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Exploring the multidimensional effects of China's coal de-capacity policy: A regression discontinuity design

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Highlights

- We explore the multidimensional effects of the coal de-capacity policy in China by a regression discontinuity design.
- The effectiveness of coal de-capacity policy implementation is mixed in economic, environmental and social dimensions.
- The multidimensional effects of coal de-capacity policy show significant spatial heterogeneity.
- Coal de-capacity policy should consider the economy, environmental protection, safety, social welfare.

Exploring the multidimensional effects of China's coal de-capacity policy: A regression discontinuity design

Abstract: Coal phase-out is a key step for China to achieve carbon peak and carbon neutrality. The Chinese government introduced a coal de-capacity policy (CDP) in 2016. However, existing studies rarely discuss the effectiveness of China's implementation of the CDP, especially regarding the policy goal of "improving quality and increasing efficiency." In this context, this study quantitatively evaluates the multidimensional effects of China's CDP in terms of economic efficiency, green production, and employee welfare using a sharp regression discontinuity design. Moreover, the spatial heterogeneity of policy effects is discussed through subsample analyses. The empirical results are as follows. First, the expected goal of the Chinese CDP has not been fully achieved. Although the CDP has achieved a significantly positive economic effect, the effectiveness of environmental benefits and social welfare remains far from ideal. Second, there is a statistically significant spatial heterogeneity in the CDP's multidimensional effects in different regions. Policy guidelines are proposed in line with the findings to support the adjustment and optimization of de-capacity policy measures for coal and other similar industries. This study thoroughly highlights the economic, environmental, and social effects of the CDP's implementation in China in 2016 and provides a periodical summary and assessment of policy effectiveness. Specifically, the findings provide valuable insights for designing coal de-capacity targets and plans for specific regions, which may help ensure better policy efficiency and feasibility in future coal capacity regulations.

Keywords: De-capacity policy; Multidimensional effects; Regression discontinuity design; China's coal industry

1. Introduction

China is the major producer and consumer of coal worldwide, and China's coal consumption accounts for more than half of the global coal consumption (Wang and Song, 2021). In response to the decelerating economic growth and increasing downward pressure on the economy since 2015, China has proposed supply side structural reforms to guide a new normal in economic development.

The country has also launched five priority tasks to ensure a reasonable quantitative growth and steady qualitative improvement in the economy. These include cutting overcapacity, reducing excess inventory, deleveraging, lowering costs, and strengthening weaknesses. Overcapacity distorts resource allocation, leads to supply imbalance, worsens enterprise performance, and reduces the overall efficiency of the economy. Therefore, effective de-capacity is a top priority of China's supply side structural reform and an inevitable requirement for high-quality economic development. In February 2016, the State Council of China identified the coal industry as a key sector in the reform to de-capacity and issued the *State Council's Guidelines on Addressing Overcapacity and Achieving a Turnaround in the Coal Industry (G.F. [2016] No. 7)*[1] (State Council, 2016). The guidelines proposed a work target of "reducing the quantity, improving the quality, and increasing the efficiency" and outlined the work plans for the period from 2016 to 2020. These include eliminating 500 Mt of coal production capacity, followed by a further reduction and restructure of 500 Mt of coal production capacity. With the continuing supply side structural reforms, coal de-capacity activities are also underway. The de-capacity work scheduled for the period from 2016 to 2020 was completed and undoubtedly achieved its targets of "reducing the quantity" (Chen, 2020). However, whether it has achieved the effect of "improving the quality and increasing the efficiency" remains debatable. It is particularly important to systematically and quantitatively evaluate the effects of the current coal de-capacity policy (CDP) implementation for two reasons: first, under the call for a global energy transition, China has proposed the goal of "… peak carbon emissions by 2030 and [to] achieve carbon neutrality by 2060" (Xinhua, 2020), which will eventually lead to a gradual reduction in the proportion of coal in the energy consumption structure. It is expected that coal overcapacity will continue to exist for a considerable amount of time in the future. Accordingly, the coal de-capacity work will continue, while the CDP will require progressive adjustment and optimization based on previous implementation effects. Second, a striking feature of China's industrial overcapacity is the widespread distribution of industries and the persistence of spillover effects. Many industries are in

[1] The policy is an implementation measure of the supply-side structural reforms policy to achieve de-capacity in China's coal industry.

a serious state of overcapacity, including steel, coal, and electricity (Yuan et al., 2016; Wang et al., 2020b). The next stage, especially during China's carbon peak, of the reform to reduce overcapacity involves formulating and implementing industrial de-capacity policies more accurately and effectively and requires a quantitative scientific basis supported with data. In summary, accurate evaluation and calibration of the effectiveness of the CDP is of great interest for the scientific governance of overcapacity in coal and other similar industries.

As an economic phenomenon, overcapacity has received extensive attention from the academia in recent years. Many scholars have conducted a series of studies from different perspectives on coal overcapacity. They focused on the influencing factors (Zhang et al., 2017; Yang et al., 2019) and formation mechanisms (Yang et al., 2018), judgment and measurement measures (Zhang et al., 2018), prediction and early warning (Wang et al., 2018), regulation measures (Yang et al., 2016), governance strategy (Shi et al., 2019, 2020), coal price fluctuations (Zhang et al., 2019), and coal consumption (Wang et al, 2020a). Regarding the effect of coal overcapacity, some scholars explored the impact of coal de-capacity on economic development (Zhang et al., 2021) and environmental regulations (Li and Yao, 2020). Accordingly, the findings provide a clear strategic direction and theoretical guidance for promoting the work of cutting coal capacity. However, existing literature has three shortcomings. First, in terms of research design, the existing studies employ qualitative and case analysis methods (Hao et al., 2019) to analyze the policy effect based on the latest, detailed data, which provides a fresh theoretical foundation for the design and optimization of the CDP, and they lack an effective empirical basis and data support. Second, in terms of research perspectives, some studies on the policy effect estimation were conducted from a single perspective or dimension and discussed economic efficiency (Zhang et al., 2021), environmental benefits (Li and Yao, 2020), and social software (Wang et al., 2020c) separately; however, there is a gap in research on the multi-dimensional effects of CDP from multiple perspectives of economy, environment, and social welfare, and the goal of improving the quality and increasing the efficiency is ignored. Hence, the credibility of the policy-effect evaluation results is weakened. Third, in terms of the research sample, the selected sample data in the existing studies mostly originate from the macro-industry level (Wang et al., 2020b) or the micro-enterprise level (Zhang et al., 2020b). These studies assume that the policy's impact on individuals (regions or enterprises) in the sample is homogeneous, ignoring the spatial heterogeneity in the policy's implementation (Deng et al., 2018). It is difficult to achieve consistent policy effectiveness in coal-production regions or coal enterprises with different characteristics (Wang et al., 2020c). Therefore, it is necessary to conduct a regional heterogeneity discussion on the CDP effect.

To fill these gaps in the literature, this study estimates the multidimensional effects of CDP using a regression discontinuity (RD) design. Economic efficiency (economic effect), green production (environmental effect), and employee welfare (social effect) of the coal industry are explored. The results indicate that, overall, the CDP has achieved a significant positive economic effect, although the environmental and social effects are not immediately obvious. This finding captures the practical background and provides meaningful suggestions to the Chinese central government for CDP optimization from multiple aspects. Additionally, we conducted subsample analyses from the perspectives of geographic regions, resource endowment conditions, and de-capacity costs to verify the spatial heterogeneity of the CDP's multidimensional effects. The results show that the effects of CDP in different dimensions are significantly heterogeneous in different regions. For example, in the eastern region of China, the CDP has a significant positive impact on the environmental benefit, and in regions with high de-capacity costs, the CDP's implementation improved employee welfare. Accordingly, this study provides a theoretical basis for designing the differentiated policies and measures across regions in future coal overcapacity regulation.

The contributions of this study are threefold: First, while previous studies use a single indicator for policy evaluation, this study may be the first to empirically explore the multi-effects of the CDP from the aspects of economic efficiency, environmental benefit, and social welfare, in addition to quantifying and identifying the positive or negative effect of the CDP. The results can benefit the Chinese government in formulating the adjusted and optimized top-level policy design in the future. Second, while previous empirical studies on the effect of the CDP mainly focus on the performance of the policy effect at the micro-enterprise level, our research discusses the spatial heterogeneity in the CDP's implementation at the provincial regional level and investigates the regional differences of the multidimensional effects, offering managerial hints to the local governments for dynamically adjusting and implementing the CDP, and thus maximize the regional benefits of coal de-capacity. Third, although there were some recent studies on the effect of the CDP using the policy simulation analysis method, the examination of the CDP effect in our study was conducted by a quasi-experimental design using the RD method, avoiding the estimation errors caused by endogeneity, and enriching the methodology and theory of the CDP evaluation research.

The remainder of this paper is organized as follows. Section 2 outlines the theoretical analysis and provides a literature review. Section 3 proposes the RD design, variable settings, and data, followed by Section 4, which reports the empirical and robustness test results. Section 5 presents the subsample analyses, and Section 6 summarizes the key conclusions, policy implications, and outlook.

2. Theoretical analysis and literature review

2.1. The notion and goal of coal de-capacity policy

At the beginning of 2016, the central government clarified a specific plan to reduce and eliminate overcapacity and allocate the work to various local provinces and central coal enterprises. Meanwhile, supporting documents for special awards and subsidy funds, finance and taxation, staff resettlement, and environmental protection were promulgated, and a systematic policy framework was developed (see Table A1 in Appendix A). Guided by the central policies, the provinces combined the framework with supply side structural reform opinions to allocate and implement their coal de-capacity tasks and requirements, thus producing a series of de-capacity policies that were successively issued by the local governments (see Table A2 in Appendix A). Fig. 1 summarizes the main coal de-capacity policies introduced in 2016, which can be summarized in terms of (i) clear top-level policy design and (ii) specific local policy implementations (Zhang et al., 2021). Under the policy guidance of, and strong promotion by the relevant departments in the central and local governments over the past five years, coal de-capacity work has achieved gradual progress and substantial results. In terms of the goal of "reducing quantity," the growth rate of coal production has slowed from 5.2% in 2018 to 0.9% in 2020 (NBS, 2021).

With significant changes in the coal supply side, the coal de-capacity work has been gradually enriched and expanded, and its primary mission transformed from total quantity control to capacity structural optimization (Wang et al. 2019a, 2020b). Accordingly, the goal of "reducing quantity, improving quality, and increasing efficiency" has become clearer (Shi et al., 2018, 2020). Fig. 2 shows the theoretical framework of the notions and goals of the coal de-capacity policy. To a certain degree, the quality of coal de-capacity work is shown to be of decisive significance for China's supply side reforms. Therefore, estimating the CDP's multidimensional effects on "improving quality and increasing efficiency" is more rational and scientific than the previous policy evaluation approach characterized by reducing quantity (Zhang et al., 2020, 2021); this will not only help in optimizing and adjusting the de-capacity plan in the next work phase, but will also serve to improve and coordinate the policy framework for coal de-capacity.

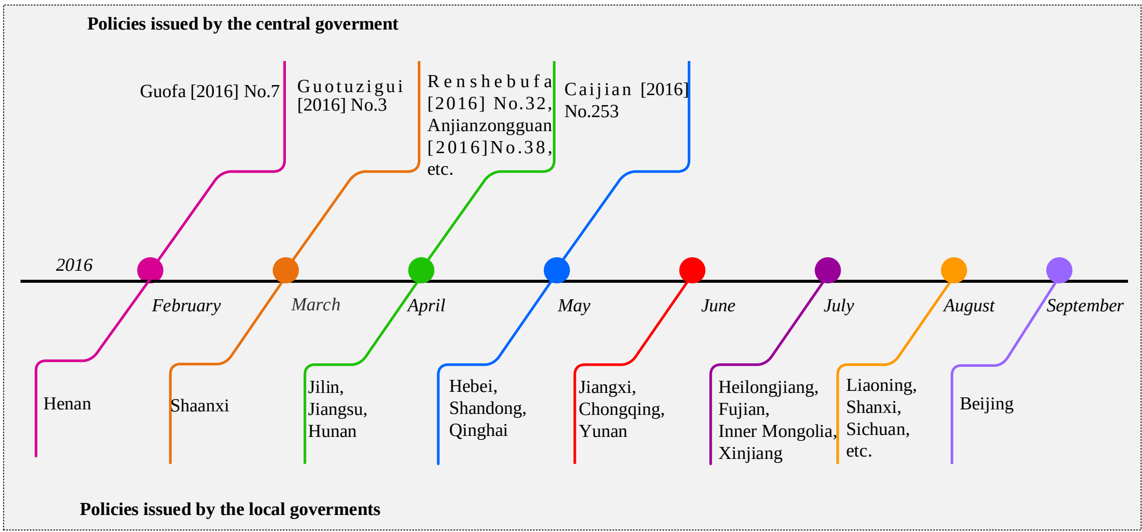

Fig. 1 Timeline of the main de-capacity policies issued in 2016.

