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How do complementary technological linkages affect carbon emissions efficiency?

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ABSTRACT

Complementary technological linkages provide access to the external technology at lower cost and compensate for weak or absent local technological capabilities, which has an important role in improving carbon emissions efficiency. This study examines this issue in the industrial sector in China. First, input–output data are reconstructed, and the industrial carbon emissions efficiency of each province in China is calculated using the super-SBM DEA method. Second, we examine patent text data to measure complementary technological linkages, applying the principle of co-occurrence. We also calculate regional technological capabilities, which are further divided into related and unrelated technological diversification. Third, we apply a benchmark model combined with moderating effect tests. The results reveal an inverted U-shaped impact of complementary technological linkages on industrial carbon emissions efficiency, while the impact of the number of interregional linkages is U-shaped. The interactive term of regional technological capabilities and complementary technological linkages have a positive effect on industrial carbon emissions efficiency, while the interactive effect of related technological diversification and complementary technological linkages on industrial carbon emissions efficiency is positive and larger than that of unrelated technological diversification. The moderating effect tests indicate that in comparison to low-income regions, the interactive term of regional technological capabilities and complementary technological linkages in high-income regions has a negative influence on industrial carbon emissions efficiency. Furthermore, unrelated technological diversification matches better with complementary technological linkages in promoting industrial carbon emissions efficiency in high-income regions than related technological diversification. The results of this study can help regional policymakers to choose different innovative strategies to achieve the green transition.

Introduction

The continuous rise of carbon (CO_2) emissions has led to the sharp acceleration of the global greenhouse effect. As the largest developing country with carbon emissions (Yang et al., 2022), China attaches great importance to mitigating climate change, taking it as a major strategy for national economic and social development. At the 75th United Nations General Assembly on September 22, 2020, China promised that the nation's "carbon dioxide emissions will reach a peak in 2030 and [China would] strive to achieve carbon neutrality by 2060," which is called "dual-carbon" goals for short. Based on current pledges, it will take 71 years for the EU, 43 years for the US, and 37 years for Japan from carbon peak to carbon neutrality, while China gave itself only 30 years. This means that China, the world's largest developing country, has pledged to take about 30 years to achieve the world's highest carbon emissions intensity reduction, also representing the shortest time to achieve peak carbon and carbon neutrality globally. Therefore, it is essential to reference China as an example to investigate its carbon mitigation process and approach and share the carbon mitigation experience with other countries.

Carbon emissions efficiency reflects the circumstances of carbon mitigation from the input–output perspective, which can also reveal economic growth patterns (Wu & Yao, 2022; Jin & Chen, 2022). Multiple factors can affect carbon emissions efficiency (Leung & Maroto-Valer, 2014; Wang et al., 2019; Sun & Huang, 2020), among which, technology innovation is key to determining input–output efficiency.

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Therefore, previous studies have focused on the impact of technological innovation on carbon emissions efficiency (Huang et al., 2020; Xie et al., 2021; He, Fu, & Liao, 2021). Gu (2022) demonstrated that technological innovation is beneficial for carbon emissions reduction, as well as serving in a negative moderating role between economic growth and carbon emissions; however, advancing renewable energy use faces various technological challenges, which can also affect further improvement in carbon emissions efficiency (Lewis & Nocera, 2006).

Regional technological capabilities refer to the collection of local advantaged technologies that are important for developing mitigation technologies and enhancing carbon emissions efficiency (Shahzad et al., 2022). A considerable number of scholars assert that regional technological capabilities are conducive to the improvement of carbon emissions efficiency (Cheng et al., 2018; Xie et al., 2021; Xu et al., 2021; Paramati et al., 2022); however, some research has demonstrated that there is a threshold for the impact of regional technological capabilities on carbon emissions efficiency. Huang et al. (2021) used the dynamic panel threshold model to investigate the nonlinear relationship between energy invention patents and carbon emissions. Liu et al. (2022) used smooth transition regression to explore the nonlinear impact of China's power generation and technological capabilities on carbon emissions reduction. Some scholars have also noted that the impact of regional technological capabilities on carbon emissions may depend on the specific regional social or economic environment (Du et al., 2019).

