the logarithm of the number of above-scale industrial enterprises in the regression can control its impact on industrial structure upgrading.

4 Fiscal decentralization (Finance)

Government revenue share (government revenue as a percentage of GDP) has been widely used as a control variable in local industrial structure and industrial agglomeration research, as local governments may generate a series of alienation behaviors to obtain fiscal revenue or local economic output, thereby affecting industrial structure upgrading [65,66]. Therefore, fiscal revenue share is selected as a method to assess the intensity of the government's impact on industrial structure.

5 Population density (PDes)

Population density refers to the ratio of total population to jurisdiction area. Some studies have shown that population density differs significantly across counties in the QMCPA, with eastern and southern areas generally higher than western and northern areas, and population density has a higher correlation with harsh natural conditions and local GDP [33]. Therefore, population density is included as a control variable in the regression.

6. Human capital level (Education)

Studies commonly use the proportion of undergraduate students to the total population or average years of education to indicate the human capital level. However, as this paper uses county-level data, it cannot obtain the number of undergraduate students over the years. For the QMCPA, the education level of residents is relatively lower than the average. There are huge education inequalities between urban and rural China, with 3.87 million rural children not completing compulsory education by 2015 [67]. Therefore, we select the number of junior high school students as an alternative indicator to measure the local human resource level.

3.3. Data collection

To ensure the differences between the treatment group and control group are not too large, leading to biases in the empirical regression results, this paper selects national-level poor counties (treatment group) and non-poor counties (control group) within the QMCPA as samples. All data comes from the China County Statistical Yearbook and local statistical bureaus.

Due to incomplete data and changes in statistical standards for the QMCPA in the statistical yearbooks, the statistical caliber or selection of indicators for various economic indicators has changed, resulting in missing data (such as total output value, number of employees, number of junior high school students, etc. of above-scale industrial enterprises). Therefore, on the premise of ensuring

Table 1
Descriptive statistics of variables.

Variable name	Description	Mean	Std.	Min	Max
inh	Industrial structure upgrading index	3.773	0.586	2.576	5.425
Finance	Fiscal decentralization	0.052	0.034	0.055	0.247
NumFirm	Number of industrial enterprises (taking logarithmic value)	3.547	1.379	0	6.320
PDes	Population density	0.025	0.024	0.0005	0.143
AveGDP	Per capita income	3.170	2.346	0.380	17.897
SGDP	GDP growth rate	0.117	0.100	−0.419	0.827
Edu	Human capital level	0.115	0.031	0.055	0.247

Source: Author's own calculation

data completeness and not affecting regression results, this paper selected variables appropriately. The descriptive statistics of variables are shown in Table 1.

4. Empirical test and results analysis

4.1. The impact of the DPA on the industrial structure upgrading

4.1.1. Basin regression

Table 2 Columpn (1) shows the results of using the DID model to examine the impact of DPA on industrial structure upgrading in the QMCPA without adding any control variables. R^2 represents the goodness of fit of the model, which is 0.494, indicating that the model fit is good. The F-test result represents the overall significance of the regression model. At this time, the F value is greater than the critical value, and the regression is overall significant.

The coefficient of the core explanatory variable is 0.078 (standard error in parentheses), with a positive sign and significance at the 1 % confidence level, indicating that the implementation of DPA has a significant promoting effect on industrial structure upgrading in the QMCPA, and the level of industrial structure upgrading has increased significantly.

Column (2) shows the regression results after adding control variables. It can be seen that after controlling for other variables, the coefficient sign and significance of the core explanatory variable have not changed, indicating that the implementation of the DPA has indeed improved the degree of industrial structure upgrading in the QMCPA and has a significant promoting role, Local governments pay attention not only to economic growth but also promote industrial structure upgrading during the growth process. This verifies Hypothesis 1 of this paper.

The GDP growth rate (SGDP) coefficient is positive, indicating that as the economic level of poor counties improves and the GDP growth rate decreases, the government will shift its attention to promoting industrial structure upgrading, not just promoting industrial manufacturing development. The fiscal decentralization coefficient (Finance) is negative, meaning that fiscal revenue decentralization has a negative impact on industrial structure upgrading. This is consistent with existing research conclusions that fiscal decentralization inhibits the development of industrial structure upgrading, and local governments may generate a series of alienation behaviors to obtain fiscal revenue. The number of above-scale industrial enterprises (NumFirm) has a positive impact on industrial structure upgrading. From the descriptive statistics in the first part, the number of industrial enterprises showed an upward trend. More industrial enterprises increased local employment and production value. Considering the development level of poor areas, the government would strengthen support for labor-intensive processing industries and services industries. Given the development level of poor areas, the government will increase support for labor-intensive manufacturing and service industries, thereby increasing the proportion of labor-intensive industries and reducing the proportion of agricultural output, gradually optimizing the industrial structure.

Table 2
Base regression and robustness test results.

	Basin Regression		Robustness Test	
	(1) Without controlling variables	(2) With controlling variables	(3) Lagged dependent variable regression	(4)Trimming Regression
$Policy_t * Poverty_i$	0.078***	0.056***	0. 066***	0.055***
	(0.021)	(0.021)	(0.022)	(0.021)
SGDP		0.504***	0. 485***	0.503***
		(0.066)	(0. 071)	(0.066)
Finance		−0.134	−0.267	−0.130***
		(0.209)	(0. 214)	(0.210)
AveGDP		−0.006	−0.007	−0.007
		(0.009)	(0. 011)	(0.009)
PDes		−2.241	−1.445	−2.208
		(1.597)	(1.7775)	(1.600)
NumFirm		0.044*	0.013	0.047*
		(0.024)	(0.028)	(0.024)
Edu		−0.011**	−0.007	−0.011**
		(0.004)	(0.005)	(0.004)
Cons	3.536***	3.478***	3.576***	3.464***
	(0.015)	(0.113)	(0.128)	(0.113)
Time Fixed Effect	Yes	Yes	Yes	Yes
Regional Fixed Effect	Yes	Yes	Yes	Yes
R^2	0.494	0.527	0.498	0.522
F-test	128.48	83.09	69.49	81.56

Note: ***, **, * indicate significance levels of 1 %($p \leq 0.01$), 5 %($0.1<p \leq 0.5$) and 10 %($0.5<p \leq 0.1$) respectively.
Source: Author's own calculation

4.1.2. Robustness test

(1) Parallel trend test

The parallel trend assumption is a prerequisite for correctly identifying the causal effect in this paper's model. The key assumption of the DID model is that in the absence of policy interventions, the changes in the treatment group and control group will follow parallel time trends [68]. The strength of identifying causal relationships depends on whether the parallel trend assumption holds.

Therefore, to ensure the accuracy of the baseline regression, this paper conducts a parallel trend test on the samples. The test results are shown in Fig. 1. Post refers to the year of policy implementation. Post 1–4 refer to the 1st-4th years after policy implementation. Before1-3 refer to the 1st-3rd years before policy implementation.

It can be seen that the coefficient estimates before the policy were mostly not significant, indicating that the pre-trends of provincial poor counties and other non-poor counties were parallel without significant differences, satisfying the parallel trend assumption. The implementation of DPA has a relatively strong causal relationship with industrial structure upgrading.

In the year of DPA implementation and the following two years, due to the inertia of policies, there were no significant differences between the treatment group and the control group. But from the third year after implementation, the coefficient estimates became significant and showed an upward trend, which is sustainable, again confirming the reliability of our results.

(2) Lagged regression of dependent variable

To further reduce endogeneity issues and ensure the stability of regression results, the independent variable was lagged one period for regression again, observing its significance. The results are shown in column (3) of Table 2.

The lagged regression results show that DPA still has a significant positive impact on industrial structure upgrading, further confirming the reliability of the basic regression results in this paper.