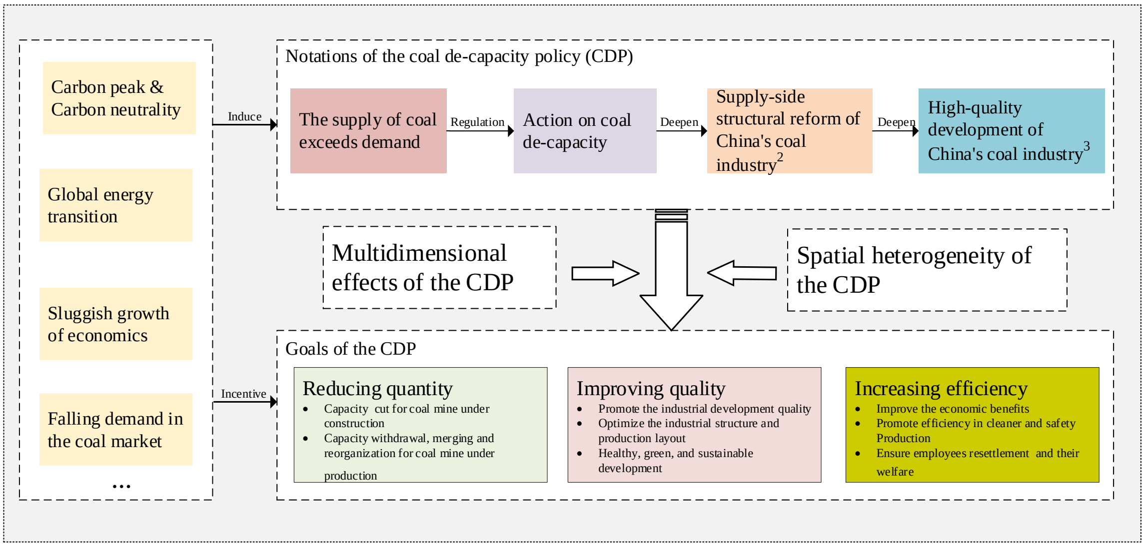

Fig. 2 Theoretical framework.

2.2. Literature review on coal overcapacity

In recent years, there has been an increasing amount of literature on coal overcapacity and coal de-capacity, which can be divided into three categories:

- **Class Ⅰ. Discussion on administrative or market regulations for coal overcapacity.** Wang et al. (2018) proposed that institutional distortion was the most important cause of coal overcapacity in China; therefore, they suggested a reliance on market mechanisms to reduce coal overcapacity. Shi et al. (2018) discussed the unintended consequences of China's coal de-capacity policy using the extended KEM-China model and demonstrated that the coal capacity cut policy of 2016 was technically infeasible. Dong et al. (2021) found that policy regulation aimed at curbing coal overcapacity was effective, timely, and modestly costly. They believed that the Chinese

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[2] It represents the supply-side structural reforms, which proposed five major tasks: de-capacity, de-stocking, de-leveraging, reducing costs, and improving weak links; the aims are to improve the quality and efficiency of the supply system and enhance the momentum of sustainable economic growth.

[3] It represents a vision of innovative, coordinated, green, open, and shared development. A clean, low-carbon, safe, and efficient coal supply system will be built, with quality and efficiency as the core and innovation as the development driving force.

government had instituted an effective mechanism of governance to coordinate the collective actions of market participants to avoid an overcapacity trap.

- **Class Ⅱ. Optimization of de-capacity scale and allocation scheme** Wang et al. (2019a, 2020b) formulated a provincial allocation scheme using a multi-objective combinational optimization method, which was more efficient, eco-friendly, cost-effective, and equitable than the government allocation scheme. Wang et al. (2019b) quantitatively analyzed the de-capacity scale in Shandong Province and proposed that market regulation played a major role in enterprise inefficiency, whereas policy regulation mainly affected highly efficient enterprises. Ma et al. (2020) considered both the efficiency and the equity in the allocation of coal de-capacity to streamline the implementation of coal capacity reduction reform.

- **Class Ⅲ. Assessment of the effect of CDP** Hao et al. (2019) conducted a qualitative analysis of the progress and effects of the coal industry de-capacity policy. Wang et al. (2020b) used the difference-in-differences model to quantitatively evaluate the treatment effect of the CDP on coal prices and concluded that the de-capacity policies in 2016 increased the coal price by 3.44%. Zhang et al. (2020b) estimated the causal effect of the CDP on the TFP of coal companies in China using a sharp RD design. Zhang et al. (2021) examined the macroeconomic effects of CDP shocks on the Chinese economy through a dynamic stochastic general equilibrium model.

- **Class Ⅳ. Discussion of coal market variation** Wang and Liu (2016, 2017) discussed the effect of China's coal consumption on the economic growth from a global perspective; they recommended that improving coal consumption efficiency is the optimum policy for Chinese coal phase-out. Jie et al. (2021) analyzed the long-term national and regional coal supply and resource allocation through a detailed multi-regional coal supply system model associated with a low-carbon transition in China's energy system. Zhang et al. (2019) examined the relationship between coal price fluctuations and pricing policies according to the generalized method of moments; their results showed that the lagging coal price and coal demand played a positive role in regulating coal prices, while coal supply and marketization had significantly negative effects on coal price fluctuations.

Although these studies made outstanding contributions to prevention measures of coal overcapacity and policy guidelines on coal de-capacity, the policy effect on the quality and efficiency of the development of coal industry should be emphasized to further adjust and optimize the coal de-capacity policy targeting.

2.3. The principle of policy effect evaluation

Some methods can be considered to examine policy effects, such as the instrumental variables (IV), difference-in-differences (DID), and synthetic control method (SCM) (Murshed, 2020; Wang et al., 2020b; Risch, 2020; Fu et al., 2021; Peng et al., 2020). However, considering the background of coal de-capacity work, the dummy variable panel data regression method can neither distinguish the effects of coal de-capacity policies from other policies nor separate the inherent trend of changes in the coal industry. The DID method can compare and analyze coal de-capacity in different regions. However, this method has strict requirements for the control group and easily leads to biased results. Moreover, the phenomenon of coal overcapacity is widespread in China, and it is difficult to find a suitable control group and satisfy the parallel time trend assumption. SCM also has similar shortcomings (Deng et al., 2018).

More specifically, the discontinuities in the CDP allow us to use the RD framework, which has clear causal effect inference, reliable results, and consistently estimated local average treatment effect (LATE). The RD design includes a sharp regression discontinuity (SRD) design and a fuzzy regression discontinuity (FRD). The previous literature on policy effects evaluation mostly adopts SRD, especially for energy and environmental policies (Zhang et al., 2020a; Zhang et al., 2020b; Risch, 2020). Moreover, the assignment variable is usually the time at which the policy is issued or the space (or the geographic boundary) in which the policy is implemented; the former is applied to time-based SRD designs, while the latter is applied to spatial SRD designs (Lee and Lemieux, 2010). When the time or space meets the requirements for policy implementation, the policy will either impact the relevant subjects or fail to achieve its objectives. Therefore, the differences in outcome variables before and after the implementation of the policy represent its causal effect. In the time-based SRD design, the assignment variable X is the fixed threshold value of time (cutoff point c). The treatment variable D is determined by whether X exceeds the cutoff point c. In the RD setting, there are two underlying relationships between the average outcomes Y and X, represented by $E[Y_i(1)|X]$ and $E[Y_i(0)|X]$. The LATE at the cutoff point c can then be estimated using $\lim_{x \downarrow c}[Y_i|X_i = x] - \lim_{x \uparrow c}[Y_i|X_i = x]$, which equals $E[Y_i(1) - Y_i(0)|X = c]$ (Hahn, 2001; Imbens and Lemieux, 2008).

3. Modeling and data

3.1. RD design

In contrast to the DID method used in the existing literature discussing the CDP effect (Wang et al., 2020b), the RD method adopted in this study can perform causal identification without meeting the assumption of complete randomness, ensuring the validity and unbiasedness of the parameter estimation (Li et al., 2020). The RD design, a widely used quasi-experimental method, was adopted to estimate policy effects. Moreover, the RD method can avoid the endogeneity problem of parameter estimation and analyze the effect of policy implementation without a control group, thus reflecting the causal relationships (Lee and Lemieux, 2010; Hausman and Rapson, 2018). Overall, the RD design can fit into the realization of the CDP effect estimation.

In this study, the rationale behind the proposed RD design is that the qualification for coal de-capacity is determined by the value of the assignment variable. The impact of the CDP on economic, environmental, and social indicators can be measured by comparing the observations below the threshold year of 2016 with those above it. Therefore, the multidimensional effects can be estimated using the proposed model:

$$Y_{it} = \alpha + \beta D_{it} + \gamma f(X_{it} - 2016) + \delta Z_{it} + Pr_{it} + Year_{it} + \varepsilon_{it} \tag{1}$$

where Y_{it} refers to the outcome variables in terms of economic efficiency, green production, and employee welfare in province i and year t, and the treatment variable D_{it} is the dummy variable indicating whether province i was affected by the CDP's implementation in year t ($D_{it} = 1$ for yes and $D_{it} = 0$ for no). β is the key coefficient to be estimated, representing the causal effect of the CDP to be investigated. In addition, we introduced a polynomial of time to eliminate endogeneity problems caused by missed time trends. $X_{it} - 2016$ represents the assignment variable, measuring the time interval of the sample individuals to the cutoff point of 2016. $f(X_{it} - 2016)$ represents the polynomial of the assignment variable. We also introduced covariates Z_{it} to improve the accuracy of the RD design and reduce the deviation caused by the small sample size. The settings of the variables are presented in Subsection 3.2. Given the limited sample size, Pr_{it} and $year_{it}$ were introduced to eliminate the individual and time-fixed effects, respectively (Dong, 2019). ε_{it} is the residual term.

Imbens and Lemieux (2008) proposed that an RD design with a limited sample size should choose a local linear polynomial or a local quadratic polynomial to estimate the results. Based on new findings by Gelman and Imbens (2019), a local polynomial regression may capture high-order nonlinear relationships between the outcome variable and the assignment variable to obtain a better fitting result; however, if the selected order is too high, the problem of overfitting may occur, leading to inference bias. Therefore, the main estimation results in this study were obtained through a local linear regression; a local quadratic polynomial was also adopted to test the robustness of the main estimation results (Hahn et al., 2001; Risch, 2020).

3.2. Variables and data

3.2.1. Outcome variables

Following the target of "reducing quantity, improving quality, and increasing efficiency" of the CDP's implementation, the outcome variables include economic efficiency, green production, and employee welfare, which can be divided into economic, environmental, and social categories, respectively.

(1) Economic category

Three indicators are determined to measure the economic efficiency of the CDP: coal capacity utilization (CU), the growth rate of total factor productivity ($GRTFP$), and the ratio of profits to cost (RPC). Specifically, CU measures efficiency in the use of productive resources (Wang et al., 2019a, 2020b), whose data are difficult to obtain directly. In this study, CU data for CU are calculated using the provincial boundary production function method (Wang et al., 2020b). The detailed calculation steps are shown in Appendix B, and the calculation results are shown in Table D1 and Appendix D. TFP essentially represents a kind of resource allocation efficiency, which is an excellent index to measure the coal industry's production efficiency (Zhang et al., 2020b). Industrial structure optimization, enterprise competition, and innovation competition due to resource reallocation can improve total factor productivity (TFP). The dynamic change in the TFP reflects the input-output efficiency variation trend. Consequently, the $GRTFP$ was selected as an economic efficiency variable. In this study, we use the Solow residual method in the form of a two-factor Cobb-Douglas production function to calculate the $GRTFP$. The specific method is shown in Appendix C, and the calculation results are presented in Table D2. The RPC is the ratio of total profits to total costs and expenses, which reflects the operating benefits of the coal industry. The higher the indicator, the bigger the profit, and the better the economic performance of the coal industry. The GRTFP data for the $GRTFP$ are taken from the Chinese Statistical Yearbook of the 25 coal-producing provinces.

(2) Environmental category

Inefficient and irregular coal mining causes ecological and environmental damage. To examine the environmental effects of the CDP, the green production indicator of energy consumption of coal production (ECC) is considered (Ma et al., 2020). It represents the energy consumption in terms of the standard coal quantity used to produce a unit of raw coal. The lower the level of the ECC, the better is the environmental effect of the CDP. The *ECC* data are taken from the Chinese Statistical Yearbook of the 25 coal-producing provinces.

(3) Social category

Reasonable payments and a safe working environment for coal workers should be enhanced through the reform of coal de-capacity. In this study, the employee welfare indicators of the average salary of coal workers ($WAGE$) and death rate per million tons ($DRPMT$) were selected to measure the social effect of the CDP. The data for $WAGE$ were obtained from the Chinese Statistical Yearbook of the 25 coal-producing provinces, while those for $DRPMT$ come from the published statistical data of the Statistical Bulletin of National Economic and Social Development, State Administration of Coal Mine Safety, and the Chinese Statistical Yearbook of the 25 coal-producing provinces. Some of the missing data were obtained from the Internet and media reports, leaders' speeches, and government documents.

3.2.2. Treatment variable

The year 2016 was selected as the cutoff point, and thus the coal de-capacity policy D was determined as the treatment variable. Hence, D is set to 1 at the time of initiating the de-capacity policy.

3.2.3. Covariates

In addition to the CDP variable, several other variables may influence the economic efficiency, green production, and employee welfare of the coal industry. This study identified covariates in three areas: the ability of local governments to intervene, regional economic development, and technical innovation.