Reaching the double-carbon goals as expediently as possible requires full use of regional technological capabilities as well as the consideration of interregional technological linkages. Interregional technological linkages refer to low-cost access to external new technologies that compensate for weak or absent regional technological capabilities (Balland & Boschma, 2021). Studies on carbon emissions efficiency have primarily focused on regional technological capabilities, neglecting complementary interregional technological linkages. Previous studies have primarily measured interregional linkages using trade linkages, labor mobility, patent cooperation, and social ties, while minimal research has explored technological cooperation due to data inaccessibility (Balland, 2012; Tavassoli & Carbonara, 2014; Miguelez & Moreno, 2018; Abbasiharofteh & Broekel, 2021), leaving considerable room for further investigation.

This study endeavors to fill these research gaps in three ways. First, to measure complementary technological linkages, we use patent co-inventors' text data to determine interregional technological linkages and identify missing regional technological capabilities by applying the principle of co-occurrence as the premise of complementary technological linkages. In contrast to the number of patents, this approach better reflects interregional technological linkages, offering a channel for identifying and developing the promising technologies in some regions. Second, the study provides deep analyses of regional technological capabilities, which is divided into related and unrelated technological diversification according to the different characteristics of local advantaged technologies. Technological diversification can advance carbon mitigation technology; however, few studies have analyzed the role of technological diversification in enhancing carbon emissions efficiency. Third, this study analyzes the interactive impact of regional technological capabilities and complementary technological linkages on carbon emissions efficiency, which could be used to examine whether the relationship between regional technological capabilities and complementary technological linkages is substitutable or complementary combined with heterogeneous region attributes. In addition to the different characteristics of local advantaged technologies, we further investigate the relationship between related (or unrelated) technological diversification and complementary technological linkages, providing theoretical evidence for coordinating the relationship between regional technological capabilities and complementary technological linkages in different regions.

Overall, limited research has focused on carbon emissions efficiency from the perspective of complementary technological linkages, and research on this issue is essential for promoting the realization of China's double-carbon goals and green economy development. Compared with existing studies, the marginal contributions of this study can be delineated as follows. First, unlike previous literature that primarily centered on the impact of technology innovation or technological linkages driving carbon emissions efficiency, this study specifically examines technological diversification, complementary technological linkages, and their interactive effects on carbon emissions efficiency. Second, this study use patent text data to measure regional technological capabilities, complementary technological linkages, and related (unrelated) technological diversification, which is more suitable to represent regional technology development. Third, this study investigates the interactive effect between regional technological capabilities and complementary technological linkages on carbon emissions efficiency, also exploring the interaction of related (unrelated) technological diversification and complementary technological linkages combined with heterogeneous region features. The findings enrich the evidence regarding China's progress in carbon mitigation from the perspective of complementary technological linkages.

The remainder of this paper is organized as follows. The second part presents a literature review and our research hypotheses. The third part details the study's methodology and data. The fourth part presents the empirical analysis. The fifth part offers our discussion, and the sixth part presents conclusions and future research.