(3) Truncation treatment

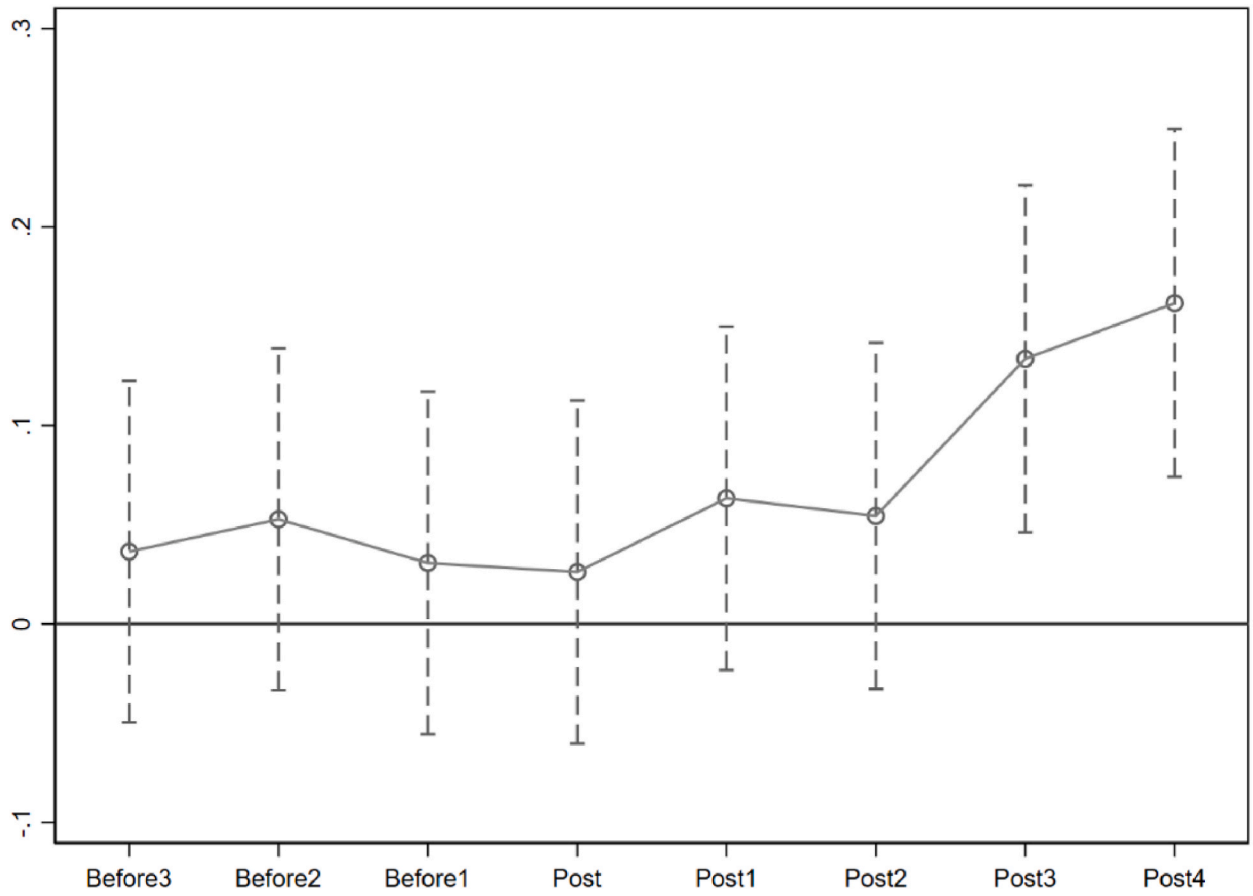

Fig. 1. Parallel trend test results.
(Source: Author's own calculation).

To eliminate the impact of outliers on regression results, we performed a 1 % tail truncation on the sample and re-ran the regression after truncation. The regression results are shown in column (4) of Table 2. Overall, the size and significance of the independent variable coefficients are consistent with the baseline regression, indicating that the model has relatively strong robustness.

4.1.3. Heterogeneity test

(1) Heterogeneity test based on regional altitude

Altitude is a very important indicator of vegetation types, biological migration, agricultural production, urban layout, village locations and population agglomeration [33].

Therefore, the altitude data of poor counties was used to calculate the local altitude to test the impact of altitude on industrial structure upgrading. The regression results are shown in columns (1) and (2) of Table 3. Column (1) shows areas with lower altitudes, where the interaction term coefficient is significant and positive. Column (2) shows areas with higher altitudes, where the interaction term coefficient is insignificant and negative.

This indicates that in areas with lower altitudes, the implementation of the DPA improved the industrial structure upgrading of poor counties; but in areas with higher altitudes, there was no significant improvement in industrial structure upgrading of poor counties.

Theoretically, the lower the altitude, the better the natural geographic conditions, the more convenient the transportation, and the more suitable for the agglomeration and layout of primary and secondary industries. The higher the altitude, the greater the terrain undulations, the more drastic the changes in water heat conditions, the more adverse the natural conditions, the more dispersed the residence, and the more difficult it is to provide more complete infrastructure and services.

Therefore, poor counties in high-altitude areas face difficulties in industrial development and lag in secondary and tertiary industries. The government is inclined to select characteristic industries adapted to high-altitude areas, such as characteristic agriculture and animal husbandry, with a relatively higher proportion of primary industry. Therefore, the promoting effect of the DPA on their industrial structure upgrading is not obvious.

(2) Heterogeneity test based on regional ecosystem quality

Some scholars point out that governments are often constrained by multiple targets. When governments face dual targets of economic growth and ecological environment protection, they may make differentiated choices based on local conditions [69,70]. Specifically, it may lead to behavioral distortions due to excessive environmental performance pressure, or neglect the environment and balanced development due to GDP performance evaluations [71–73].

Since the remote sensing ecological index (RSEI) can effectively measure regional ecological quality [74,75], we use the RSEI of each poor county as the basis for grouping to examine whether DPA has improved local industrial structure upgrading in areas with different ecological qualities.

The regression results are shown in columns (3) and (4) of Table 3. Column (3) shows the regression results for areas with lower RSEI, and column (4) shows the results for areas with higher RSEI. It can be seen that the interaction term coefficient of poor counties

Table 3
Heterogeneity test.

	Altitude		RSEI	
	(1)	(2)	(3)	(4)
$Policy_t * Poverty_i$	0.116***	−0.059	0.087***	0.016
	(0.022)	(0.052)	(0.027)	(0.035)
SGDP	0.353***	0. 695***	0. 257***	0.909***
	(0.075)	(0.141)	(0. 081)	(0.113)
Finance	0.163	−0.248	0.282	−0.205
	(0.366)	(0. 304)	(0.440)	(0.248)
PDes	−2. 600**	5.730	−2.844*	9.003
	(1.378)	(19.201)	(1.571)	(7.136)
AveGDP	0.017***	−0. 033	0.016	−0. 043**
	(0.010)	(0.022)	(0.011)	(0.019)
NumFirm	0.008	0.073	−0.002	0.090**
	(0.027)	(0. 048)	(0.031)	(0.038)
Edu	−0.019***	0. 016	−0.021***	0.014
	(0.005)	(0.010)	(0.005)	(0.009)
Cons	3.713***	2.916***	3.900***	2.625***
	(0.136)	(0.278)	(0.148)	(0.228)
Time fixed effect	Yes	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes	Yes
R^2	0.577	0.509	0.526	0.573

Note: ***, **, * indicate significance levels of 1 %($p \leq 0.01$), 5 %($0.1<p \leq 0.5$) and 10 %($0.5<p \leq 0.1$) respectively.
Source: Author's own calculation

with lower ecological environmental quality is significantly higher than that of poor counties with higher ecological environmental quality.