(1) The marketization index

Most top coal enterprises in each province are state-owned (Wang et al., 2018). Under China's system and mechanism, the development of state-owned enterprises is often subject to the direct intervention of local governments. Thus, the intervention ability of local governments often affects the development efficiency of the coal industry in a province (Zhang et al., 2017; Fan et al, 2019). The marketization index (MI) refers to the level of development of regional marketization and reflects the relationship between the government and the market in a particular region. Therefore, we selected MI to measure the ability of local governments to intervene in industrial development. The data for this indicator were derived from Wang et al.'s (2019c) research data. The latest statistical data were obtained in 2016. For the missing data, from 2017 to 2019, this study uses estimates (suitably adjusted) based on the proportion of non-state-owned enterprises in the total industrial output value in the region.

(2) The GDP index

The regional economic development level often affects the progress and effect of coal industry capacity management (wang et al., 2020; Qin et al., 2017). Provinces with developed economic development levels, such as Jiangsu Province, tend to have better economic efficiency, green production levels, and employee welfare of industrial industries (Zhang et al., 2021;). Here, the GDP index ($GDPI$; the value of the last year equals 100) was selected to measure the level of regional economic development. The data were obtained from the National Bureau of Statistics of China's[4] website.

(3) RD expenditure

Technological innovation is the direct driving force for improving the economic efficiency and green production of the coal industry, which indirectly affects the welfare of coal workers (Fu et al., 2020; Wang et al., 2020b). RD expenditure (RD) is often used to measure the level of technological innovation in previous studies. Therefore, in this study, RD was selected as a covariate. The RD data were obtained from the Chinese Statistical Yearbook of 25 coal-producing provinces. In summary, there are six outcome variables, a treatment variable, and three covariates, as shown in Table 1.

Table 1 Variables setting.

Type	Variable	Symbol	Illustration	Reference source
Outcome variables	Coal capacity utilization	CU	It represents the capacity utilization of the coal industry, which is calculated by the ratio of coal production to coal capacity.	Wang et al., 2019a；Wang et al., 2020b
	Growth rate of TFP	$GRTFP$	It represents industrial upgrading level and productivity development and is used to measure the industrial productivity.	Zhang et al., 2020b；Wang et al., 2020b
	Ratio of profits to cost	RPC	It represents how much profit can be obtained for every unit of cost and measures the operating returns for operating expenses.	Wang et al., 2020b

[4] Data source: NBSC. http://www.stats.gov.cn/.

	Energy consumption of coal production	ECC	It represents the energy consumption in terms of standard coal in the coal production and measures the green production level.	Ma et al., 2020
	Death rate per million tons	$DRPMT$	It measures the production safety level of the coal industry.	Liu et al., 2019
	Average salary of coal workers	$WAGE$	It measures the average labor remuneration of coal industry employees.	Wang et al., 2018
Treatment variable	De-capacity policy	D	D equals zero before 2016, while D equals one in 2016 and after.	Hausman and Rapson, 2017
Covariates	The marketization index	MI	It represents the development of regional marketization.	Fan et al, 2019
	The GDP index (Last year =100)	$GDPI$	It represents the relative number of changing trends and degree of regional GDP in a certain period and measures regional economic development.	Qin et al., 2017
	R&D expenditure	RD	It represents expenditures on the development of basic research, applied research, and experiment, and measures the level of industrial technological innovation.	Fu et al., 2020

3.3. Descriptive statistics

In this study, we collected annual panel data on 25 coal-producing provinces in China from 2010 to 2019 for empirical analysis, which comprises 250 observations[5] divided into two groups based on whether the years were treated by the CDP's implementation. The treated group and the control group comprised 75 and 175 observations, respectively. Table 2 presents the summary statistics for the sample of outcome variables and covariates. There were distinct initial differences between the

[5] Generally, RD design requires a large sample size of high-frequency data. Considering that only annual data can be obtained for related indicators of the coal industry, the sample size available for this study is relatively limited. Fortunately, the Stata command package of *rdlocrand* developed by Professor Cattano et al. from Princeton University in the United States can overcome the defect appropriately. Moreover, Zhag et al. (2020b) and Dong's (2019) research have confirmed the feasibility of sample selection.

control and treated groups. Additionally, the changes in CU and $GRTFP$ of the coal industry in 25 coal-producing provinces from 2010 to 2019 are shown in Fig. 3. Clearly, CU and $GRTFP$ of most provinces, such as Ningxia and Shanxi, experienced significant fluctuations in 2016. Therefore, it is essential for causal inferences to use a locally random identification strategy and to control for individual characteristics. Given that the dimensions, magnitudes of original data, and properties of the variables are different, we conducted a data standardization process using the Z-score method, which is currently the most common method (Milligan and Cooper, 1998). Specifically, after the original data were standardized, the mean value and standard deviation were 0 and 1, respectively. The calculation formula is $x^* = {}^{x - \bar{x}}/_{\sigma}$ where $\bar{x}$ is the mean value, σ is the standard deviation of the original data, and $x^*$is the standardized data.

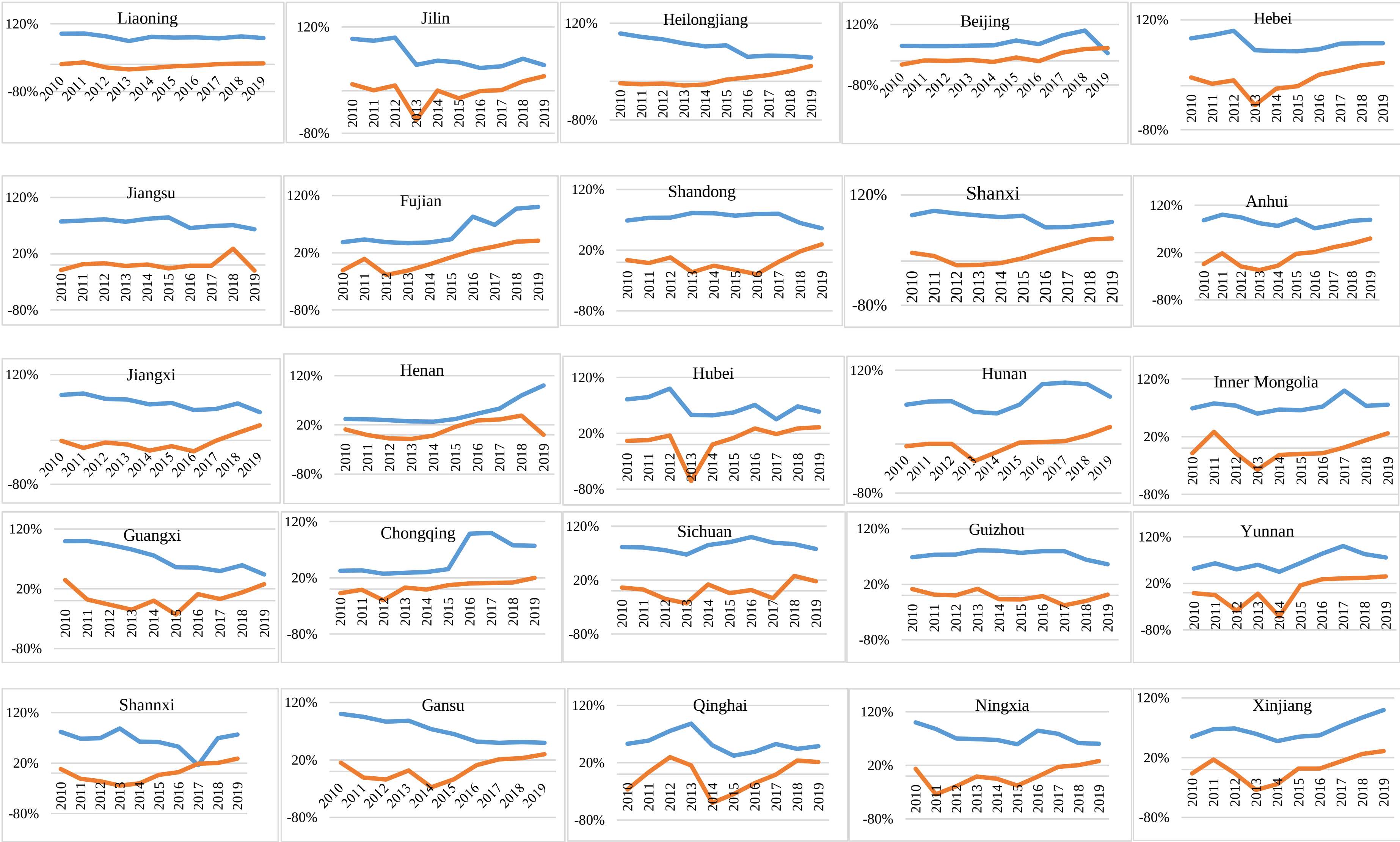

Fig.3 Change of CU and TFP of the coal industry in 25 coal-producing provinces from 2010 to 2019 (Legend: CU GRTFP)

Table 2 Sample summary statistics of the main variables.

Variables	Unit	Full sample		Control group		Treated group	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
CU	%	69.243	18.850	69.066	19.34967	70.25	18.4
$GRTFP$	%	0.037	0.190	-0.049	0.155	0.201	0.156
RPC	%	8.875	9.742	8.368	9.471	12.139	9.91
ECC	Ten thousand tons of standard coal	5911.942	9243.837	6025.408	9393.961	5689.783	8877.985
$DRPMT$	%	0.853	1.187	1.0238	1.223	0.497	0.952
$WAGE$	Ten thousand yuan	61762.4	21450.120	53348.05	14775.12	78716.96	24430.98
MI	/	6.062	1.637	5.817	1.638	6.407	1.578
$GDPI$	/	109.256	2.961	110.736	2.657	106.871	1.435
RD	Ten thousand yuan	2652073	3762400	2102455	2894826	3661067	4932796

4. Results

4.1. Validity tests for the RD design

4.1.1. Continuity test of the assignment variable

The continuity assumption of the breakpoint regression design includes two points (Imbens and Lemieux, 2008): First, the economic actor cannot make strategic choices by precisely controlling for the assignment variables. Second, except for the impact of policy changes, the changes in the other variables are continuous. Regarding the first point, the standard approach is to test whether the economic actor chooses strategic actions benefitting themselves at the cutoff point. However, the McCrary (2008) density test, which is standard in cross-sectional RDs, is typically not applicable when time is a running variable. It is generally believed that the assignment variable of time cannot be manipulated by other factors. The reasons for this are as follows: First, governments promulgated policies, and the implementation of the de-capacity policy is mainly time-driven. Second, following the central policy of *G.F. [2016] No. 7*, all 25 coal-producing provinces formulated and implemented specific de-capacity policy measures and work plans to reduce overcapacity in 2016; thus, the cutoff point is consistent among the 25 provinces. Third, the time cutoff point was selected as 2016, a year in which there was no dramatic change in the economic and political environments. Consequently, the assignment variable cannot be manipulated by other factors. Therefore, the first point of the continuity assumption is satisfied.

4.1.2. Continuity test of the covariates

The second point in the continuity assumption is also called the smoothness hypothesis. Specifically, except for the outcome variables, all the covariates should have no treatment effect at the cutoff point, that is, the variates have no jump on the two sides of the de-capacity cutoff point. If the covariates jump at the cutoff point, the jump in the outcome variables cannot be fully explained by the jump in the assignment variable, and the causal inference will fail. Graphical analysis is always selected as the testing method, as well as the method in which the covariates are selected as the placebo outcomes in the RD regression analysis. In this study, we used the local linear regression method (Nichols, 2016) to test the smoothness hypothesis by replacing the outcome variables with the covariates and obtaining the variation coefficient of the covariates at the cutoff point (as shown in Table 3). The regression estimation results under different bandwidths show that placebo outcomes have no statistically significant change near the cutoff point. Fig. 4 further confirms that the three covariates show smooth continuous curves without noticeable jumps at the cutoff point. Therefore, we consider that the proposed covariates in the RD design meet the smoothness hypothesis. Thus, the second point of the continuity assumption is satisfied, and the differences in the outcome variables are caused by the implementation of the CDP.

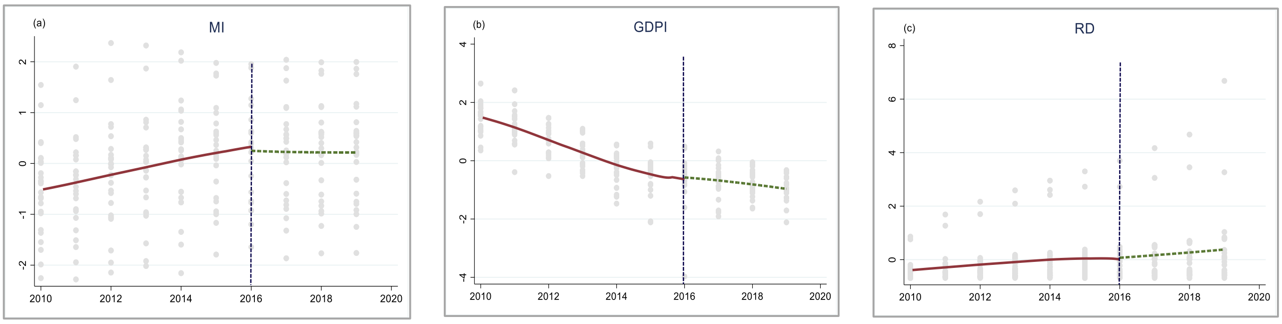

Fig. 4 Change of the covariates at the cutoff point[6].