Literature review and research hypotheses

Complementary technological linkages and carbon emissions efficiency

Technological innovation activities that are internally self-reliant for a long period may become stagnant due to the lack of novel ideas and information (Boschma, 2005). This circumstance could be solved through the development of technological linkages that provide new opportunities and advantages that are not locally available (Cao et al., 2022). Technological linkages are channels of access to other regions' knowledge, information, and technology (Bathelt et al., 2004), while complementary technological linkages are connections to compensate for missing local knowledge, information, and technology that is abundant in other regions. Such linkages can further facilitate firms' introduction to low-carbon technologies and increase the carbon emissions efficiency. Complementary interregional linkages are built on mutual trust and understanding between partners that are not always definitive; therefore, the communication of interregional complementary knowledge, information, and technology is uncertain, and risky. The maintenance of complementary technological linkages is also quite complex and requires a certain level of absorptive capacity, while identifying, evaluating, and absorbing new technologies from elsewhere usually incurs significant costs. A surplus of complementary interregional linkages increases the difficulty of processing and absorbing technologies within a region (Dahlander & Frederiksen, 2012; Breschi & Lenzi, 2015), which may crowd out, or slow down the introduction of low-carbon technologies and even weaken carbon emissions efficiency. Based on these arguments, we propose the following hypothesis:

$H1_a$: The impact of complementary technological linkages on carbon emissions efficiency is an inverted U shape, and an optimal level of complementary technological linkages is possible.

Scholars have also highlighted the important role of gatekeepers who create unique connections with external firms locally (Gallo & Plunket, 2020). Gatekeepers can exploit technological capabilities to translate and recode knowledge absorbed from the outside world so that it can be easily understood, processed, and used by firms within the region (Giuliani & Bell, 2005; Morrison, 2008). The gatekeeper acts as an "interface" between the region and beyond, enabling what is known as a pipeline, promoting the communication of information and knowledge within and beyond the region. This means that a wider range of information and knowledge can be accessed, contributing to the update and expansion of regional technological capabilities (Breschi & Lenzi, 2015). Interregional linkages are conduits for the flow of information and knowledge, and the number of ties determines the degree of connectivity between regions (Phelps et al., 2012). When the number of interregional linkages is lower, there is a lack of opportunity for reorganization with external knowledge between firms in the region, reducing the complexity and diversification of technology, and ultimately leading to a decline in regional creativity. When the number of linkages between regions is higher, the region gains more opportunities for information exchange, advancing regional creativity, and accelerating the regional development of new low-carbon technologies, ultimately enhancing carbon emissions efficiency. Based on this, we propose the following hypothesis:

$H1_b$: When the number of interregional linkages exceeds a certain threshold limit, continuing to increase the number of interregional linkages enhances carbon emissions efficiency.

Complementary technological linkages, regional technological capabilities, and carbon emissions efficiency

Regional technological capabilities are the combination of local advantaged technologies that are developed mostly from existing local factor endowment. If a region is not equipped with relevant factor endowment, it may be difficult to develop local advantaged technologies. Innovation is not a random event and is often partially path-dependent (Kogler et al., 2013; Balland & Boschma, 2021). Regions are more likely to develop new technologies related to locally existing advantaged technologies that provide similar (but not identical) capabilities, such as knowledge, skills, and institutions (Boschma, 2017). Clustering reduces search and transaction costs for firms and makes the exchange and provision of knowledge, information, and services easier, establishing beneficial conditions for regional low-carbon development (Xu et al., 2022). Combined with the above assertions, these findings suggest that local technological capabilities and complementary technological linkages are equally important for advancing low-carbon technology innovation. Added value can be created when local technology is combined in new ways with externally accessible complementary technology. Firms within a cluster no longer rely solely on internal technologies but actively seek out useful complementary external technologies. Without complementary interregional linkages, regional technology breakthroughs are likely to converge in the direction of overlap and homogeneity, increasing the risk of technology lock-in and stagnation. Conversely, without intensive complementary interregional linkages, the value of new technology gained through interregional linkages is likely to be unrealized. Technological linkages and local technology complement one another, establishing a virtuous cycle of technology innovation and promoting the development of carbon mitigation technology; therefore, we propose the following hypothesis:

$H2_a$: Complementary technological linkages and regional technological capabilities jointly boost carbon emissions efficiency.