As mentioned earlier, China's poor counties often overlap with ecologically vulnerable areas. For poor areas with relatively good ecological environment quality, local governments have the ability to balance economic development and ecological environment protection. When the ecological environmental quality is at a relatively low level, considering the high environmental maintenance costs and urgency of tasks, the government will not invest too much in ecological environment protection but focus on economic growth, so that the growth of the regional total economy drives industrial structure upgrading. Therefore, DPA's promotion of industrial structural optimization is particularly significant.

In summary, we find that DPA can significantly improve the level of industrial structure upgrading in poor areas, echoing the contents of existing research that DPA will promote industrial structural adjustment in various ways to achieve the goal of poverty alleviation. However, this promoting effect will be affected by the inherent characteristics of poor areas such as altitude and ecological environmental quality, leading to different results.

Although some scholars argue that the current promotion of industrial structure upgrading and ecological environment protection faces conflicts that may hinder industrial development, existing studies have proved that industrial structure upgrading can alleviate the contradictions between economic growth and environmental protection, and is an excellent choice for poor areas. The Chinese government can achieve green development in poor areas through environmentally friendly industries without damaging local ecology.

4.2. *Industrial structure diversification in the QMCPA*

This paper calculates the degree of industrial structure diversification in the QMCPA from the dimensions of county, city and province respectively. The degree of industrial structure diversification at the county level is shown in Fig. 2. It can be seen that until 2015, the degree of industrial structure diversification fluctuated but remained at roughly the same level. Therefore, before the implementation of the DPA, there was no significant difference in industrial structure between counties (the weighted deviation fluctuated more stably by comparison).

In 2016, the degree of industrial structure diversification increased significantly, which is more obvious in the weighted curve. This shows that the DPA did promote various places to choose appropriate characteristic industries for poverty alleviation based on local development conditions and the natural environment. The change occurred in 2016 rather than 2015 when the policy was implemented, which is also traceable. Due to the late release of policies, as well as the inertia of policies and the time needed for local governments to select and develop characteristic industries, the improvement of industrial structure diversification degree occurred in the year after policy implementation. However, this growth did not continue. From 2017, industrial structure diversification began to decline again. The decline in regional industrial structure diversification represents a convergence of industrial structure, indicating

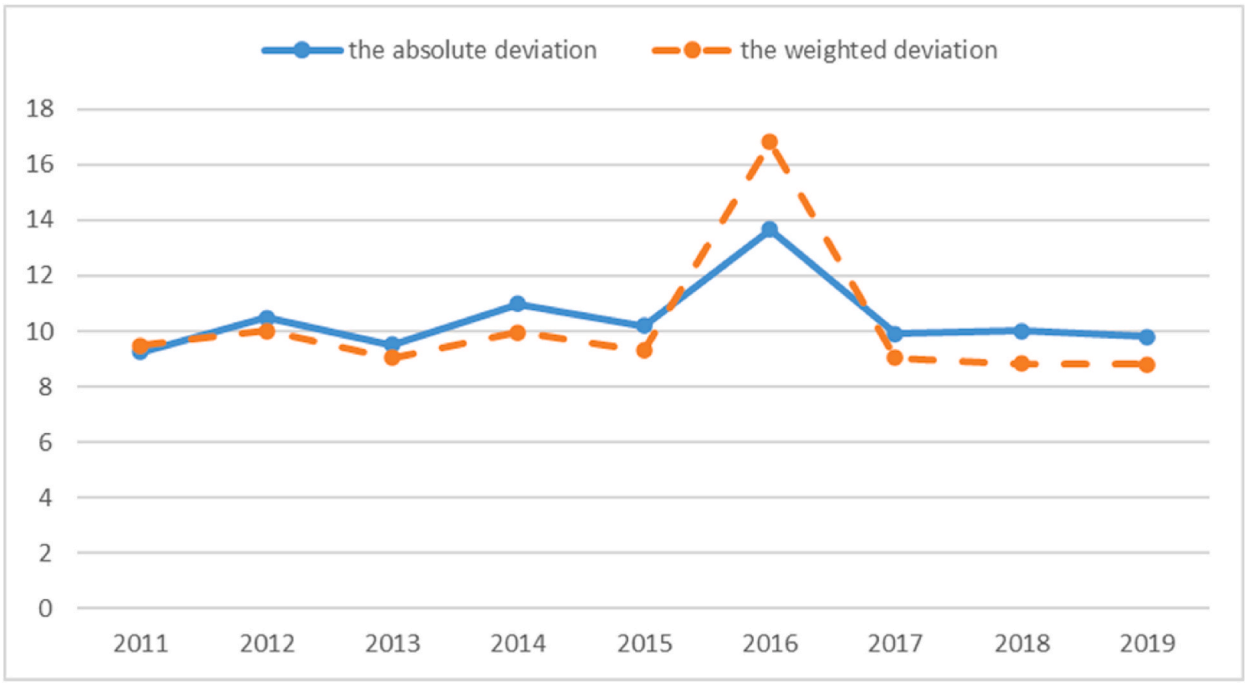

Fig. 2. Industrial structure diversification at the county level in QMCPA
(Source: Author's own calculation)

that various places failed to maintain the specialized development of industries. This may be because the QMCPA failed to achieve the characteristic industrial development required by the DPA. It may also be limited by their economic level and unable to meet the conditions for regional specialized development.

As shown in Fig. 3, the diversification of industrial structure at the city level is generally consistent with the trend at the county level, with some absolute value differences related to the calculation method. The industrial structure deviation of each region is obtained by summing the absolute deviations of each region. The number of regions at the county level is more than that at the city level. Therefore, the value of industrial structure deviation will decrease with the increase of the calculation unit.

Fig. 3 shows that the degree of change in industrial structure diversification before and after policy implementation was not significant, with a remarkable upward trend only in 2016, almost doubling from 2015, slightly higher than the 0.8-fold increase at the county level. This shows that the diversification of industrial structure between counties and cities is similar, which should be because the diversification of industrial structure between cities is based on the county level. That is, in the QMCPA, there is no significant difference between the two. Whether from the county level or the city level, we can consider that the DPA for characteristic industries has brought about changes in industrial structure, although this change is short-term and discontinuous.

Next, we conducted a tracking analysis of industrial structure diversification at the provincial level (Fig. 4). Compared with the county and city levels, the overall changing trend at the provincial level is similar to the previous two dimensions.

In 2016, the industrial structure diversification within the QMCPA showed an upward trend (although the weighted deviation did not reflect a higher degree of increase). However, the extent of change at the peak was not as significant as the remarkable changes at the county and city levels, only slightly higher than the diversification before policy implementation. This means that real and effective changes did occur in industrial structure diversification between provinces, but this change was relatively weak and there were other factors causing this weak change.

These phenomena may be caused by impact factors that we have not observed yet, or may be due to heterogeneity between provinces, where the originally existing industrial structure diversification between provinces partially offset the impact of the DPA. In other words, based on the differences in administrative areas leading to the expansion of industrial structure differences, we cannot accurately identify the impact of DPA. Therefore, we chose to construct virtual provinces to test whether industrial structure diversification was affected by policies at the provincial level mentioned later.

Before constructing virtual provinces, we first used a more specific boundary effect model to examine the difference in industrial structure between poor counties in different provinces before and after the implementation of the DPA. If the regression results are significant, it indicates that there were significant differences in industrial structure between provinces. The regression results are shown in Table 4.

Table 4 shows the results of the initial regression: Column (1) shows the results without controlling any fixed effects; Columns (2), (3) and (4) show the results controlling for time or regional fixed effects. Table 4 shows that whether controlling for regional fixed effects or time fixed effects, the coefficients of the independent variables are all significantly positive.