Table 3 Regression estimation results of covariates at the cutoff point.

Bandwidth \ Covariates	MI	$GDPI$	RD
Lward	-0.079（0.315）	0.062（0.324）	0.063（0.395）
Lward 50	0.036（0.474）	-0.145（0.214）	0.060（0.375）
Lward 200	-0.116（0.246）	0.330（0.203）	-0.078（0.265）

Note: ***, **, and * represent p≤0.01， p≤0.05, and p≤0.10, respectively. Standard errors are presented in parentheses. Lward, Lward 50, and Lward 200 represent the optimal bandwidth, half the optimal bandwidth, and twice the optimal bandwidth, respectively.

4.2. RD results

4.2.1. Graphical analysis

When using the RD design, it has become a standard practice to use graphs to represent the relationship between outcome variables and the assignment variable before the regression estimation, which is also the reason that the RD design is more transparent than other causal effect test methods. The goal of graphical analysis is to determine whether there is a jump phenomenon on the two sides near the cutoff point, that is, the treatment effect. In this study, the curves of the six outcome variables near the cutoff point were fitted using the non-parametric local linear regression estimation method.

[6] These figures present the local linear fitting results that were obtained from regressions using the triangular kernel and the optimal bandwidth choice of cross-validation method. The ordinate represents the values of the covariates, and the abscissa represents the distances to the year 2016. The vertical dashed line is the cutoff point.

The results are shown in Figs. 5(a), (b), and (c). The outcome variables for the economic dimension, that is, CU, $GRTFP$, and RPC, exhibit a relatively noticeable jump at the cutoff point. From Figs. 5(d), (e), and (f), the outcome variables for the environmental and social dimensions, that is, ECC, $DRPMT$, and $WAGE$, show a non-apparent discontinuity at the cutoff point. Therefore, based on Fig. 5, we preliminarily determined that the CDP has a significant positive impact on the economic indicators, whereas it has no significant influence on the environmental and social indicators. The results of CU, $GRTFP$, and RPC are illustrated in Figs. 5(a), (b), and (c), respectively. The local linear regression curve of CU increases significantly after the cutoff point, and then reaches a plateau in the long run, while the curves of $GRTFP$ and RPC show a significant and continuous upward tendency after the cutoff point. The results indicate that, between 2016 and 2019, the implementation of the CDP has improved the CU with a steady long-term effect, while gradually enhancing the $GRTFP$ and RPC. It should be noted that the graphical analysis is only a preliminary and visual observation; a more accurate evaluation of the policy effect is obtained through further examination by the RD analysis and robustness tests, which are shown in detail in the Subsections 4.2.2 and 4.3.

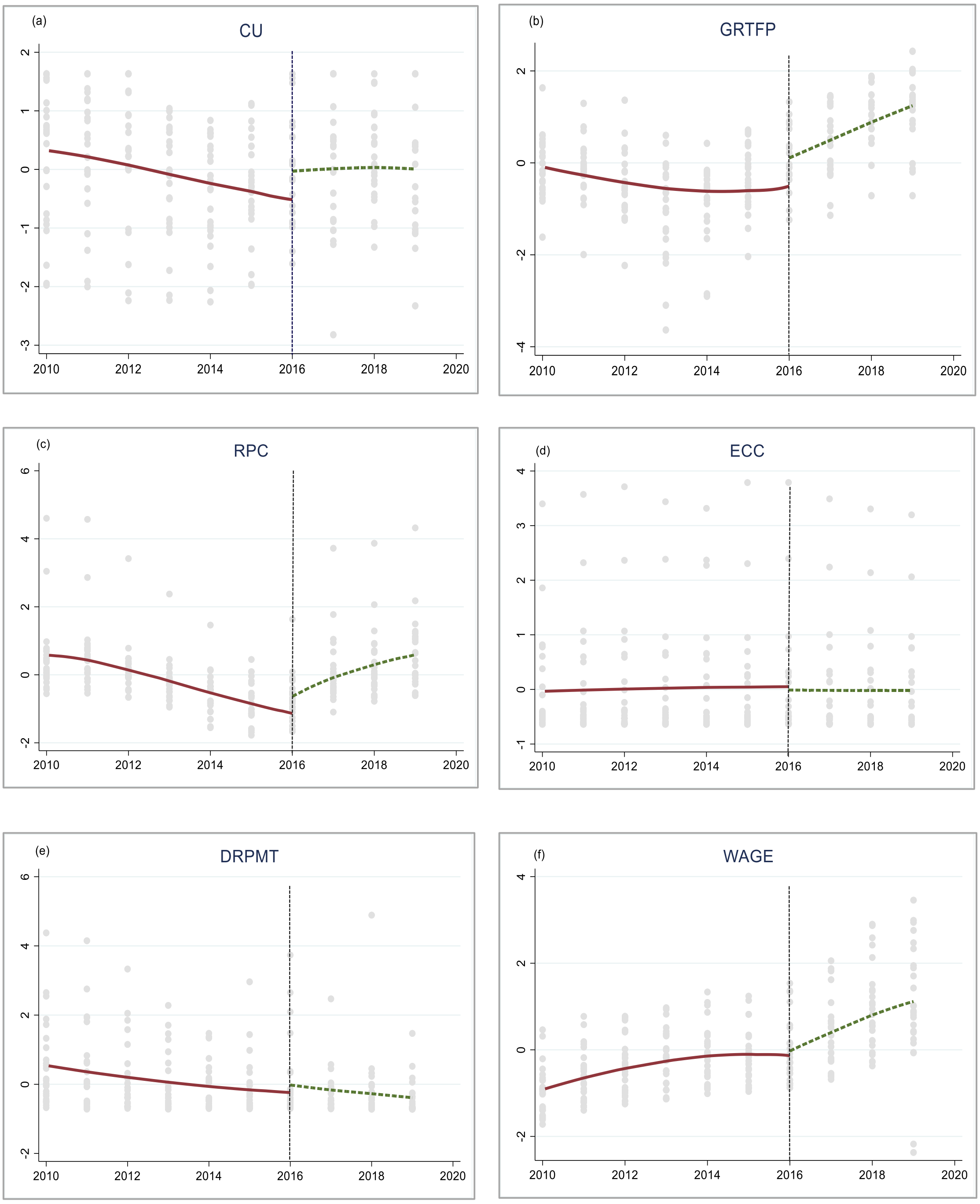

Fig. 5 Treatment effects at the cutoff point[7].

[7] These figures present the local linear fitting results that were obtained from regressions using the triangular kernel function and the corresponding optimal bandwidth. The ordinate represents the values of the outcome variables, and the abscissa represents the distances to the year 2016. The vertical dashed line is the cutoff point.

4.2.2. Estimation results

We explore the multidimensional effects of the CDP's implementation in terms of the economic, environmental, and social dimensions of the RD design, which eliminates the endogeneity problem. In the RD framework, the local linear regression estimation method was adopted, and the individual and time-fixed effects were controlled for. We also used a local quadratic polynomial regression estimation method for comparison. By varying the polynomial order of the assignment variable, the experimental results can be checked for robustness by observing whether a significant change was caused in the correlation coefficient. Moreover, the triangular kernel function was adopted, being more suitable for boundary estimation (Lee and Lemieux, 2010), and the bandwidth choice was based on the cross-validation method (Imbens and Kalynaraman, 2012). Table 4 lists the RD estimation results.

From the results of Columns 1, 3, and 5 in Table 4, the CDP has a positive and significant impact on the economic indicators CU, $GRTFP$, and RPC. Notably, in the triangular kernel function estimation, the regression coefficient of CU is 0.125 at the 5% significance level, and those of $GRTFP$ and RPC are 0.112 and 0.5, respectively, at the 10% significance level. These estimation results indicate that CDP implementation promotes the economic efficiency and industrial profitability of the coal industry. This result is consistent with that reported by Zhang et al. (2020). For the three outcome variables of ECC,$DRPMT$, and $WAGE$, the regression estimation coefficients are positive, but none of them pass the significance test (see Columns 7, 9, and 11 in Table 4), indicating that the expected policy effects in terms of environmental benefit and social welfare are not achieved as expected. This finding is consistent with the actual situation (Hao et al., 2019) and empirical evidence (Xiao et al., 2020; Zhang et al., 2021) from China.

In summary, the CDP has achieved a significant positive economic effect, although environmental and social effects have not been realized. Additionally, comparing the results of the local quadratic polynomial regression (see Columns 2, 4, 6, 8, 10, and 12 in Table 4) and local linear regression, the regression coefficients of the outcome variables are all positive, indicating that the direction of the impact of the CDP has not changed. However, their regression coefficients are not statistically significant, suggesting that the local linear regression estimation method is more suitable for the proposed RD design. Accordingly, the reliability of the RD estimation results in Columns 1, 3, 5, 7, 9, and 11 in Table 4 is further verified.

Table 4 RD estimation results.

Item \ Estimator	CU		$GRTFP$		RPC		ECC		$DRPMT$		$WAGE$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
D	0.125**	0.128	0. 112*	0.003	0.500*	0.447	0.006	0.009	0.220	0.250	0.108	0.164
	(0.427)	(0.417)	(0.343)	(0.402)	(0.300)	(0.365)	(0.374)	(0.212)	(0.300)	(0.420)	(0.260)	(0.331)
Kernel function	Tri	Tri	Tri	Tri	Tri	Tri	Tri	Tri	Tri	Tri	Tri	Tri
Polynomial order	1	2	1	2	1	2	1	2	1	2	1	2
Fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: ***, **, and * represent $p \leq 0.01$， $p \leq 0.05$, and $p \leq 0.10$, respectively. Standard errors are presented in parentheses.

4.3. Robustness tests

4.3.1. Sensitivity test of bandwidth

The choice of bandwidth may affect the robustness of RD estimation results (Lee and Lemieux, 2010). The validity and robustness of the RD estimation depend on the size of the selected bandwidth. There are many methods for determining the optimal bandwidth using the non-parametric estimation method. A recent study noted that the most common methods are the IK algorithm or the CCT algorithm (Imbens and Kalyanaraman, 2012). Although the former is a data-driven method, Calonico et al. (2014) believe that the optimal bandwidth obtained by the IK method may be too large, leading to bias in the corresponding confidence interval, which may lead to excessive rejection of the null hypothesis of no treatment effect. Consequently, we use the CCT method instead to investigate the sensitivity of the estimation results to the choice of optimal bandwidth, 0.5 times the optimal bandwidth, and two times the optimal bandwidth. The results are listed in Table 5. The regression coefficients of the CU,$GRTFP$, and RPC are sensitive to the choice of bandwidth but with consistent signs. Specifically, the policy effect is more significant under two times the optimal bandwidth, which may be related to the rigidity of the coal industry and the cumulative effect of policies. Moreover, the estimators for ECC, $DRPMT$, and $WAGE$ remain statistically insignificant. Therefore, it is reasonable to assume that the RD design passes the robustness test of the alternative bandwidth.

Table 5 RD estimation results with different bandwidths.

Bandwidth \ Estimator	CU	$GRTFP$	RPC	ECC	$DRPMT$	$WAGE$
CCT	0.125**	0. 112*	0.500*	0.006	0.220	0.108
	(0.427)	(0.343)	(0.300)	(0.374)	(0.300)	(0.260)
0.5 CCT	0.210*	0.235	0.150	0.004	0.255	0.257
	(0.256)	(0.254)	(0.180)	(0.298)	(0.439)	(0.201)
2 CCT	0.486*	0.611**	0.637***	-0.061	0.297	-0.070
	(0.261)	(0.206)	(0.190)	(0.266)	(0.243)	(0.183)

Note: ***, **, and * represent $p \leq 0.01$, $p \leq 0.05$, and $p \leq 0.10$, respectively; Standard errors are presented in parentheses; CCT, 0.5 CCT, and 2 CCT represent the optimal bandwidth, 0.5 times of the optimal bandwidth, and 2 times of the optimal bandwidth respectively.

4.3.2. Adding covariates

In the RD design, the advantage of adding covariates is that if these covariates have explanatory power for outcome variables, the variance of the disturbance terms can be reduced, leading to accurate estimation results. Although all covariates discussed above are continuous and do not jump at the cutoff point, they may affect the consistency of the estimates and treatment outcomes. Therefore, we introduce some covariates in the RD design to check the robustness of the estimated results. Table 6 presents the RD estimation results after adding the covariates. The estimators were almost unaffected by the inclusion of the three covariates. Specifically, following the addition of the covariates, all the estimators for the outcome variables show changes in the numerical value, although the direction of influence and significance level are maintained. Therefore, we can conclude that the estimated results in Tables 5 and 7 are stable, regardless of the addition of covariates, that is, the proposed RD design can be considered valid and rational.

Table 6 RD estimation results with adding covariates.