Regional technological diversification not only withstands the negative effects of interregional technological linkages, but also matches with interregional linkages as a pathway for reducing carbon emissions (Frenken et al., 2007). This is an endogenous and dynamic process that depends on local technological capabilities (Whittle, Lengyel, & Kogler, 2020). Linkages also reflect the different types of regional advantaged technologies. According to the relatedness between local advantaged technologies, technological diversification is divided into related technological and unrelated technological diversification. Related technological diversification refers to higher relatedness between regional advantaged technologies, while unrelated technological diversification indicates lower relatedness between regional advantaged technologies. As technologies are often associated with specific products and production processes (Frenken & Boschma, 2007; Frenken et al., 2007), the contribution of technology to improving efficiency primarily depends on the kind of technology that is introduced and how well this technology matches existing regional technological capabilities. Therefore, we not only need to consider external technological linkages, but also must identify whether they complement local technological capabilities to nurture new technology development and further enhance the efficiency (Boschma et al., 2008).

Complementary technological linkages provide technology that a region does not possess, from which it is more likely for related regional technological diversification to occur for added benefits because the complementary technologies are missing in the region. It paves the way to complement the weak or absent regional carbon emissions reduction technologies. In contrast, unrelated technological diversification is a collection of advantaged technologies that almost have no similar technology base that matches regional capabilities. It is more probable for regional unrelated technological diversification to overlap with complementary external technologies, rendering complementary technological linkages less effective in contributing to the weak or lacking local carbon emissions reduction technologies; thus, we propose the following hypothesis:

$H2_b$: The impact of related technological diversification and complementary technological linkages on carbon emissions efficiency is greater than that of unrelated technological diversification.

The moderating role of the regional economy

The effect of technological diversification on carbon emissions efficiency may be influenced by the regional level of economic development (Du et al., 2019; Milindi & Inglesi-Lotz, 2022). Furthermore, the joint effects of interregional technological linkages and regional technological capabilities may depend on local conditions (Breschi & Lenzi, 2015). Due to the uneven regional economic development in China, differences in regional technological capabilities may exist (Du et al., 2014). Regions with high levels of economic development tend to have superior knowledge accumulation and are more open and inclusive, meaning that incumbent firms may face information overload, making external complementary technologies substitutable for local technological capabilities (Ter Wal et al., 2016; Eriksson & Lengyel, 2019). At the same time, diversification is also closely related to local technological capabilities (Boschma, 2017). Incumbent firms in regions with high levels of economic development tend to dominate the regional economy through technology agglomeration in the long term, generating a greater need for breakthrough technology changes to increase the potential for economic growth, which could be achieved by unrelated technological diversification (Zheng et al., 2021). Therefore, the complementary effects of unrelated technological diversification are likely to be higher compared to related technological diversification, and the opposite could hold for regions with low levels of economic development. Based on the above analysis, we propose the following hypotheses:

$H3_a$: In comparison to low-income regions, the interaction of complementary technological linkages and regional technological capabilities in high-income regions has a negative effect on industrial carbon emissions efficiency.

$H3_b$: In comparison to low-income regions, unrelated technological diversification matches better with complementary technological linkages in high-income regions than related technological diversification for enhancing the industrial carbon emissions efficiency.

Methodology and data

Model construction

To investigate the impact mechanism of complementary technological linkages on carbon emissions efficiency, we propose the following benchmark model:

$$CEE_{it} = \alpha + \beta_2 \ln CL_{it} + \beta_3 \ln CL_{it}^2 + \beta_4 \ln NL_{it} + \beta_5 \ln NL_{it}^2 + \sum_{k=1}^{3} \gamma_k X_{it} + \eta_i + \theta_t + \varepsilon_{it} \tag{1}$$

where i refers to the region, t is the time, *CEEit* represents carbon emissions efficiency in industry i at time t, and ln*CLit*, and ln*NLit* denote the logarithm of complementary technological linkages and the logarithm of number of interregional linkages, respectively. *Xit* represents three control variables, including industrial structure (*ISit*), energy structure (*ESit*) and ownership structure (*MSit*). η_i, θ_t, and$\varepsilon_{it}$are region fixed effects, time fixed effects, and the random error term.To test whether the interaction of regional technological capabilities and complementary technological linkages improves industrial carbon emissions efficiency, referencing Zheng & Ran (2021), we further investigate the relationship between technological diversification and complementary technological linkages on industrial carbon emissions efficiency, transforming the benchmark model as follows:

$$CEE_{it} = \alpha + \beta_1 M_{it} \times \ln CL_{it} + \beta_2 \ln CL_{it} + \beta_3 \ln CL_{it}^2 + \beta_4 \ln NL_{it} + \beta_5 \ln NL_{it}^2 + \sum_{k=1}^{3}\gamma_k X_{it} + \eta_i + \theta_t + \varepsilon_{it} \tag{2}$$

where *Mit* represents regional technological capabilities (*DEit*), related technological diversification (*REit*), and unrelated technological diversification (*UNit*), respectively. $\beta_1 ... \beta_5$ and $\gamma_1 ... \gamma_3$are the estimated coefficients. The meanings of other variables are the same as above.

We also investigate the moderating role of the regional economy to draw different conclusions regarding the relationship between complementary technological linkages and industrial carbon emissions efficiency by comparing different regional economic levels. To do so, we introduce the variable *lnpgdp* into the Eq. (2), and the detailed model is as follows:

$$\begin{aligned} CEE_{it} = \alpha &+ \beta_1 M_{it} \times \ln CL_{it} \times \ln pgdp + \beta_2 \ln CL_{it} \times \ln pgdp \\ &+ \beta_3 \ln CL_{it}^2 \times \ln pgdp + \beta_4 \ln NL_{it} \times \ln pgdp + \beta_5 \ln NL_{it}^2 \\ &\times \ln pgdp + \ln pgdp + \sum_{k=1}^{3}\gamma_k X_{it} + \eta_i + \theta_t + \varepsilon_{it} \end{aligned} \tag{3}$$

Variables setting

Carbon emissions efficiency (CEE). The data envelopment analysis (DEA) method proposed by Charnes et al. (1978) is a non-parametric efficiency evaluation approach that applies a mathematical programming model to calculate the efficiency scores of multiple decision making units (DMUs). To address the defects of the DEA model in managing undesirable outputs, Tone (2001) was the first to propose the slacks-based measure (SBM). Zhou et al. (2010) expanded the SBM model, which is widely used as the "super" SBM model and can better manage undesirable outputs, non-radial, and non-oriented measurements.

In this study, a super-SBM DEA model with undesirable outputs is calculated to evaluate the carbon emissions efficiency of China's industrial sector. Here, a production system with N DMUs is constructed, each of which includes three factors, including inputs (X), desirable outputs (yd), and undesirable outputs (yu). Each unit produces *S1* desirable outputs and *S2* undesirable outputs through m inputs. The input and output vectors are defined as follows:

$$X = [x_1, x_2, ..., x_n] \in R^{m\times n},\ y^d = [y_1^d, y_2^d, ..., y_n^d] \in R^{r_1\times n},\ y^u = [y_1^u, y_2^u, ..., y_n^u] \tag{4}$$

Assuming that all values are positive in Eq. (4), the SBM model can be written as follows:

$$\min\rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} S_i^- / X_{ik}}{1 + \frac{1}{s_1+s_2}\left(\sum_{p=1}^{r_1} \frac{S_p^d}{y_{pk}^d} + \sum_{q=1}^{r_2} \frac{S_q^u}{y_{qk}^u}\right)}$$

$$s.t.\begin{cases} X_{ik} = \sum_{j=1}^{n} x_{ij}\lambda_j + S_i^- \\ y_{pk}^d = \sum_{j=1}^{n} y_{pj}^d\lambda_j - S_p^d \\ y_{qk}^u = \sum_{j=1}^{n} y_{qj}^u\lambda_j + S_q^u \end{cases} \tag{5}$$