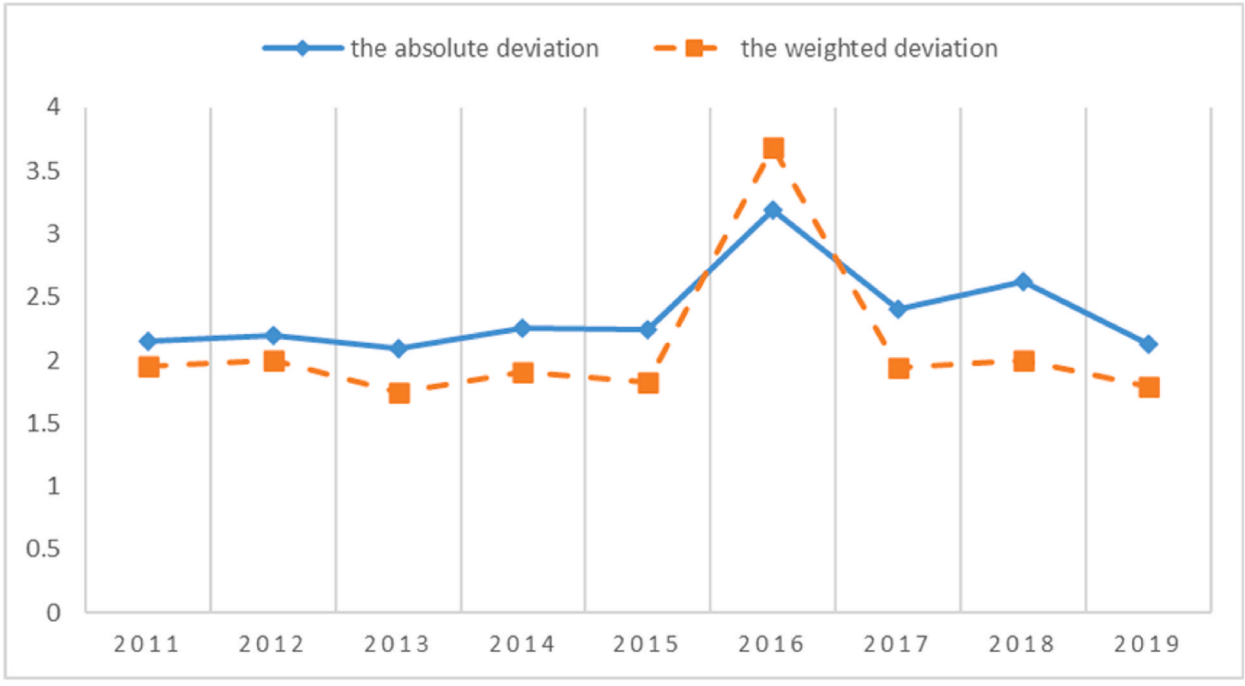

Fig. 3. Industrial structure diversification at the city level in QMCPA
(Source: Author's own calculation)

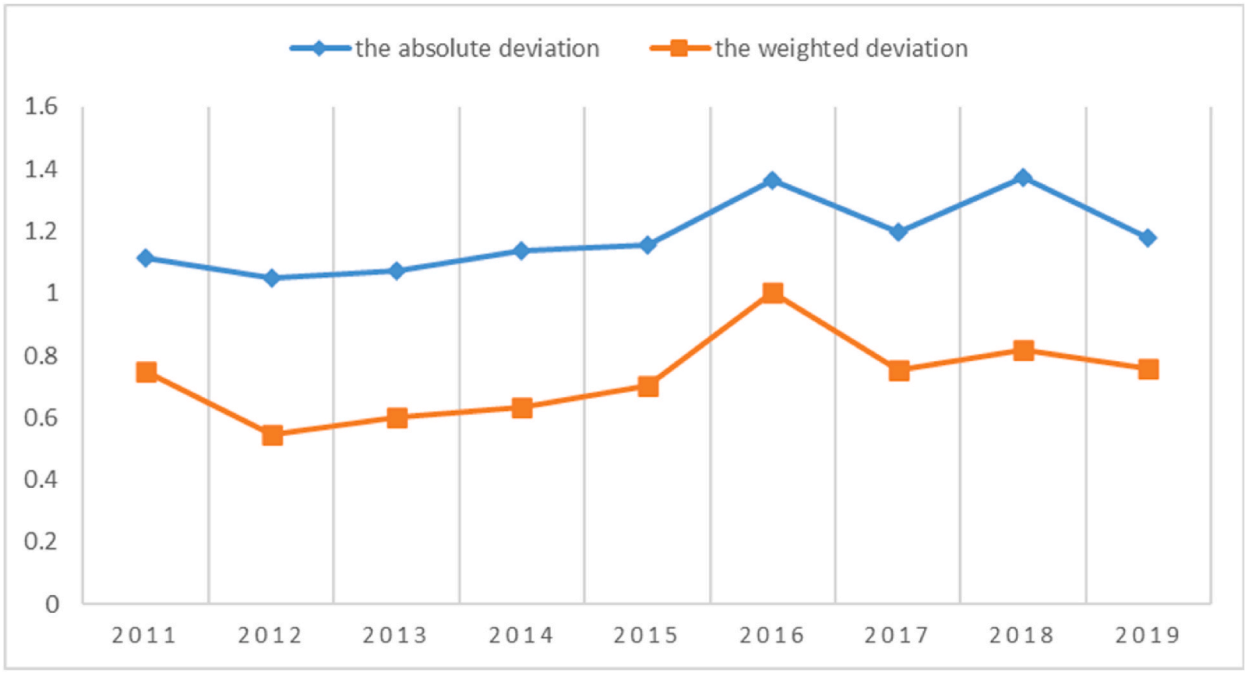

Fig. 4. Industrial Structure Diversification at the Provincial Level in QMCPA.
(Source: Author's own calculation)

Table 4
Boundary effects test.

	(1)	(2)	(3)	(4)
Cross-province	0.0984***	0.1460***	0.0984***	0.1460***
Cons	0.2995***	0.2133***	0.2385***	0.1523***
Regional fixed effect	No	Yes	No	Yes
Time fixed effect	No	No	Yes	Yes
R^2	0.0213	0.0468	0.1587	0.1838
F-test	16.24	21.03	5.35	10.91

Note: ***, **, * indicate significance levels of 1 %($p \leq 0.01$), 5 %($0.1<p \leq 0.5$) and 10 %($0.5<p \leq 0.1$) respectively.
Source: Author's own calculation

This initial regression result shows that cross-provincial boundaries would significantly expand the differences in industrial structure between adjacent poor counties on both sides of the provincial boundary in comparisons of industrial structures, but this difference does not change with time. This also re-explains why from the perspective of cross-provincial industrial structure differences, the fluctuations of industrial structure diversification at the provincial level were not as dramatic as the other two dimensions.

After validating the significant differences in industrial structure between provinces, we immediately constructed virtual provinces to test whether the changes in industrial structure diversification in the QMCPA with virtual provinces as the smallest units are consistent with the changing trends when actual provinces are the smallest units. As shown in Fig. 5, the trend of industrial structure changes in virtual provinces is consistent with the county and city levels, although the weighting curve fluctuates less. Each inflection point shows the same changing trend.

By dispersing the division effects between actual provinces to virtual provinces through the construction method, the trend of industrial structure diversification at this time shows that DPA had a significant impact on the QMCPA after excluding the "provincial boundary effect".Comparing actual provinces with constructed virtual provinces, it can be found that the degree of industrial structure dispersion in virtual provinces is lower than in real provinces. This also proves from another aspect that some "common forces" in provincial characteristics or development processes affect industrial structure and make the degree of dispersion higher. Otherwise, the degree of industrial structure diversification in virtual provinces should be higher.

Since the industrial structure diversification within the QMCPA is the sum of the overall level, it is impossible to judge the degree of industrial structure changes in each province. Therefore, we examined the industrial structure diversification within poor counties in each province. The purpose is to judge which provinces had the largest changes and which provinces responded most strongly to the implementation of the DPA through the changes in industrial structure within each province. The results are shown in Fig. 6.