Estimator / Covariates	CU	$GRTFP$	RPC	ECC	$DRPMT$	$WAGE$
Covariates(N)	0.125**	0. 112*	0.500*	0.006	0.220	0.108
	(0.427)	(0.343)	(0.300)	(0.374)	(0.300)	(0.260)
Covariates(Y)	0.103**	0.002*	0.491*	0.002	0.168	0.117
	(0.427)	(0.310)	(0.287)	(0.189)	(0.286)	(0.253)

Note: ***, **, and * represent p≤0.01， p≤0.05, and p≤0.10. respectively. Standard errors are presented in parentheses. N represents no covariates, and Y represents the opposite.

4.3.3. Parametric estimation test

We adopted the local linear regression estimation method to conduct the RD analysis, which is a non-parametric estimation approach. As the results may be sensitive to the choice of estimation approach, we implemented a non-parametric estimation approach with the rectangular kernel function, which is equal to the parameter estimation based on local samples. If the estimation results obtained by different kernel functions are consistent, the proposed RD design passes the sensitivity check with respect to the estimation approach. The estimation results obtained using the triangular kernel and rectangular kernel functions are listed in Table 7. The estimated coefficients of CU,$GRTFP$, and RPC are all significant, with small differences in the numerical values between the two estimation kernel functions. The estimated coefficients of ECC,$DRPMT$, and $WAGE$ are still not significant, although the impact direction of ECC is changed. Moreover, the difference in the estimates between the two kernel functions is very small. Thus, we conclude that the proposed RD design passes the robustness test with respect to the choice between the parametric and non-parametric estimation methods.

Table 7 RD estimation results by different estimated kernel functions.

Estimator / Kernel function	CU	$GRTFP$	RPC	ECC	$DRPMT$	$WAGE$
Triangular kernel	0.125**	0. 112*	0.500*	0.006	0.220	0.108
	(0.427)	(0.343)	(0.300)	(0.374)	(0.300)	(0.260)
Rectangular kernel	0.118*	0.130*	0.547*	-0.005	0.191	0.136

	(0.420)	(0.346)	(0.303)	(0.360)	(0.312)	(0.313)

Note: ***, **, and * represent p≤0.01， p≤0.05, and p≤0.10, respectively. Standard errors are presented in parentheses.

4.3.4. Placebo test

The robustness test results verified the validity of the results of the RD empirical test. However, it cannot be excluded whether the results contain disturbances of other policy effects. Consequently, we implemented a placebo test based on different policy cutoff points to test the sensitivity of selection of the years to the RD estimation results. Since 2016 was selected as the original cutoff point, we chose the years 2015[8] and 2017 as the falsification cutoff points. Table 8 reports the RD regression results for this placebo test, which show that, except for the variable RPC, the effect of the CDP's implementation on other outcome variables is not significant at the two falsification cutoff points, with and without the additional covariates. Consequently, we concluded that it would be inaccurate to select either 2015 or 2017 as the policy cutoff point, thus confirming that the accurate selection of the original policy cutoff point in the proposed RD design.

Table 8 RD estimation results at different cutoff points.

[8] In 2015, the National Energy Administration issued the Action Plan for Clean and Efficient Use of Coal (2015-2020). In 2017, The State Council promulgated the Notice on the Comprehensive Work Plan for Energy Conservation and Emission Reduction during the 13th Five-Year Plan Period. According to industrial relevance theory, these policies may have some influence on the economic efficiency and production level of coal industry development.

Cutoff point \ Estimator	CU	$GRTFP$	RPC	ECC	$DRPMT$	$WAGE$
Year 2016	0.125**	0. 112*	0.500*	0.006	0.220	0.108
	(0.427)	(0.343)	(0.300)	(0.374)	(0.300)	(0.260)
Year 2015(N)	0.380	0.171	-0.009	-0.127	0.070	-0.288
	(0.297)	(0.397)	(0.248)	(0.330)	(0.283)	(0.236)
Year 2015(Y)	0.417	0.191	-0.100	-0.007	-0.025	-0.244
	(0.287)	(0.364)	(0.240)	(0.228)	(0.255)	(0.229)
Year 2017(N)	-0.083	-0.074	0.852***	0.012	-0.491	0.306
	(0.462)	(0.361)	(0.277)	(0.352)	(0.516)	(0.348)
Year 2017(Y)	-0.753	-0.300	0.806***	-0.067	-0.465	0.258
	(0.456)	(0.348)	(0.280)	(0.191)	(0.515)	(0.344)

Note: ***, **, and * represent $p\leq0.01$, $p\leq0.05$, and $p\leq0.10$, respectively. Standard errors are presented in parentheses.

5. Further discussions

In the context of the supply side structural reform of the 13th Five-Year Plan, the phased work of coal de-capacity from 2016 to 2020 has entered its final stage. It has been five years since the intensive implementation of the CDP in the 25 coal-producing provinces commenced in 2016. A discussion of policy implementation effects in these regions is warranted. The actual situations and previous studies (Wang et al., 2019a, 2020b) show that due to the heterogeneity of economic development, resource constraints, and industrial structure, among others, there will be differences in work emphasis and policy implementation in the different regions. Therefore, some questions should be considered, such as whether there is spatial heterogeneity in the implementation effect of the CDP. Consequently, subsample regression analyses are conducted based on different group criteria to estimate the regional policy effects, thus establishing the spatial heterogeneity of the CDP's multidimensional effects.

5.1. Subsample discussion by geographic region

The 25 coal-producing provinces were divided into two subsamples: the eastern and the central-western regions. The sample grouping results are shown in Columns 1 and 2 in Table E1. The provinces in the eastern region, such as Jiangsu, and those in the central-western regions, such as Guizhou, differ in financial capacity, degree of economic development, and governance capacity of the government. We obtained 60 observations from the eastern region and 190 observations from the central and western regions. The results of the RD estimation for the two subsamples are presented in Table 9. A comparative analysis showed some spatial heterogeneity in the effect of the CDP, owing to the differences between the geographical locations. Specifically, (1) for the economic indicators, the regression coefficients of CU, $GRTFP$, and RPC are all negative in the subsample from the eastern region, whereas they are all positive in the subsample from the central-western region, indicating that the CDP has a significant positive economic effect in the central-western region and a negative economic effect in the eastern region. This may be because compared with the coal mines in the central-western region[9], those in the eastern region demonstrate a high proportion of advanced capacity because of their fine management and low-cost mechanized mining, in addition to the stronger absorption capability of the coal market in the eastern region. Hence, given the policy implementation mode of "one size fits all," the administrative intervention instruction with respect to coal overcapacity has prevented the attainment of economic benefits that should have been obtained during a normal coal capacity operation in the eastern region. (2) With respect to the environmental effect, the CDP's implementation reduces the ECC of the coal industry in the eastern region, while it has no significant effect in the central-western region. The level of ECC depends on whether coal mining technology is advanced and the extent to which the local government is serious about environmental quality management. Accordingly, compared with the lagging coal capacity management and backward coal mining technology in the central-western region, the environmental benefits of coal production in the eastern region, with advanced development and strong scientific and

[9] For example, in some provinces located in the western region, such as in Inner Mongolia, Shanxi, and Guizhou provinces, the coal mine management and mechanical mining significantly lagged compared to those in the provinces in the eastern region. The proportion of backward capacity is very high, caused by the disorderly and unregulated mining. Driven by the goal of improving quality and increasing efficiency, the CDP significantly increased the concentration of the coal industry in the central and western regions and enhanced the operating efficiency of the entire industry, which explains why the economic effect of the CDP in the western region is remarkable and positive.

technological input, have been significantly improved, driven by the CDP's target of "improving the quality and increasing efficiency." (3) In terms of social indicators, the CDP does not have a significant effect on $DRPMT$, although it significantly increases the $WAGE$ level of coal workers in the central-western region. This may be because, on the one hand, the central financial support to the central-western region is significantly more skewed than that to the eastern region[10]; on the other hand, the differences in the industrial and employment structure between the eastern and western regions also lead to the difference in the CDP's impact on $WAGE$.

Based on the foregoing analyses, the CDP has produced opposite economic effects in the eastern and central-western regions and played a significant promotional role in the central-western region, improving the economic efficiency of the coal industry. However, the CDP has achieved a positive environmental effect in the eastern region, significantly reducing the comprehensive energy consumption level of coal production, although the effect is unclear in the central-western region. Moreover, the CDP has achieved a positive and significant social effect in the central-western region, whereas that in the eastern region is not ideal. Zhang et al.'s (2017) view that the local government is accountable for overcapacity in the coal industry supports our results. Hence, we proved that CDP implementation can vary because of the large size of the country and diverse local conditions.

Table 9 RD estimation results of the subsamples in different geographical areas.

Subsample \ Estimator	CU	$GRTFP$	RPC	ECC	$DRPMT$	$WAGE$
Eastern region	-0.036*	-0.081*	-0.442**	-0.0008*	0.261	0.094
(Observations=60)	(0.774)	(0.455)	(0.397)	(1.051)	(0.206)	(0.521)
Central-western	0.175*	0.008*	0.522***	0.169	0.240	0.106*

[10] On May 18, 2016, the Central Ministry of Finance announced the *Administrative Measures for Special Awards and Supplementary Funds for Industrial Enterprise Structural Adjustment* through its official website. A special award and subsidy fund with a total scale of CNY 100 billion has been set up to provide subsidies for local and central enterprises to resolve the excess capacity in the steel and coal industries. For provinces that have overfulfilled the task of eliminating production capacity, cascade bonus funds will be allocated as rewards.

region	(0.507)	(0.425)	(0.375)	(0.275)	(0.401)	(0.291)
(Observations =190)						

Note: ***, **, and * represent p≤0.01， p≤0.05, and p≤0.10, respectively. Standard errors are presented in parentheses.

5.2. Subsample discussion by coal resource endowment

The endowment of coal resources mainly concerns factors such as coal reserves, coal quality, geological conditions, and mine disasters, and are the primary factors in the production cost of coal. We calculated the average annual coal production in 25 coal-producing provinces from 2010 to 2019. Using the median as the dividing point, the full sample was split into two subsamples: a high-resource endowment subsample (H-resource endowment) and a low resource endowment subsample (L-resource endowment). The sample grouping results are shown in Columns 3 and 4 of Table E1 in Appendix E, in which the H-resource endowment subsample has 130 observations, and the L-resource endowment subsample has 120 observations. The RD estimation results for the two subsamples are presented in Table 10. A comparative analysis shows that (1) for the economic effect, the CDP's implementation significantly improves the economic indicators CU, $GRTFP$, and RPC in the L-resource endowment region, whereas it has a negative impact on the CU and RPC in the H-resource endowment region; (2) for the environmental effect, the CDP's implementation has no statistically significant impact on the ECC in either region; (3) for the social effect, the regression coefficient of $DRPMT$ is negative in the H-resource endowment region, but that of $WAGE$ is positive, indicating that the CDP's implementation significantly improved the level of coal mine production safety and the coal workers' salaries.

Therefore, the CDP's implementation realized a positive economic effect in the L-resource endowment region and a positive social effect in the H-resource endowment region. A possible reason is that, compared with high-endowment areas, coal mining in low-endowment areas is more difficult, with higher mining costs. The call to "eliminate outdated coal capacity and develop advanced coal capacity" has optimized the allocation of coal production resources in these provinces to a certain extent, thus increasing economic efficiency. In line with our view, Ma et al. (2020) hold that the benefits of larger coal production regions are more likely to be negatively affected because they undertake most of the coal de-capacity.

Table 10 RD estimation results of the subsamples with different resource endowment conditions.

Subsample \ Estimator	CU	$GRTFP$	RPC	ECC	$DRPMT$	$WAGE$
H-resource endowment	-0.089*	-0.203*	0.592***	0.201	-0.180*	0.189**
(Observations=130)	(0.571)	(0.440)	(0.432)	(0.824)	(0.162)	(0.355)
L-Resource endowment (Observations=120)	0.359**	0.203*	0.400**	0.0008	0.322	0.320
	(0.619)	(0.545)	(0.418)	(0.418)	(0.621)	(0.391)

Note: ***, **, and * represent p≤0.01, p≤0.05, and p≤0.10, respectively. Standard errors are presented in parentheses.

5.3. Subsample discussion by coal de-capacity cost

Based on the cost calculation results in the government's capacity plan in Wang et al. (2020b), the full sample is divided into two subsamples based on the median of the de-capacity cost of the 25 coal-producing provinces. The sample grouping results are shown in Columns 5 and 6 of Table E1 in Appendix E, in which the subsample of H-de-capacity cost has 130 observations and that of L-de-capacity cost has 120 observations. The RD estimation results for the two subsamples are presented in Table 11. A comparative analysis shows that, (1) in the L-de-capacity cost region, the economic indicator CU is significantly improved. However, in the H-de-capacity cost region, CDP implementation significantly reduces the CU. This is due to the local government's profit-seeking and labor-intensive nature. The cost of reducing overcapacity in the coal industry is directly related to regional finances; therefore, the L-de-capacity cost provinces are more inclined to actively respond to the policies. (2) The CDP has a significant positive impact on RPC in both the H-de-capacity cost and the L-de-capacity cost regions, with a stronger impact in the former regions. This shows that the areas with H-de-capacity costs, such as Shanxi, Shaanxi, and Inner Mongolia, are more sensitive to changes in operating efficiency because of the implementation of the CDP. This may be because there are some large coal mines in these areas that are more active in the implementation of the CDP. Consequently, the CDP optimized the allocation of coal production resources and improved the operating efficiency of coal enterprises in the H-de-capacity region. (3) In the H-de-capacity cost region, the CDP implementation raised the coal workers' salaries, which is logically consistent with the estimated results of the $WAGE$ estimator in Table 10. This may be because the areas with high resource endowment tend to have higher de-capacity costs, such as Guizhou and Xinjiang provinces, corroborating the conclusions as credible and robust.