where *Xik* denotes the i input value of *DMUk*, $y^d pk$, and $y^u pk$ are the desirable outputs and undesirable outputs.λ is the weighted vector. Only when $\rho = 1$ and the slack variables ($S_i^- = 0$, $S_p^d = 0$, and $S_p^u = 0$) meet the conditions, can *DMUk* be determined to be efficient in a SBM model. The value ofρ is between 0 and 1; if $\rho < 1$, the inputs and outputs must be improved. To further rank the *DMUs* by efficiency state, the improved super-SBM model (Tone, 2004) can be expressed as follows:

$$\phi^* = \min \frac{\frac{1}{m}\sum_{i=1}^{m} \frac{\bar{X}}{X_{ik}}}{\frac{1}{r_1+r_2}\left(\sum_{p=1}^{r_1} \frac{\bar{y^d}}{y_{pk}^d} + \sum_{q=1}^{r_2} \frac{\bar{y^u}}{y_{qk}^u}\right)}$$

$$s.t.\begin{cases} x_- \geq \sum_{j=1,\neq k}^{n} x_{ij}\lambda_j \\ y^{d-} \leq \sum_{j=1,\neq k}^{n} y_{pj}^d\lambda_j \\ y^{u-} \geq \sum_{j=1,\neq k}^{n} y_{qj}^u\lambda_j \\ \lambda_j > 0, x_- \geq x_k, y^{d-} \leq y_k^d, y^{u-} \geq y_k^u \end{cases} \tag{6}$$

where ϕ^* is the efficiency value of the *DMUs* that can be greater than 1, and the definitions of other variables are the same as in Eq. (5). The super-SBM model includes undesirable outputs and can effectively avoid the slackness problem. Moreover, *DMUs* are effectively ranked in this model. Thus, a super-SBM model in this study is constructed to evaluate total factor carbon emissions efficiency.

To evaluate efficiency more accurately, referencing previous studies, we select the three inputs of capital (K), labor (L), and energy (E) (Xie et al., 2021; Fang et al., 2022), industrial added value (Y) is the desirable output, and the undesirable output is industrial carbon emissions (*CO2*) (Zhou & Nei, 2012; Tu, 2008; Chen, 2009). Due to the inaccessibility and calculation complexity of the depreciation rates of fixed assets in various industry sectors, we use the annual average of industrial net fixed assets to measure capital input. The average number of employees in the industrial sector is used as labor input. Terminal consumption of various energy sources in the industrial sector (raw coal, coke, gasoline, kerosene, diesel oil, fuel oil, liquefied petroleum gas, natural gas, heat, and electricity) represents total energy

Table 1
Indicators for measuring carbon emissions efficiency.

Dimensions	Components	Unit
Inputs	Capital	10,000 yuan
	Labor	1000 people
	Energy	Billion Btus
Desired outputs	Industrial added value	10,000 yuan
Undesired outputs	CO_2 emissions	Million ton

consumption. Some missing data is determined using linear interpolation and moving average methods. CO2 emissions are calculated using the following formula given by 2006 Intergovernmental Panel on Climate Change Guidelines for National Greenhouse Gas Inventories:

$$E_{CO_2} = \sum\nolimits_i E_i \cdot S_i \cdot Ef_i \tag{7}$$

where ECO2 is the CO2 emissions from energy consumption; *Ei* represents the consumption of fossil energy, in which *i* indicates the kind of fossil fuel; and *Si* and *Efi* refer to the standard coal equivalent coefficient and the CO2 emissions factor, respectively. The indicators for measuring CEE are presented in Table 1 below.