Sichuan Province has the highest degree of industrial structure diversification, followed by Gansu Province, with Chongqing having

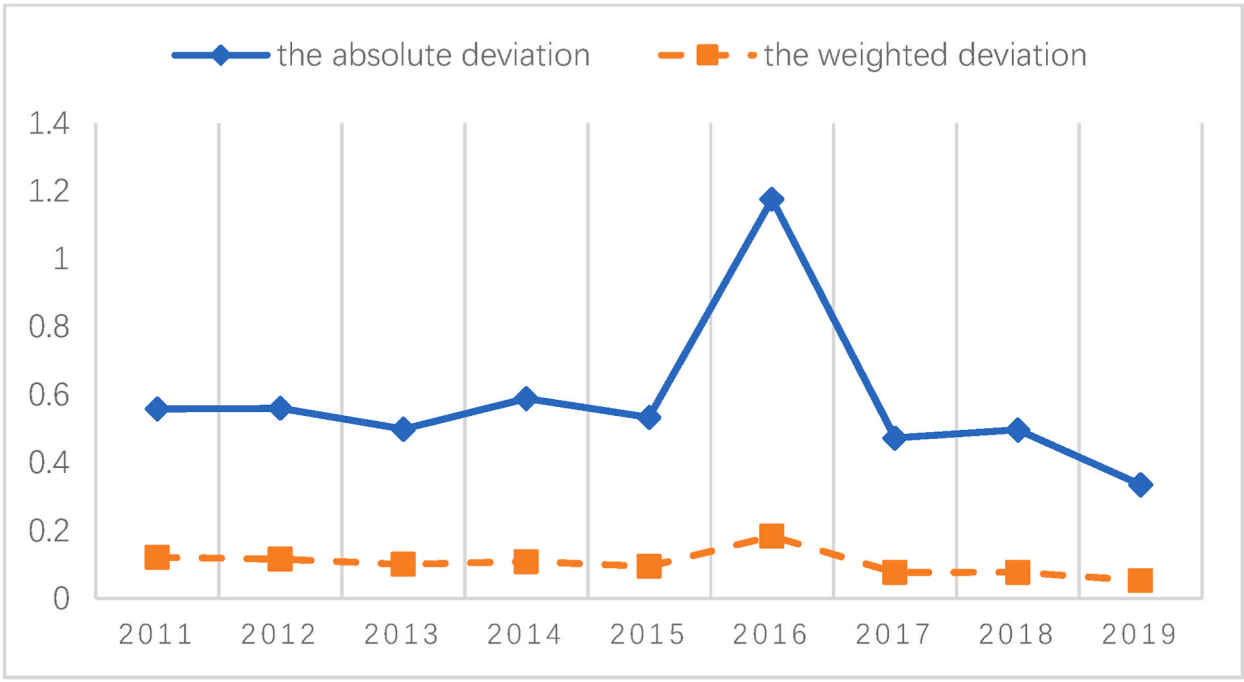

Fig. 5. Industrial structure diversification at the virtual provincial level in QMCPA
(Source: Author's own calculation)

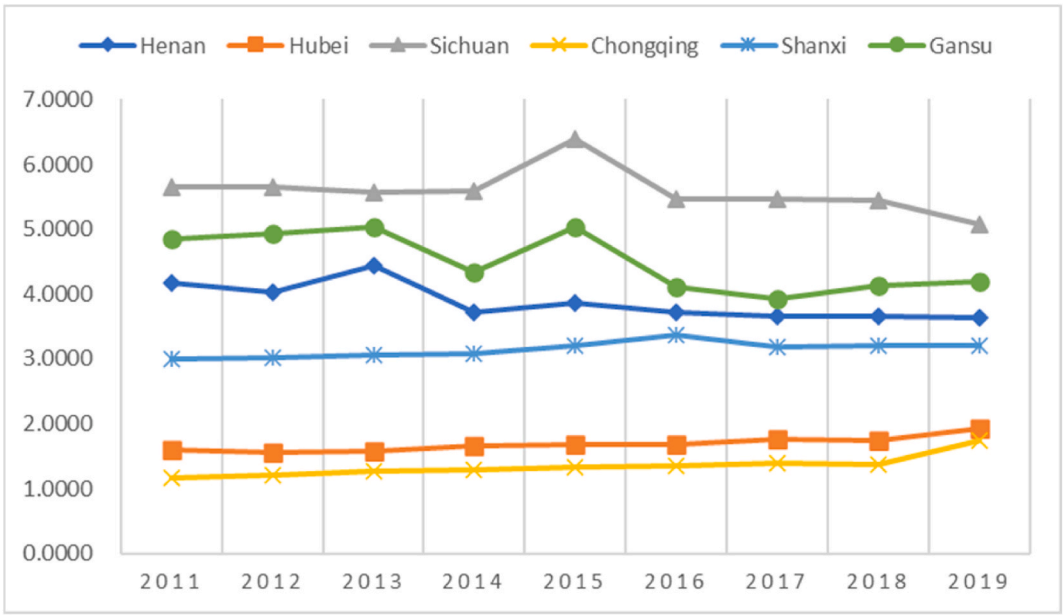

Fig. 6. Changes in industrial structure diversification in provinces within the QMCPA
(Source: Author's own calculation)

the lowest. Overall, the industrial structures of Sichuan and Gansu underwent significant changes after the implementation of the DPA, with diversification first increasing and then decreasing, consistent with the overall trend. The peak appeared in 2015 rather than 2016, which is different from the overall peak of diversification in the QMCPA. The reasons are: 1) the speed of industrial structure adjustment within the two provinces was faster than the entire QMCPA. 2) The changes in industrial structure diversification of the two provinces were not enough to immediately change the diversification of the entire QMCPA.

The other four provinces did not respond strongly to the DPA in terms of industrial structure diversification, possibly because the

direction of industrial development they chose was consistent with the original DPA, or they may have been affected by other provincial factors, such as different industrial policies that offset each other, making the role of characteristic industries in poverty alleviation very small and industry-based poverty alleviation was not the main poverty alleviation path relied on locally.

Based on the above analysis, it is not difficult to find that the industrial structure in the QMCPA underwent significant changes after the issuance of the DPA. This change was reflected at the county, city and provincial levels, indicating that local governments chose suitable characteristic industries as poverty alleviation paths in accordance with local conditions under the guidance of central policies, striving to achieve the goal of "one county, one industry".

Due to local characteristics and endowments, the QMCPA are rich in biological diversity resources and have great potential for development and utilization, with sufficient resources to develop related industries such as Chinese medicine planting, biological preparations, and processed industries mainly based on characteristic agricultural, forestry and livestock products. This means that each poor county has a great deal of autonomy to choose industries with comparative advantages. For the whole QMCPA, industrial structure diversification is conducive to its economic growth. As a resource-dependent region, it should focus on selecting the leading industries that need to be developed [75,76].

Unfortunately, the change in industrial structure diversification did not last long. After just one year, the degree of diversification gradually decreased again and reverted to industrial structure convergence. Combined with existing research analyses, the reasons for the decline in industrial structure diversification may be multi-faceted. In addition to the insignificant impact of the DPA, local protectionism may have hindered regional specialized division of labor, leading to a decline in industrial structure diversification [77]. Local governments may have distorted characteristic industries in the DPA to achieve economic targets of increasing per capita income [27].

Therefore, in order to help poor areas develop stably and sustainably in the long run and further promote regional characteristic development to smoothly enter the rural revitalization stage, local governments need to formulate more targeted policies again, especially for resource-based areas. During industrial structure transformation, they should focus on selecting the leading industries that need to be developed, rather than simply upgrading industrial types.