According to Shi et al. (2018), regional heterogeneity will likely cause regional markets to respond differently to capacity cut policies, resulting in varied production patterns. This subsample analysis has a consensus view. In terms of economic effect, the CDP implementation has a positive impact on coal capacity utilization and business operation efficiency in the L-de-capacity region, thus significantly improving the economic benefits of the coal industry. Moreover, for the social effect, the CDP implementation significantly improved coal workers' salaries in the H-de-capacity region.

Table 11 RD estimation results of the subsamples with different coal de-capacity costs.

Estimator / Subsample	CU	$GRTFP$	RPC	ECC	$DRPMT$	$WAGE$
H-de-capacity cost	-0.246*	-0.007	0.627***	0.200	0.122	0.151*
(Observations=130)	(0.502)	(0.365)	(0.463)	(0.814)	(0.191)	(0.321)
L-de-capacity cost	0.560**	-0.009	0.352**	0.001	0.286	0.091
(Observations=120)	(0.581)	(0.613)	(0.387)	(0.422)	(0.557)	(0.435)

Note: ***, **, and * represent p≤0.01, p≤0.05, and p≤0.10, respectively. Standard errors are presented in parentheses.

5.4. Our research vs. existing literature

Through the above RD analyses and subsample discussions, the mixed multidimensional effects of the CDP implementation and its spatial heterogeneity in different regions are revealed. Some interesting and significant findings include the following: First, the CDP implementation has improved capacity utilization, the growth rate of TFP, and the ratio of profits of the coal industry. Although the goal of the CDP is to “improve quality and increase efficiency," its performance in environmental benefit and social welfare is not as good as economic efficiency. Second, due to the different geographic region characteristics, resource endowments, and de-capacity costs in each coal-production province, the implementation of the CDP shows significant spatial heterogeneity. For example, the CDP has produced a positive economic effect in central-western regions and has significantly improved the green production level of the coal industry in the eastern region. These findings will contribute to providing the central government with practical CDP optimization recommendations for the enhancement of environmental benefits and social welfare in the coal de-capacity process. In addition, these may offer targeted management suggestions to the local government in formulating a future coal de-capacity work plan that balances efficiency, cost, environment, and fairness.

Some recent literature from different research aims and perspectives is related to our research. To highlight the innovation and contribution of the above research findings, we systematically compare them. Zhang et al. (2021) proposed a dynamic stochastic general equilibrium model to examine the macroeconomic effects of CDP shocks on the Chinese economy. They concluded that the impact of three policy tools (i.e., advanced capacity replacement, eliminating outdated capacity, and direct production cut) on the macroeconomic system gradually increased. Li and Yao (2020) and Xiao et al. (2020) revealed the effect of the CDP on air pollution and emission production, but simply regarded the CDP as a reduction in coal production, which weakens the reliability of the evaluation results. Several scholars have investigated the policy effects on coal prices (Shi et al., 2018; Zhang et al., 2018; Wang et al., 2020b), TFP (Zhang et al., 2020b), and coal miners' livelihoods (Wang et al., 2020c). These studies have performed a good job for CDP evaluation. Unfortunately, these studies only evaluate the effects of policies from a single perspective, such as macroeconomic, environmental, or price fluctuations, which makes it difficult to fully evaluate the multi-dimensional effectiveness of the CDP. Hence, we attempted to bridge this gap by focusing on the economic, environmental, and social effects of the CDP, and first discussed the spatial heterogeneity of the policy effects in regions with different characteristics. Specifically, our work accurately and quantitatively solved questions that are practically significant to coal capacity regulation, such as "were the periodic goals of the CDP to reduce the quantity, improve the quality, and increase the efficiency achieved?" and "was there a heterogeneous policy effect in the coal-production provinces with different characteristics?"

6. Conclusions and policy implications

6.1. Key conclusions

Given that there is a literature gap in examining the multidimensional effects of the CDP, this study exploits a sharp discontinuity in the introduction of the CDP implementation in 2016 to identify the economic, environmental, and social effects. Moreover, the spatial heterogeneity of policy effects is discussed. The main conclusions are as follows:

(1) The expected goal of the Chinese CDP has not been fully achieved. Since the CDP was implemented in 2016, despite obtaining a significant economic effect, its environmental and social effects were not ideal. In addition, the RD results show the changing trend of indicators of economic efficiency, environmental benefit, and social welfare quantitatively over time. For example, the impact of the CDP on coal capacity utilization tends to stabilize gradually after being improved, while the growth rate of total factor productivity and profitability tends to increase gradually with time. The findings obtained in this study will provide not only a theoretical basis for the optimization of China's future coal de-capacity policies, but also provide a solid reference for drawing up a de-capacity plan to maximize the economic, environmental, and social benefits.

(2) The multidimensional effects of CDP showed significant spatial heterogeneity. In regions with different characteristics, such as the coal resource endowment conditions and the cost of coal de-capacity, the policy effectiveness in the economic, environmental, and social dimensions is significantly different. Specifically, in the eastern region, the CDP improved the environmental indicators, but reduced the economic efficiency of the local industrial development of coal. Coal workers' salaries were improved due to the implementation of the CDP in the central-western region. For the regions with a high resource endowment, the CDP implementation significantly improved the production safety level of the coal industry; however, this was not achieved in the other regions. The spatial heterogeneity of the policy effects suggests that the coal de-capacity policy should be differentiated across regions and local circumstances. In other words, designing coal de-capacity targets and plans for specific regions or even producers could help ensure better policy efficiency and feasibility.

6.2. Policy implications

Based on the above research conclusions, some policy implications are proposed to optimize future coal de-capacity work and ensure the smooth operations and high-quality development of China's coal industry.

(1) The design of a coal de-capacity policy should assume a multidimensional perspective and consider aspects such as the industrial economy, environmental protection, and employee welfare. Although the CDP has achieved a positive economic effect, its social welfare and environmental benefits are unclear. Therefore, when formulating policy measures in the next phase of the CDP, the government should not only consider the economic performance of the coal industry, but also focus on the multi-objectives of green and safe production and social welfare. It should shift the focus of capacity regulation from capacity reduction in total quantity to capacity structure optimization, adjust the single regulation mechanism of coal overcapacity to diversify management, thus promoting sustainable and high-quality development of China's coal industry. Moreover, the government should regularly monitor the effects of policy implementation to dynamically adjust relevant strategies. Diversified and effective evaluation systems should be formulated for policy effects among the coal industry's green, safety, and performance indicators instead of concentrating on a single indicator of coal production or capacity utilization. Such a move may help measure the effectiveness of coal de-capacity policies in a comprehensive, quantitative, and dynamic manner to ensure timely adjustment and targeted implementation of coal capacity regulation strategies.

(2) The heterogeneity of fiscal capacity, resources and environmental bases, and government management levels among different provinces should be considered in the implementation of coal de-capacity policies. Specifically, the central government should thoroughly consider the diverse characteristics of different regions, such as economic strength, resource endowment conditions, and welfare cost, and change the approach from "one size fits all" to "classification management." Meanwhile, local governments should match their natural resource attributes and industrial development conditions when formulating regional capacity plans and policy measures. This will reduce the conflict of interest caused by unfair de-capacity methods and smoothly eliminate outdated

production capacity. For example, Guizhou Province, as a resource-rich province in Southwest China, has a heavy coal de-capacity task. The presence of many small and poorly equipped coal mines increases the cost of de-capacity. The focus of de-capacity policies in this area should encourage coal enterprises to merge and restructure, eliminate spare production capacity, overcome the environmental and social problems caused by the disorderly, inefficient, and illegal mining activities as well as improve the concentration and competitiveness of the coal industry to maximize the social, environmental, and economic benefits. Jiangsu Province, an economically developed province in eastern China, has a lighter coal de-capacity task. The de-capacity policies for this region should focus on transforming outdated capacity into advanced capacity by increasing investment in technological transformation and innovation, in addition to extending the upstream and downstream industrial coal chain, which would accelerate the transformation, upgrading, and structure optimization of the coal industry, eventually promoting its high-quality development.

6.3. Outlook

The main objective of this study is to quantify the multidimensional effects of China's coal de-capacity policy introduced in 2016. Some interesting and important findings are presented. However, this study has some limitations. The data sample selected was the annual data on the variables involved. Although the indicators are detailed, some data in 2020 are difficult to obtain owing to a lack of unpublished official statistics. Given that the RD method requires a certain amount of data before and after the cutoff point, the time-lag effect of the policy is difficult to examine using the current data sample. In the future, the time-lag effect of the coal de-capacity policy can be further discussed with sufficient data.

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Appendix

Appendix A. *Summary of China's coal de-capacity policies issued in 2016*

Table A1 Policies issued by the central government in 2016

Type	Promulgation time	Policy number	Policy name	Notes
Programmatic policy	February 5, 2016	Guofa [2016] No.7	*State Council's Guidelines on Addressing Overcapacity and Achieving a Turnaround in the Coal Industry*	This document is a programmatic document of coal supply-side reform, and also the mainline of coal de-capacity work. The introduction of this policy marks the transition of coal supply reform from the research to the policy release.
Supporting policies	March 30, 2016	Guotuzigui [2016] No.3	*Opinions of the Ministry of land and resources on supporting the steel and coal industry to resolve overcapacity and achieve development out of difficulties*	With the introduction of supporting policy documents, coal de -capacity work has entered a new stage. The coal supply-side reform has been implemented, and the implementation has been gradually strengthened. The plans and targets of various provinces and cities to reduce production capacity are further refined. Local governments and coal enterprises all have announced specific plans of reducing
	April 7, 2016	Renshebufa [2016] No.32	*Opinions of the Ministry of Human Resources and Social Security, the Development and Reform Commission, the Ministry of Industry and Information Technology, the Ministry of Finance, the Ministry of Civil Affairs, the State-Owned Assets Supervision and Administration Commission, and the All-China Federation of Trade Unions on the resettlement of employees in the process of resolving the overcapacity of the steel and coal industry and extricating itself from difficulties*	

April 15, 2016	Anjianzongguan [2016] No.38	*Opinions of the State Administration of Work Safety and the State Administration of Coal Mine Safety on supporting the steel and coal industry to resolve overcapacity and achieve development out of difficulties*	staff and closing coal mines.
April 16, 2016	Guozhijianjian [2016] No.193	*Opinions of the General Administration of Quality Supervision, Inspection and Quarantine on resolving the surplus of the steel industry and realizing the development of extricating from difficulties*	
April 17, 2016	Huandaqi [2016] No.47	*Opinions of the Ministry of Environmental Protection, the National Development and Reform Commission, and the Ministry of Industry and Information Technology on supporting the steel and coal industry to resolve overcapacity and achieve development out of difficulties*	
April 17, 2016	Yinfa [2016] No.118	*Opinions of the People's Bank of China, China Banking Regulatory Commission, China Securities Regulatory Commission, and China Insurance Regulatory Commission on supporting the steel and coal industry to resolve overcapacity and achieve development out of difficulties*	
April 17, 2016	Caijian [2016] No.151	*Opinions of the Ministry of Finance and the State Administration of Taxation on supporting steel and coal industry to resolve overcapacity and achieve development out of difficulties*	
May 10, 2016	Caijian [2016] No.253	*Measures of the Ministry of Finance for printing and distributing the special reward and subsidy funds for the structural adjustment of industrial enterprises*	

Table A2 Policies issued by the local governments of 25 coal-producing provinces in 2016

Province	Promulgation time	Policy number	Policy name	Measures
Liaoning	August 15, 2016	Liaozhengfa [2016] No.55	*Implementation opinions of Liaoning Provincial People's Government on promoting industrial supply-side structural reform*	In 2016, the crude steel production capacity will be reduced by 6.02 million tons, and the coal overcapacity will be reduced by 30.4 million tons by 2020.
Jilin	April 12, 2016	Jizhengfa [2016] No.11	*Notice of Jilin Provincial People's Government on printing and distributing the guiding opinions and five implementation opinions on promoting the supply-side structural reform and implementing the task of "three removals, one reduction, and one subsidy"*	Coal industry: in 2-3 years, it will reduce 27.33 million tons of production capacity, withdraw 132 coal mines, and retain 21.64 million tons of production capacity and 25 coal mines. Based on greatly reducing coal production capacity, the existing coal mines have achieved quality standardization of more than two levels.
Heilongjiang	July 21, 2016	Heizhengbanfa [2016] No.77	*Notice of the general office of the people's Government of Heilongjiang Province on printing and distributing the implementation plan for resolving coal overcapacity in Heilongjiang Province*	Starting from 2016, it will take three to five years to withdraw 44 coal mines with a production capacity of 25.67 million tons (450,000 tons outside the province). Among them, the Longmei group led to the withdrawal of 24 coal mines (2 places outside the province) with a production capacity of 18.14 million tons (450,000 tons outside the province); 20 local coal mines with a production capacity of 7.53 million tons. During the 13th Five Year Plan period, 62,000 people will be resettled in the whole province, including 50000 in the Longmei group and 12000 in local coal mines.