Complementary technology linkage (CL) and regional technological capabilities (TD)

Following Balland & Boschma (2021), complementary technological linkages make up for insufficient regional technological capabilities with the help of other regions. However, regional technological capabilities are measured by comparative advantage technologies (Hidalgo et al., 2007). In this study, we use listed companies' patent text data to calculate the comparative advantage technology field in detail as follows:

$$RTA_{ik}^{t} = \begin{cases} 1, & \dfrac{patent_{ik}^{t}/\sum_k patent_{ik}^{t}}{\sum_i patent_{ik}^{t}/\sum_i\sum_k patent_{ik}^{t}} \geq 1 \\ 0, & else \end{cases} \tag{8}$$

where *t* represents time, *i* denotes province, and *k* is the technology field, which is denoted by the four-digit patent classification code according to the International Patent Classification principle. $RTA^{t}ik$ is a binary variable indicating whether province *i* has a comparative advantage in technology field *k* at time *t*. Furthermore, we also identify technology field *h*, which has not achieved the comparative advantage, but is related to the comparative advantage technology field *k* by the principle of co-occurrence. Technology field *h* is more likely to have comparative advantage than other technology fields that are unrelated to the comparative advantage technology field *k*. It also represents the main direction of future research and development.

Referencing Balland & Boschma (2021), given technology field *h* at time *t* for province *i*, we add up all comparative advantage technology fields (*k*') related the technology field *h* in province *i*' and province *i*, and each *k*' that is not within the range of all the comparative advantage technology fields *k* associated with the technology field *h* in province *i* at time *t*. Province *i*' technology help is the ratio of all *k*' and the sum of all the technology fields (*d*) associated with technology field *h* at time *t*. Here, if technology field *k*' and *d* are present, then *Ihk' = 1* and *Ihd = 1*, specifically

$$CTD_{i'h}^{t} = \frac{\sum_{h\in i,k'\in i',k'\neq h,k'\notin K} I_{hk'}}{\sum_{h\in i,d\neq h} I_{hd}} \tag{9}$$

After calculating the $CTD_{i'h}^{t}$, we next determine the number of interregional linkages ($NL_{ii'}^{t}$) between province *i* and province *i*' by the principle of co-occurrence of patent applicant information on the same patent. If both patent applicants occur in the same patent information together, an interregional linkage is established. The number of interregional linkage ($NL_{ii'}^{t}$) is measured by calculating the interregional linkage between province *i* and province *i*' at time *t*.

Finally, we calculate the multiplication of $CTD_{i'h}^{t}$and$NL_{ii'}^{t}$ and $NL_{ii'}^{t}$ for all province *i*' as the complementary technological linkages (CL_{ih}^{t}) as follows:

$$CL_{ih}^{t} = \sum\nolimits_{i'} (CLD_{i'h}^{t} \times NTL_{ii'}^{t} \times 100) \tag{10}$$

In addition, referencing Hialgo et al. (2007) and Boschma & Capone (2015), given the technology field *h* at time *t* for province *i*, regional technology capability is measured by the ratio of all comparative advantage technology fields (*k*) related to technology field *h* at time *t* for province *i* and the sum of all technology fields (*d*) related to the technology field *h* at time *t*, as follows:

$$TD_{ih}^{t} = \frac{\sum_{k\in i,k\neq h} I_{hk}}{\sum_{d\neq h} I_{hd}} \times 100 \tag{11}$$

Furthermore, if different comparative advantage technology fields are related for a province, this indicates that the province is more likely to achieve related technological diversification. In contrast, if a province has more unrelated comparative advantage technology fields, this indicates that the province will more likely reach unrelated technological diversification. Incremental and Schumpeter innovation have the characteristics of related technological diversification (Li & Jian, 2021), representing two different aspects of regional technological capabilities with differing impacts on CEE. Referencing Zheng et al. (2021), we calculate the related and unrelated technological diversification as follows:

$$\omega_{ih}^{t} = \frac{TD_{ih}^{t} - \langle TD_{i}^{t} \rangle_{o}}{\sigma_{o}(TD_{i}^{t})} \tag{12}$$

where O_{it} represents the collection of technology fields that does not have comparative advantage in province *i* at time *t*, $\langle TD_{i}^{t} \rangle_{o}$ represents the average technological capabilities within the ensemble, and $\sigma_{o}(TD_{i}^{t})$ represents the standard deviation of the technological capabilities within the ensemble. If $\omega_{ih}^{t} < 0$, this indicates that the capability of the technology field is relatively small and the corresponding technological diversification is considered to be unrelated technological diversification for province *i*. If$\omega_{ih}^{t} > 0$, the corresponding technological diversification is related technological diversification for province *i*. Based on this, we determine the number of related and unrelated technological diversification fields as the value of variable *RE* and *UN*, respectively.