5. Conclusion

This study uses data from 2011 to 2019 in the successfully poverty-alleviated counties in the QMCPA to analyze the changes in the industrial structure of poor counties through DID model and the boundary effect model. The following conclusions are drawn:

Firstly, industry poverty alleviation prominently promoted industrial structure upgrading of poor counties, and industrial structure upgrading is the foundation for long-term stable development. Industrial structure upgrading is also affected by the altitude and ecological environment of poor counties. The lower the altitude and poorer the ecological environment, the greater the impact of the DPA on industrial structure upgrading. Compared with low-altitude areas, governments should select industries adapted to plateau climate for high-altitude poor counties to help residents become prosperous. Attention should also be paid to environmental quality in areas with relatively poor ecological environment to avoid falling into the trap of environmental poverty.

Secondly, the DPA can significantly improve industrial structure diversification in the QMCPA. The trends of industrial structure diversification calculated from the three dimensions of county, city and province are identical over time. However, the degree of deviation is slightly different at the provincial dimension due to heterogeneity between provinces. Crossing provincial administrative regions would markedly enlarge the difference in industrial structures between the two regions. The three dimensions of industrial structure diversification all prove that after implementing the DPA, the governments of QMCPA selected suitable characteristic industries for poverty alleviation according to local resource endowments. However, the gradual decline in later industrial structural bias indicates that some poor county governments failed to adhere to the development of advantageous characteristic industries as the principle of characteristic industry poverty alleviation, abandoning advantageous industries such as characteristic agriculture, forestry, aquaculture and processing and manufacturing, resulting in deviations from expected targets despite achieving the ultimate goal of poverty alleviation.

However, this study still has some limitations. First, due to data limitation, only industrial structure sophistication indicators could be used to study the impact of the DPA on industrial structure upgrading without calculating the rationalization of industrial structure in poor areas for more comprehensive research. Second, in traditional DID models, the stable unit treatment value assumption (SUTVA) requires that entities in the treatment group would not affect those in the control group. However, there must be close interactions and frequent trade between counties/cities in QMCPA, meaning policy spillovers are inevitable. Entities in the control group may be partially affected by those in the treatment group, leading to potential errors in estimating the net policy effects. Therefore, future research should consider using more precise methods to evaluate policies. Meanwhile, as the DPA was empirically tested as a whole rather than divided into specific policy measures (such as e-commerce poverty alleviation, tourism poverty alleviation, characteristic agriculture, etc.), its specific measures' contributions cannot be determined. Future research should consider expanding the sample nationwide, further classifying the DPA policies, and conducting grouped/regional research to examine which policies have made key contributions to industrial structure upgrading and economic growth.

Based on the research conclusions of this paper, the following policy implications can be derived.

First, to promote long-term development in poor areas, local governments should focus on long-term industry development based on local resource endowments, avoid falling into the trap of low production cycles for short-term interests, and attract external investment through fiscal and tax support policies to promote industrial structure upgrading while ensuring income of the poor is not reduced.

Second, local conditions such as resource endowments, ecological environment, and existing industrial development foundations in

poor areas need prudent analysis to comprehensively select industries suitable for long-term development. After determining the industrial development direction, governments should leverage comparative advantages to develop characteristic industries through active policies to increase per capita income and economic development. Risk diversification and information-sharing mechanisms among local governments should also be established to improve regional specialization cooperation and risk resistance capacity of poor areas, striving to build high value-added industry chains with market orientation and cultivate large leading enterprises to jointly brand characteristic industries, forming brand effects and ultimately realizing effective and stable industrial structure diversification and regional specialized cooperation.

Third, central governments should accurately identify the development level of poor areas in planning key industries and formulating general requirements for characteristic industries, and implementing effective poverty alleviation policies. The implementation intensity and distortion of characteristic industry policies by lower-level governments need consideration. Industrial structure development and economic growth should be jointly evaluated with strengthened intensity to avoid policy failures due to excessive local intervention or local protectionism. Heterogeneity in economic conditions between different poor areas needs attention in policy implementation to avoid "one-size-fits-all" approaches through specific action plans considering diversity and tailoring to areas with deeper poverty for results. This can ensure long-term stable economic development in poor areas by addressing weaknesses in poverty alleviation work.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

CRediT authorship contribution statement

He Jun: Writing – review & editing, Conceptualization. **Tingrou Li:** Writing – original draft, Data curation. **Chen Lin:** Writing – review & editing, Funding acquisition, Data curation, Conceptualization. **Yunwei Gao:** Resources, Methodology, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] T.J. Bartik, Evaluating the Impacts of Local Economic, Development policies on local economic outcomes, 2005.
[2] E.L. Glaeser, J.D. Gottlieb, The economics of place-making policies, Brook, Pap. Econ. Act. 2008 (2008) 155–239.
[3] M. Liu, X. Feng, S. Wang, H. Qiu, China's poverty alleviation over the last 40 years: successes and challenges, Aust. J. Agric. Resour. Econ. 64 (1) (2020) 209–228, https://doi.org/10.1111/1467-8489.12353.
[4] M. Liu, X. Feng, S. Wang, Y. Zhong, Does poverty-alleviation-based industry development improve farmers' livelihood capital? J. Integr. Agric. 20 (4) (2021) 915–926, https://doi.org/10.1016/S2095-3119(20)63449-9.
[5] Q. Ren, Q. Huang, C. He, M. Tu, X. Liang, The poverty dynamics in rural China during 2000–2014: a multi-scale analysis based on the poverty gap index, J. Geogr. Sci. 28 (10) (2018) 1427–1443, https://doi.org/10.1007/s11442-018-1554-1.
[6] N. Li, X. Cong, X. Gong, Governance of poverty alleviation : research on the current situation of industrial poverty alleviation under the background of targeted poverty alleviation - taking the a town of s province as the example, in: Proceedings of the 2Nd International Seminar on Education Research and Social Science (Iserss 2019), 2019, pp. 625–628, 322.
[7] Xinhuanet, The decision of the cpc central committee and state council on winning the battle against poverty. http://www.gov.cn/xinwen/2015-12/07/content_5020963.htm, 2015.
[8] Xinhuanet, Poverty alleviation: China's experience and contribution. http://www.xinhuanet.com/english/2021-04/06/c_139860414.htm, 2021.
[9] S. Olivia, J. Gibson, S. Rozelle, J. Huang, X. Deng, Mapping poverty in rural China : how much does the environment matter? Environ. Dev. Econ. 16 (2011) 129–153, https://doi.org/10.1017/S1355770X10000513.
[10] S. Dai, W. Zhang, Y. Wang, G. Wang, Examining the impact of regional development policy on industrial structure upgrading: quasi-experimental evidence from China, Int. J. Environ. Res. Publ. Health 19 (9) (2022) 5042, https://doi.org/10.3390/ijerph19095042.
[11] D. Ferraz, F.P.S. Falguera, E.B. Mariano, D. Hartmann, Linking economic complexity, diversification, and industrial policy with sustainable development: a structured literature review, Sustainability 13 (3) (2021) 1265, https://doi.org/10.3390/su13031265.
[12] G. Hou, Z. Zou, T. Zhang, Y. Meng, Analysis of the effect of industrial transformation of resource-based cities in northeast China, Economies 7 (2) (2019) 40, https://doi.org/10.3390/economies7020040.
[13] P.S. Ward, Transient poverty, poverty dynamics, and vulnerability to poverty : an empirical analysis using a balanced panel from rural China, World Dev. 78 (2016) 541–553, https://doi.org/10.1016/j.worlddev.2015.10.022.
[14] J. Tollefson, Can randomized trials eliminate global poverty? Nature 524 (7564) (2015) 150–153, https://doi.org/10.1038/524150a.
[15] S. Rozelle, A. Park, V. Benziger, C.Q. Ren, Targeted poverty investments and economic growth in China, World Dev. 26 (12) (1998) 2137–2151, https://doi.org/10.1016/S0305-750X(98)00104-1.
[16] A. Ahmed, A. Gasparatos, Multi-dimensional energy poverty patterns around industrial crop projects in Ghana : enhancing the energy poverty alleviation potential of rural development strategies, Energy Pol. 137 (2020), https://doi.org/10.1016/j.enpol.2019.111123.