Beijing	September 30, 2016	/	*Circular on resolving the target task of coal production capacity in 2016*	In 2016, its coal production capacity was 1.8 million tons, including 1 million tons from Changgouyu coal mine in June and 800,000 tons from coal mines in Wangping Village in August. Beijing will take five years to actively guide the withdrawal of coal production capacity of 6 million tons, to achieve the goal of all coal mines withdrawal.
Hebei	May 4, 2016	Jizhengfa [2016] No.18	*Implementation plan for resolving overcapacity and realizing development out of difficulties of the coal industry in Hebei Province*	In three to five years, 123 coal mines and 51.03 million tons of production capacity will be withdrawn. By 2020, the number of remaining coal mines in the province will reach about 60 and the production capacity will be controlled at about 70 million tons. The organizational structure of coal enterprises will be more intensive, the technology will be more advanced, the product structure will be more in line with the needs of clean utilization, the comprehensive competitiveness of enterprises will be significantly improved, and substantial progress will be made in the transformation and development of the industry.
Jiangsu	April 6, 2016	Suzhengfa [2016] No.50	*Opinions of Jiangsu provincial government on the implementation of supply-side structural reform to reduce production capacity*	It is preliminarily determined that by 2020 (the end of the 13th five-year plan), 8 million tons of coal production capacity will be withdrawn and reduced. By 2018, the coal and steel industry will be operating at a loss, the loss of enterprises will be significantly reduced, and the coal industry will achieve 90% of the capacity reduction target of the 13th five-year plan. In 2016, 6 million tons of coal production capacity will be withdrawn and reduced.
Fujian	July 31, 2016	Minzhengbanfa [2016] No.123	*Notice of the general office of Fujian Provincial People's Government on printing and distributing the implementation plan for resolving overcapacity in the coal industry*	Starting from 2016, it will take three to five years to resolve the excess capacity of about 6 million tons per year and withdraw more than 78 coal mines; from 2016 to 2018, it will concentrate on tackling the difficulties and withdraw more than 71 coal mines. During the period of the 13th Five Year Plan, the coal production capacity of the whole province was controlled within 15 million tons

				per year.
Shandong	May 19, 2016	/	*Implementation opinions of Shandong provincial Party committee and Shandong Provincial People's Government on further promoting supply-side structural reform*	From 2016 to 2018, the capacity utilization rate of the "5 + 4" overcapacity industries (steel, cement, electrolytic aluminum, flat glass, ships, oil refining, tires, coal, chemical industry) will strive to rise to more than 80% and complete the national task of resolving overcapacity on time, in which the capacity of steel and coal will be reduced by more than 10 million tons and 45 million tons respectively.
Shanxi	August 16, 2016	Jinzhengbanfa [2016] No.114	*Notice of the general office of the People's Government of Shanxi Province on accelerating the resolution of overcapacity in the coal industry*	In 2016, the province's target task is to close, withdraw, reduce and restructure, reduce 21 coal mines, withdraw 20 million tons per year, and resettle 27122 employees.
Anhui	August 19, 2016	Wanzhengfa [2016] No.76	*Anhui Province issued the implementation opinions on resolving excess capacity and realizing the development of extricating from difficulties in the coal industry*	From 2016 to 2020, the provincial and local coal enterprises plan to close 21 pairs of coal mines, withdraw 31.83 million tons of production capacity per year, and resettle more than 70000 workers. By 2020, the number of coal mines in the whole province will be reduced to 37 pairs, and the production capacity will be controlled at about 110 million tons/year; the production and operation costs and the asset-liability ratio of coal enterprises will be further reduced, the total labor productivity and enterprise profitability will be significantly improved, the modern enterprise system will be further improved, and the market competitiveness and the ability to resist risks will be significantly enhanced.
Jiangxi	June 18, 2016	Ganfutingzi [2016] No.81	*Notice of the general office of the People's Government of Jiangxi Province on printing*	During the period of the 13th Five-Year Plan, more than 283 coal mines were closed and withdrawn, with a production capacity of more than 18.68 million

			and distributing the implementation plan of Jiangxi coal industry to resolve overcapacity and achieve development out of difficulties	tons. The reserved coal mines have been fully realized normal mining, the coal mine safety guarantee ability has been significantly improved, the industrial structure has been optimized, and the transformation and upgrading of enterprises and the development of extricating from difficulties have achieved remarkable results.
Henan	February 20, 2016	Yuzhengfa [2016] No.10	*Opinions of Henan Provincial People's Government on promoting the coal industry to solve difficulties*	From 2016, in principle, the approval of the construction of mines that do not meet the requirements of the state, the technical transformation projects of new production capacity, and the nuclear increase projects of coal mine production capacity will be stopped within three years; if the new production capacity is needed due to the structural adjustment, transformation, and upgrading, the reduction and replacement will be implemented.
Hubei	August 3, 2016	Ezhengbanhan [2016] No.72	*Notice of the general office of the provincial people's Government on printing and distributing the implementation plan for resolving overcapacity in the steel and coal industry of Hubei Province*	Since 2016, the crude steel production capacity will be reduced by 2.99 million tons in three years (excluding the production capacity reduction of WISCO's enterprises in Hubei), of which 2.28 million tons are reduced in 2016 so that the capacity utilization rate reached a reasonable level, the benefits of the enterprise and the product quality and high-end product supply capacity improve significantly.
Hunan	April 18, 2016	Xiangzhengbanfa [2016] No.28	*Implementation plan for resolving overcapacity and achieving development out of difficulties in Hunan coal industry*	Complete the work of closing and withdrawing outdated small coal mines in an all-around way. Starting from 2016, it will take 3-5 years to resolve the outdated production capacity of 15 million tons and control the total number of coal mines in the province at about 200.

Inner Mongolia	July 13, 2016	/	*Preliminary plan for resolving overcapacity and realizing development out of difficulties in the coal industry*	An Endeavor will be made to use three to five years to resolve about 179 million tons of excess capacity in the coal industry, of which 49.59 million tons will be withdrawn and 129 million tons will be reduced to use three to five years to resolve about 179 million tons of excess capacity in the coal industry, of which 49.59 million tons will be withdrawn and 129 million tons will be reduced.
Guangxi	August 3, 2016	Guigongxinnengyuan [2016] No.535	*Notice on tasks related to resolving coal overcapacity and achieving development goals in Guangxi in 2016*	In 2016, the first batch of 12 coal mines was withdrawn in our district, and the excess coal production capacity of 2.27 million tons was eliminated. We attached great importance to the safety production work of production withdrawal mines and earnestly did a good job in the resettlement of workers.
Chongqing	June 24, 2016	Yuzhengfa [2016] No.39	*Notice of Chongqing Municipal People's Government on printing and distributing the implementation plan of Chongqing's coal industry to resolve overcapacity and achieve development out of difficulties*	Starting from 2016, it will take two to three years to close about 340 coal mines and eliminate about 23 million tons of outdated production capacity. In 2016, the number and production capacity of coal mines with a production capacity of 90000 tons/year and below in all coal-producing areas and counties should be reduced by more than 50%. Through the implementation of coal mine closure and exit and structural adjustment, the number of coal mines will be reduced to less than 70, and the coal production capacity will be reduced to less than 20 million tons/year. The overcapacity of the coal industry will be effectively resolved, the industrial structure will be optimized, and substantial progress will be made in the transformation and upgrading.
Sichuan	August 19, 2016	Chuanzhengbanfa [2016] No.59	*Implementation opinions of the general office of Sichuan Provincial People's Government on resolving overcapacity and realizing extricating development of the coal*	Starting from 2016, it will take three to five years to withdraw and close about 215 coal mines and dissolve the capacity of about 33.03 million tons, including 18 provincial state-owned key coal mines with a capacity of about 12.09 million tons. It will effectively dissolve the excess capacity of the coal industry, basically balance the market supply and demand, significantly reduce the

			industry	number of coal mines, optimize the industrial structure, and achieve substantial progress in transformation and upgrading. The social functions of state-owned enterprises should be separate and the problem of the separation and resettlement of the retired coal mine workers will be properly dealt with.
Guizhou	August 28, 2016	Qianfubanhan [2016] No.187	*Notice on the implementation plan of Guizhou coal industry to resolve excess capacity and realize poverty alleviation*	Starting from 2016, 510 coal mines will be closed in three to five years, and the scale of coal mines will be reduced by more than 70 million tons. Besides, the staff and workers who have retired from coal enterprises will be properly arranged. By 2020, the total number of coal mines in the province will be reduced to 750, the output will be controlled at about 200 million tons, and the coal mines of less than 300000 tons/year will be eliminated.
Yunnan	June 21, 2016	Yunzhengfa [2016] No.50	*Implementation opinions of Yunnan Provincial People's Government on resolving overcapacity of the coal industry and realizing development out of difficulties*	By 2018, the total coal production capacity of the province will be controlled by 70 million tons. Based on ensuring to resolve 20.88 million tons of coal production capacity in the target responsibility letter signed by the state and our province to resolve coal overcapacity, the guidance and withdrawal will be further strengthened.
Shaanxi	April 4, 2016	/	*Notice of Shaanxi Provincial Development and Reform Commission on releasing the list of the coal industry to resolve overcapacity and guide the withdrawal of coal mines in 2016*	In 2016, Shaanxi Cangcun Coal Industry Co., Ltd. and other 61 coal mines were closed.
Gansu	August 13, 2016	Ganfagainengyuan [2016] No.731	*Implementation plan for resolving overcapacity and extricating development of coal industry in Gansu Province*	In 2016-2020, the province will resolve the steel industry de-capacity target of 1.6 million tons of excess capacity of steel and 1.74 million tons of crude steel (including 1.6 million tons of reduced pig steel capacity and 1.44 million tons

				of crude steel capacity in 2016), and the coal industry de-capacity target of 70 outdated coal mines and 9.91 million tons of capacity (including 48 coal mines and 3.97 million tons of capacity in 2016).
Qinghai	May 1, 2016	Qingzhengfa [2016] No.41	*Opinions of the People's Government of Qinghai Province on the implementation of the supply-side structural reform project in the industrial field*	Strive to complete the reduction target of withdrawing 2.76 million tons of coal production capacity three years ahead of schedule.
Ningxia	August 2, 2016	Ningzhengbanfa [2016] No.124	*Notice of the general office of the People's Government of Ningxia Autonomous Region on printing and distributing the implementation plan for the iron and steel industry to resolve overcapacity and achieve development out of difficulties*	In the next five years, by actively encouraging and guiding enterprises to actively exit, promoting mergers and acquisitions, the province will strive to reduce and integrate the existing production capacity, optimize the industrial structure, significantly improve the efficiency of resource utilization, and gradually improve the economic benefits of enterprises.
Xinjiang	July 22, 2016	Xinzhengbanfa [2016] No.100	*Notice on printing and distributing the implementation plan and 2016 annual work plan for resolving coal overcapacity in Xinjiang Autonomous Region*	In 2016, it is planned to shut down 17 coal mines and withdraw a production capacity of 2.38 million tons per year.

Appendix B. *Estimation of Coal Boundary Production Function for provinces*

The boundary production function is a common method used to estimate potential output and technical efficiency. This method, based on economic growth theory, can reveal the relationship between inputs and outputs, is widely used in various production management fields. In this study, therefore, the boundary production function is adopted to measure the coal capacity and capacity utilization rate for each province. The main steps are as follows. First, the appropriate production function form is determined and the average production function equation is estimated using the ordinary least squares (OLS) method. Second, the average production function equation estimated above is shifted upward until the residual value is less than or equal to zero; that is, the boundary production function is obtained by taking the maximum residual value estimated by OLS and adding it to the constant term of the average production function. Finally, the coal capacities of different provinces are calculated, based on the estimated boundary production function.

In this study, the boundary production function is set as the widely used Cobb-Douglas production function. Its basic form is:

$$Y = A \times K^{\alpha} \times L^{\beta} \times e^{-u} \qquad (u \geq 0) \tag{B.1}$$

where Y is actual output, K is capital input, and L is labor input. A is technological level, α and β are the respective output elasticities of capital and labor, and e^{-u} is production inefficiency. Taking the logarithms of both sides of equation (1), we get:

$$\ln Y = \ln A + \alpha \ln K + \beta \ln L - u \tag{B.2}$$

Let $\ln A = \lambda$ and $E(u) = \delta$, and formula (2) can be rewritten as:

$$\ln Y = (\lambda - \delta) + \alpha \ln K + \beta \ln L - (u - \delta) \tag{B.3}$$

As $E(u - \delta) = 0$, the OLS method is used to estimate parameters, and we then get the average production function as follows:

$$\ln \bar{Y} = \varepsilon + \hat{\alpha} \ln K + \hat{\beta} \ln L \tag{B.4}$$

where $\varepsilon = \lambda - \hat{\delta}$. According to the property that all actual output is below the boundary production function, the maximum residual value $\hat{\delta}$ can be further obtained as:

$$\max(\ln Y - \ln \bar{Y}) = \max(u) = \max\{\ln Y - (\hat{\varepsilon} + \hat{\alpha}\ln K + \hat{\beta}\ln L)\} \tag{B.5}$$

We get the value of $\hat{\lambda}$ by incorporating $\hat{\delta}$ into formula (4). Therefore, the estimated boundary production function is:

$$Y^* = e^{\hat{\lambda}} \cdot K^{\hat{\alpha}} \cdot L^{\hat{\beta}} \tag{B.6}$$

where Y^* is coal capacity. Finally, the coal capacity utilization rate CU is:

$$CU = Y/Y^* \tag{B.7}$$

Appendix C. *Calculation of TFP growth for provinces, based on Solow's residual value method*

As an important index to measure the quality of economic growth, TFP can truly reflect the efficiency of the transformation of overall economic input into output. Therefore, it is necessary to introduce the concept of TFP in the coal de-capacity allocation model. Based on the comprehensive consideration of data availability, applicability, and algorithm consistency, in this study we use the Solow residual method in the form of a two-factor Cobb-Douglas production function to calculate the TFP growth rate. The basic idea is that the average production function is estimated first; the residual error is then calculated by deducting the growth rate of each input factor from the output growth rate, which can be used to estimate the TFP growth rate for the provinces. The steps are as follows.