[17] S. Hutasavi, D. Chen, Exploring the industrial growth and poverty alleviation through space-time data mining from night-time light images : a case study in eastern economic corridor (eec), Thailand, Int. J. Rem. Sens. (2022), https://doi.org/10.1080/01431161.2022.2112111.
[18] T. Santika, K.A. Wilson, E.A. Law, F.A.S. John, K.M. Carlson, H. Gibbs, C.L. Morgans, M. Ancrenaz, E. Meijaard, M.J. Struebig, Impact of palm oil sustainability certification on village well-being and poverty in Indonesia, Nat. Sustain. 4 (2) (2021) 109, https://doi.org/10.1038/s41893-020-00630-1.
[19] X. Zhao, B. Yu, Y. Liu, Z. Chen, Q. Li, C. Wang, J. Wu, Estimation of poverty using random forest regression with multi-source data: a case study in Bangladesh, Rem. Sens. 11 (4) (2019), https://doi.org/10.3390/rs11040375.
[20] S. Rozelle, J.K. Huang, L.X. Zhang, Poverty, population and environmental degradation in China, Food Pol. 22 (3) (1997) 229–251, https://doi.org/10.1016/S0306-9192(97)00011-0.
[21] P.A. Tedong, Z.A.S. Zyed, R. Jani, F.A. Fazlie, Rural residents' perceptions on the poverty alleviation and governance in sarawak, Malaysia, Int. J. Bus. Soc. 23 (2) (2022) 649–664, https://doi.org/10.33736/ijbs.4831.2022.
[22] Y. Li, B. Su, Y. Liu, Realizing targeted poverty alleviation in China, China Agric, Econ. Rev. 8 (3) (2016) 443–454, https://doi.org/10.1108/CAER-11-2015-0157.
[23] D. Acemoglu, C. García-Jimeno, J.A. Robinson, State capacity and economic development: a network approach, Am. Econ. Rev. 105 (8) (2015) 2364–2409, https://doi.org/10.1257/aer.20140044.
[24] T. Glauben, T. Herzfeld, S. Rozelle, X. Wang, Persistent poverty in rural China : where, why, and how to escape? World Dev. 40 (4) (2012) 784–795, https://doi.org/10.1016/j.worlddev.2011.09.023.
[25] T. Zhou, G. Jiang, R. Zhang, Q. Zheng, W. Ma, Q. Zhao, Y. Li, Addressing the rural in situ urbanization (risu) in the beijing–tianjin–hebei region: spatio-temporal pattern and driving mechanism, Cities 75 (2018) 59–71, https://doi.org/10.1016/j.cities.2018.01.001.
[26] M. Tan, C. Qi, Research on the path and countermeasures of accelerating the poverty alleviation to a well-off society for the characteristic agricultural industry in the southwest mountainous area, Revista Cercetare şi Intervenţie Socială 69 (2020) 410–434.
[27] T. Chen, The development of China's solar photovoltaic industry: why industrial policy failed: table 1, Camb. J. Econ. 40 (3) (2016) 755–774, https://doi.org/10.1093/cje/bev014.
[28] A.O. Krueger, B. Tuncer, An empirical-test of the infant industry argument - reply, Am. Econ. Rev. 74 (5) (1984) 1112–1113.
[29] G.O.O.T. China, Report on the implementation of China's rural poverty alleviation and development program (2001-2010). http://www.gov.cn/zhengce/content/2016-09/23/content_5111138.htm, 2015.
[30] J. Wu, H. Yang, T. Ahmed, An assessment of the policy of poverty alleviation in continuous poverty-stricken areas : evidence from yunnan province, China, Environ. Dev. Sustain. 25 (9) (2023) 9757–9777, https://doi.org/10.1007/s10668-022-02459-4.
[31] Y. Guo, Y. Zhou, Y. Liu, Targeted poverty alleviation and its practices in rural China: a case study of fuping county, hebei province, J. Rural Stud. 93 (2022) 430–440, https://doi.org/10.1016/j.jrurstud.2019.01.007.
[32] W. Jiao, Analyzing multidimensional measures of poverty and their influences in China's Qinba mountains, Chinese Journal of Population, Resources and Environment 18 (3) (2020) 214–221, https://doi.org/10.1016/j.cjpre.2021.04.002.
[33] S. Chen, M.S. Mehmood, S. Liu, Y. Gao, Spatial pattern and influencing factors of rural settlements in Qinba mountains, shaanxi province, China, Sustainability 14 (16) (2022) 10095, https://doi.org/10.3390/su141610095.
[34] F. Su, J. Chang, H. Shang, Coupling coordination analysis of livelihood efficiency and land use for households in poverty-alleviated mountainous areas, Land 10 (11) (2021) 1115, https://doi.org/10.3390/land10111115.
[35] H. Long, J. Zou, Y. Liu, Differentiation of rural development driven by industrialization and urbanization in eastern coastal China, Habitat Int. 33 (4) (2009) 454–462, https://doi.org/10.1016/j.habitatint.2009.03.003.
[36] D. He, M. Zheng, W. Cheng, Y. Lau, Q. Yin, Interaction between higher education outputs and industrial structure evolution: evidence from hubei province, China, Sustainability 11 (10) (2019) 2923, https://doi.org/10.3390/su11102923.
[37] Q. Lin, X. Luo, G. Lin, T. Yang, W. Su, Impact of relocation and reconstruction policies on the upgrading of urban industrial structure in old industrial districts, Front. Environ. Sci. 10 (2022), https://doi.org/10.3389/fenvs.2022.1002993.
[38] Y. Liu, Y. Guo, Y. Zhou, Poverty alleviation in rural China: policy changes, future challenges and policy implications, China Agric. Econ. Rev. 10 (2) (2018).
[39] C. Yian, Misallocation of human capital and productivity: evidence from China, Economic Research-Ekonomska Istraživanja 32 (1) (2019) 3348–3365, https://doi.org/10.1080/1331677X.2019.1663546.
[40] M.H. Khan, Rural poverty in developing countries implications for public policy, Econ. Issues 26 (2001).
[41] C. Ma, Y. Zhu, T. Li, Regional Industrial Layout under Local Government Competition, Institute of Economic Research, Chinese Academy of Social Sciences, 2021, pp. 141–156 (in chinese), vol. 56.
[42] Q. Wang, H.X. Li, G.J. Chen, Y. Chen, Analysis on poverty in mountain areas based on off-farm industries, Chin. Geogr. Sci. 13 (4) (2003) 359–363, https://doi.org/10.1007/s11769-003-0043-2.
[43] S.J. Redding, E. Rossi-Hansberg, Quantitative spatial economics, Annual Review of Economics 9 9 (2017) 21–58, https://doi.org/10.1146/annurev-economics-063016-103713.
[44] M. Cristescu, R. Nerisanu, M. Flori, F. Stoica, F.L. Stoica, Analysing the stock market as an economic lever, using a qualitative and a quantitative model, Mathematics 9 (19) (2021), https://doi.org/10.3390/math9192369.
[45] A.C. Baker, D.F. Larcker, C.C.Y. Wang, How much should we trust staggered difference-in-differences estimates, J. Financ. Econ. 144 (2) (2022) 370–395, https://doi.org/10.1016/j.jfineco.2022.01.004.
[46] J.B. Lee, Do health vouchers broaden the choices of citizens with low socioeconomic status ? An analysis of medicaid in brooklyn, Public Manag. Rev. 25 (3) (2023) 459–476, https://doi.org/10.1080/14719037.2021.1974715.
[47] B. Zhou, C. Zhang, Q. Wang, D. Zhou, Does emission trading lead to carbon leakage in China ? Direction and channel identifications, Renew. Sustain. Energy Rev. 132 (2020), https://doi.org/10.1016/j.rser.2020.110090.
[48] Y. Gao, M. Li, J. Xue, Y. Liu, Evaluation of effectiveness of China's carbon emissions trading scheme in carbon mitigation, Energy Econ. 90 (2020), https://doi.org/10.1016/j.eneco.2020.104872.
[49] X. Wang, Y. Feng, The effects of national high-tech industrial development zones on economic development and environmental pollution in China during 2003-2018, Environ. Sci. Pollut. Res. 28 (1) (2021) 1097–1107, https://doi.org/10.1007/s11356-020-10553-1.
[50] R. Ran, Z. Ni, L. Hua, T. Li, Does China's poverty alleviation policy improve the quality of the ecological environment in poverty-stricken areas? Front. Environ. Sci. 10 (2022) https://doi.org/10.3389/fenvs.2022.1067339.
[51] R. Ran, M. Xie, L. Hua, How to break the environment-economic trap in rocky desertification contiguous poverty-stricken areas: the mediating effect of industrial structure upgrading, Int. J. Sustain. Dev. World Ecol. 30 (5) (2023) 576–590, https://doi.org/10.1080/13504509.2023.2169966.
[52] R. Ran, L. Hua, J. Xiao, L. Ma, M. Pang, Z. Ni, Can poverty alleviation policy enhance ecosystem service value ? Evidence from poverty-stricken regions in China, Econ, Anal. Policy 80 (2023) 1509–1525, https://doi.org/10.1016/j.eap.2023.10.032.
[53] R. Ran, L. Hua, T. Li, Y. Chen, J. Xiao, Why have China's poverty eradication policy resulted in the decline of arable land in poverty-stricken areas? Land 12 (10) (2023) https://doi.org/10.3390/land12101856.
[54] R. Gu, C. Li, D. Li, Y. Yang, S. Gu, The impact of rationalization and upgrading of industrial structure on carbon emissions in the beijing-tianjin-hebei urban agglomeration, Int. J. Environ. Res. Publ. Health 19 (13) (2022) 7997, https://doi.org/10.3390/ijerph19137997.
[55] S. Guan, J. Liu, Y. Liu, M. Du, The nonlinear influence of environmental regulation on the transformation and upgrading of industrial structure, Int. J. Environ. Res. Publ. Health 19 (14) (2022) 8378, https://doi.org/10.3390/ijerph19148378.
[56] A. Young, The razor's edge: distortions and incremental reform in the people's Republic of China, Q. J. Econ. 115 (4) (2000) 1091–1135, https://doi.org/10.1162/003355300555024.
[57] C. Gaigné, S. Riou, J. Thisse, How to make the metropolitan area work? Neither big government, nor laissez-faire, J. Publ. Econ. 134 (2016) 100–113, https://doi.org/10.1016/j.jpubeco.2015.12.002.

[58] J. Mccallum, National borders matter - Canada-us regional trade patterns, Am. Econ. Rev. 85 (3) (1995) 615–623.
[59] A. Alberini, M. Filippini, Response of residential electricity demand to price: the effect of measurement error, Energy Econ. 33 (5) (2011) 889–895, https://doi.org/10.1016/j.eneco.2011.03.009.
[60] Q. He, M. Sun, Does fiscal decentralization promote the inflow of fdi in China, Econ. Modell. 43 (2014) 361–371, https://doi.org/10.1016/j.econmod.2014.09.009.
[61] C.A. Holz, No razor's edge: reexamining alwyn young's evidence for increasing interprovincial trade barriers in China, Rev. Econ. Stat. 91 (3) (2009) 599–616, https://doi.org/10.1162/rest.91.3.599.
[62] P. Krugman, Increasing returns and economic geography, J. Polit. Econ. 99 (3) (1991) 483–499, https://doi.org/10.1086/261763.
[63] Z. Xin-Gang, Z. Jin, Industrial restructuring, energy consumption and economic growth: evidence from China, J. Clean. Prod. 335 (2022) 130242, https://doi.org/10.1016/j.jclepro.2021.130242.
[64] L. Chen, W. Ye, C. Huo, K. James, Environmental regulations, the industrial structure, and high-quality regional economic development: evidence from China, Land 9 (2020), https://doi.org/10.3390/land9120517.
[65] B. Lin, Y. Zhou, How does vertical fiscal imbalance affect the upgrading of industrial structure? Empirical evidence from China, Technol. Forecast. Soc. Change 170 (2021) 120886, https://doi.org/10.1016/j.techfore.2021.120886.
[66] J. Liu, X. Hu, J. Wu, Fiscal decentralization, financial efficiency and upgrading the industrial structure: an empirical analysis of a spatial heterogeneity model, J. Appl. Stat. 44 (1) (2017) 181–196, https://doi.org/10.1080/02664763.2016.1252733.
[67] E. Xue, X. Zhou, Education and anti-poverty: policy theory and strategy of poverty alleviation through education in China, Educ. Philos. Theor. 50 (12) (2018).
[68] J.D. Angrist, J. Pischke, Mostly Harmless Econometrics: an Empiricist's Companion, 2009.
[69] P. Zhang, Target interactions and target aspiration level adaptation: how do government leaders tackle the "environment-economy" nexus? Public Adm, Rev. 81 (2) (2021) 220–230, https://doi.org/10.1111/puar.13184.
[70] L. Hua, R. Ran, M. Xie, T. Li, The capacity of land carbon sinks in poverty-stricken areas in China continues to increase in the process of eradicating extreme poverty : evidence from a study of poverty-stricken counties on the qinghai-tibet plateau, Environ. Dev. Sustain. (2023), https://doi.org/10.1007/s10668-023-03337-3.
[71] R. Eisenberger, J. Aselage, Incremental effects of reward on experienced performance pressure: positive outcomes for intrinsic interest and creativity, J. Organ. Behav. 30 (1) (2009) 95–117, https://doi.org/10.1002/job.543.
[72] T. Harrison, G. Kostka, Balancing priorities, aligning interests, Comp. Polit. Stud. 47 (3) (2014) 450–480, https://doi.org/10.1177/0010414013509577.
[73] M.S. Mitchell, R.L. Greenbaum, R.M. Vogel, M.B. Mawritz, D.J. Keating, Can you handle the pressure? The effect of performance pressure on stress appraisals, self-regulation, and behavior, Acad. Manage. J. 62 (2) (2019) 531–552, https://doi.org/10.5465/amj.2016.0646.
[74] L. Hua, R. Ran, M. Xie, T. Li, China's poverty alleviation policy promoted ecological-economic collaborative development: evidence from poverty-stricken counties on the qinghai-tibet plateau, Int. J. Sustain. Dev. World Ecol. 30 (4) (2023) 402–419, https://doi.org/10.1080/13504509.2022.2155882.
[75] R. Zhou, H. Zhang, X. Ye, X. Wang, H. Su, The delimitation of urban growth boundaries using the clue-s land-use change model: study on xinzhuang town, changshu city, China, Sustainability 8 (11) (2016) 1182, https://doi.org/10.3390/su8111182.
[76] Q. Yanbo, J. Guanghui, M. Wenqiu, L. Zitong, How does the rural settlement transition contribute to shaping sustainable rural development? Evidence from shandong, China, J. Rural Stud. 82 (2021) 279–293, https://doi.org/10.1016/j.jrurstud.2021.01.027.
[77] C. Bai, Y. Du, Z. Tao, S.Y. Tong, Local protectionism and regional specialization: evidence from China's industries, J. Int. Econ. 63 (2) (2004) 397–417, https://doi.org/10.1016/S0022-1996(03)00070-9.