According to the estimation result of **Appendix B**, the average production function of the coal industry is $\ln \bar{Y} = \varepsilon + \hat{\alpha}\ln K + \hat{\beta}\ln L$, so the production function at the time t is:

$$Y_t = e^{\varepsilon_t} \times K_t^{\hat{\alpha}} \times L_t^{\hat{\beta}} \tag{C.1}$$

where Y_t, K_t, and L_t are the actual output, capital input, and labor input at the time t. Taking the derivative of both sides of this equation with respect to t and dividing both sides by Y, we get:

$$\frac{1}{Y}\frac{dY}{dt} = \frac{1}{e^{\varepsilon}}\frac{d(e^{\varepsilon})}{dt} + \hat{\alpha}\frac{1}{K}\frac{dK}{dt} + \hat{\beta}\frac{1}{L}\frac{dL}{dt} \tag{C.2}$$

Since the presupposition of Solow's residual method is constant returns to scale, it is necessary to normalize the elastic coefficient of production factors; therefore we let:

$$\alpha = \frac{\hat{\alpha}}{\hat{\alpha}+\hat{\beta}}, \quad \beta = \frac{\hat{\beta}}{\hat{\alpha}+\hat{\beta}}$$

Then $\alpha + \beta = 1$ and the TFP growth rate $T\dot{F}P$ is:

$$T\dot{F}P = \frac{1}{e^{\varepsilon}}\frac{d(e^{\varepsilon})}{dt} = \frac{1}{Y}\frac{dY}{dt} - \alpha\frac{1}{K}\frac{dK}{dt} - \beta\frac{1}{L}\frac{dL}{dt} \quad \text{(C.3)}$$

Considering the availability and consistency of the data, the raw coal output index of the coal industry in 25 coal-producing provinces is used to measure the actual output Y, the annual average balance of fixed assets (price in 1990) is used to measure the capital input K, and the annual average number of all employees in the coal industry is used to measure labor input L. The above data are respectively taken from the statistical yearbook of 25 coal-producing provinces and China's Industrial Economy Statistics Yearbook. The data of the fixed asset investment price index is taken from China's Price Statistics Yearbook.

Appendix D. *Calculation results of CU and $GRTFP$*

Table D1 The capacity utilization of 25 coal-producing provinces from 2010 to 2019

Province	2010	2011	2012	2013	2014
Liaoning	90.67%	91.54%	83.21%	69.08%	81.18%
Jilin	97.96%	94.08%	100.00%	49.00%	56.47%
Heilongjiang	98.71%	91.64%	86.85%	78.17%	71.89%
Beijing	49.57%	48.56%	48.97%	50.58%	51.23%
Hebei	86.15%	91.87%	100.00%	64.75%	63.06%
Jiangsu	77.54%	79.23%	81.15%	76.82%	82.04%
Fujian	38.42%	43.22%	38.64%	36.75%	38.02%
Shandong	68.89%	73.18%	73.40%	81.17%	80.78%
Shanxi	83.37%	91.38%	86.59%	82.88%	79.92%
Anhui	88.23%	100.00%	94.46%	82.27%	76.73%
Jiangxi	82.83%	85.77%	75.99%	74.70%	65.79%

Henan	32.04%	31.51%	29.51%	27.15%	26.64%
Hubei	80.86%	84.92%	100.00%	53.19%	52.34%
Hunan	63.75%	69.12%	69.60%	51.95%	49.59%
Inner Mongolia	69.09%	77.44%	73.60%	59.80%	67.19%
Guangxi	99.79%	100.00%	93.99%	85.93%	75.62%
Chongqing	32.56%	33.23%	27.04%	28.79%	30.31%
Sichuan	81.40%	80.54%	75.35%	67.26%	85.02%
Guizhou	68.89%	73.18%	73.40%	81.17%	80.78%
Yunnan	51.56%	63.00%	50.03%	59.97%	44.56%
Shaanxi	82.04%	68.58%	69.74%	88.86%	62.72%
Gansu	100.00%	95.23%	86.82%	88.20%	73.57%
Qinghai	52.99%	58.35%	75.49%	87.98%	50.60%
Ningxia	100.00%	87.65%	70.15%	68.78%	67.30%
Xinjiang	54.96%	67.71%	69.10%	60.09%	47.82%

(Continued)

Province	2015	2016	2017	2018	2019
Liaoning	79.61%	79.81%	77.07%	82.85%	77.71%
Jilin	53.27%	42.90%	46.22%	60.37%	48.61%
Heilongjiang	73.96%	50.67%	53.00%	52.14%	49.09%
Beijing	67.25%	55.33%	84.40%	100.00%	25.36%
Hebei	62.60%	66.49%	76.55%	77.37%	77.61%
Jiangsu	84.80%	65.70%	69.23%	70.91%	63.68%
Fujian	43.65%	83.03%	68.39%	96.98%	100.00%
Shandong	76.72%	79.54%	79.71%	64.56%	55.97%
Shanxi	82.43%	61.20%	61.63%	65.65%	70.93%
Anhui	89.90%	71.50%	78.38%	87.14%	89.27%
Jiangxi	68.41%	55.47%	57.34%	67.30%	51.37%
Henan	31.96%	42.89%	53.12%	79.74%	100.00%
Hubei	57.28%	70.76%	45.13%	68.24%	58.88%
Hunan	63.91%	97.08%	100.00%	97.29%	76.99%
Inner Mongolia	65.84%	72.07%	100.00%	73.26%	75.52%
Guangxi	56.12%	55.30%	49.61%	59.36%	43.86%
Chongqing	35.41%	98.69%	100.00%	77.91%	76.81%
Sichuan	90.43%	100.00%	89.43%	86.84%	77.77%
Guizhou	76.72%	79.54%	79.71%	64.56%	55.97%
Yunnan	63.54%	83.17%	100.00%	82.69%	75.45%
Shaanxi	61.93%	52.44%	16.06%	69.63%	76.62%
Gansu	65.15%	51.82%	49.72%	50.90%	49.95%
Qinghai	32.27%	38.93%	52.53%	44.24%	48.75%
Ningxia	59.01%	84.50%	78.85%	61.30%	60.00%
Xinjiang	55.06%	57.57%	73.54%	87.33%	100.00%

Table D2 The growth rate of total factor productivity of 25 coal-producing provinces from

2010 to 2019

Province	2010	2011	2012	2013	2014
Liaoning	0.006	0.06	-0.093	-0.152	-0.105
Jilin	0.122	0.011	0.099	-0.55	0.004
Heilongjiang	-0.039	-0.062	-0.045	-0.087	-0.064
Beijing	-0.12	0.011	0	0.033	-0.03
Hebei	0.153	0.038	0.096	-0.354	-0.051
Jiangsu	-0.092	0.013	0.032	-0.019	0.007
Fujian	-0.108	0.09	-0.189	-0.113	-0.003
Shandong	0.036	-0.012	0.078	-0.164	-0.057
Shanxi	0.151	0.094	-0.075	-0.069	-0.032
Anhui	-0.042	0.186	-0.093	-0.167	-0.074
Jiangxi	-0.006	-0.135	-0.039	-0.073	-0.183
Henan	0.107	-0.004	-0.073	-0.085	-0.015
Hubei	0.065	0.078	0.16	-0.652	0
Hunan	-0.036	0.002	0.003	-0.277	-0.131
Inner Mongolia	-0.087	0.283	-0.089	-0.376	-0.116
Guangxi	0.347	0.02	-0.066	-0.15	0
Chongqing	-0.073	-0.014	-0.199	0.027	-0.009
Sichuan	0.062	0.025	-0.146	-0.235	0.118
Guizhou	0.116	0.014	0.001	0.119	-0.067
Yunnan	-0.009	-0.055	-0.386	-0.023	-0.513
Shaanxi	0.081	-0.111	-0.158	-0.245	-0.203
Gansu	0.151	-0.108	-0.138	0.018	-0.275
Qinghai	-0.269	0.032	0.296	0.151	-0.503
Ningxia	0.136	-0.341	-0.19	-0.01	-0.053

Xinjiang	-0.065	0.17	-0.06	-0.34	-0.243

(Continued)

Province	2015	2016	2017	2018	2019
Liaoning	-0.057	-0.032	0.012	0.027	0.034
Jilin	-0.144	-0.007	0.015	0.179	0.273
Heilongjiang	0.033	0.078	0.128	0.209	0.317
Beijing	0.108	-0.009	0.272	0.391	0.423
Hebei	-0.009	0.198	0.281	0.371	0.418
Jiangsu	-0.06	-0.013	-0.014	0.289	-0.098
Fujian	0.122	0.238	0.309	0.391	0.409
Shandong	-0.123	-0.198	0.009	0.178	0.294
Shanxi	0.053	0.178	0.289	0.395	0.411
Anhui	0.173	0.209	0.315	0.389	0.498
Jiangxi	-0.106	-0.198	-0.007	0.139	0.275
Henan	0.165	0.289	0.309	0.389	0
Hubei	0.116	0.289	0.189	0.287	0.309
Hunan	0.023	0.031	0.045	0.139	0.276
Inner Mongolia	-0.1	-0.087	0.012	0.138	0.256
Guangxi	-0.233	0.108	0.029	0.138	0.275
Chongqing	0.069	0.098	0.109	0.118	0.198
Sichuan	-0.045	0.017	-0.139	0.276	0.178
Guizhou	-0.075	-0.013	-0.179	-0.098	0.013
Yunnan	0.157	0.289	0.309	0.318	0.348
Shaanxi	-0.032	0.019	0.189	0.205	0.291
Gansu	-0.135	0.109	0.211	0.234	0.298
Qinghai	-0.349	-0.159	-0.009	0.237	0.212
Ningxia	-0.178	-0.009	0.169	0.204	0.281

Xinjiang	0.016	0.019	0.138	0.264	0.309

Appendix E. *Sample partitioning results from different perspectives*

Table E1 Subsamples

Subsample	Province	Subsample	Province	Average coal production (unit: Ten thousand tons)	Subsample	Province	Coal de-capacity cost (unit: ten thousand yuan)
Eastern region	Beijing	H-resource endowment region	Inner Mongolia	94960.014	H-de-capacity cost region	Shanxi	677.955
	Hebei		Shanxi	89430.302		Anhui	419.923
	Jiangsu		Shaanxi	51378.369		Shandong	299.667
	Fujian		Xinjiang	15845.641		Hebei	290.609
	Shandong		Guizhou	15641.604		Henan	254.351
	Liaoning		Henan	15036.56		Guizhou	202.917
Central-western region	Shanxi		Shandong	14378.571		Shaanxi	185.528
	Anhui		Anhui	12884.059		Inner Mongolia	179.323
	Jiangxi		Ningxia	7820.384		Liaoning	171.342
	Henan		Hebei	7816.456		Xinjiang	139.336
	Hubei		Sichuan	7403.842		Heilongjiang	133.974
	Hunan		Heilongjiang	7167.921		Jilin	108.26
	Jilin		Yunnan	6297.945		Sichuan	100.232
	Heilongjiang	L-resource endowment region	Liaoning	4972.521	L-de-capacity cost region	Jiangxi	92.121
	Chongqing		Hunan	4857.108		Hunan	87.512
	Inner		Gansu	4296.297		Yunnan	80.596

Mongolia				
Guangxi	Jilin	3189.628	Jiangsu	73.749
Sichuan	Chongqing	2993.369	Chongqing	65.625
Guizhou	Jiangxi	1835.398	Hubei	49.397
Yunnan	Jiangsu	1727.107	Ningxia	39.125
Shaanxi	Fujian	1580.864	Gansu	36.372
Gansu	Qinghai	1537.753	Fujian	35.053
Qinghai	Hubei	698.879	Beijing	20.989
Ningxia	Guangxi	569.635	Guangxi	14.264
Xinjiang	Beijing	368.596	Qinghai	10.285

Note: The criteria for the division of the eastern and western regions are derived from the National Bureau of Statistics; The data of average coal production was obtained from the statistical yearbook of 25 coal-producing provinces; The data of cutting capacity cost comes from Wang et al. (2020b).