Control variables

Control variables include industrial structure (*IS*), energy structure (*ES*), and ownership structure (*MS*). Specifically, referencing Wei et al. (2008) and Pang, Li, & Lu (2011), industrial structure (*IS*) is defined as the proportion of added value of the secondary industry in the GDP of each province, energy structure (*ES*) is defined as the proportion of coal consumption in industrial energy consumption of each province, and ownership structure (*MS*) is defined as the proportion of the number of employees of state-owned enterprises in the total number of regional employees.

Data sources

This study uses annual panel data in 30 provinces of China between 2000 and 2019 (due to missing data on energy consumption and carbon dioxide emissions in the relevant years for Tibet, our study is limited to 30 provinces and regions of China, excluding Tibet). Specifically, the data used to calculate the *CEE* include labor, capital, and industrial output collected from the China Statistical Yearbook and the China Industrial Economy Statistics Yearbook for 2000−2019. To eliminate the influence of inflation, capital and

Table 2
Descriptive statistics.

Variable	Obs.	Mean	SD	Min	Max
CEE	28,058	0.692	0.357	0.131	1.533
TD	28,058	3.301	6.494	0.000	100.000
RE	28,058	52.678	31.739	0.000	133.000
UN	28,058	78.871	44.391	0.000	173.000
lnCL	28,058	4.210	3.934	0.000	11.401
lnNL	28,058	6.068	1.612	0.000	8.919
IS	28,058	0.436	0.099	0.162	0.596
ES	28,058	0.430	0.150	0.070	0.801
MS	28,058	0.796	1.492	0.013	12.908

Table 3
Findings from panel Fisher−PP unit root test.

Variables	Level		First difference	
	chi-squared	p-value	chi-squared	p-value
CEE	183.5060***	0.000	370.9175***	0.000
lnCL	173.1722***	0.000	357.1096***	0.000
lnNL	199.3842***	0.000	374.6976***	0.000
$lnCL^2$	168.1568***	0.000	358.5322***	0.000
$lnNL^2$	196.8752***	0.000	374.5746***	0.000
*TD**lnCL*	161.3560***	0.000	362.3568***	0.000
*RE**lnCL*	160.0282***	0.000	213.6033***	0.000
*UN**lnCL*	161.9939***	0.000	358.3368***	0.000
IS	187.3883***	0.000	368.1161***	0.000
ES	191.7149***	0.000	369.9973***	0.000
MS	195.8072***	0.000	381.5258***	0.000

Note: *** indicates 1% significance level.

Table 4
Benchmark regression results.

Variable	Model1	Model2	Model3	Model4
*TD**lnCL*		0.0008*** (18.78)		
*RE**lnCL*			0.0004*** (38.63)	
*UN**lnCL*				0.0004*** (43.47)
lnCL	0.0237*** (12.22)	0.0173*** (8.82)	0.0252*** (13.31)	0.0276*** (14.67)
$lnCL^2$	−0.0027*** (−11.74)	−0.0025*** (−10.64)	−0.0060*** (−24.70)	−0.0071*** (−28.64)
lnNL	−0.2576*** (−45.69)	−0.2554*** (−45.59)	−0.2100*** (−37.30)	−0.1952*** (−34.60)
$lnNL^2$	0.0340*** (68.31)	0.0332*** (66.87)	0.0280*** (55.03)	0.0266*** (51.87)
IS	−0.1809*** (−8.49)	−0.1861*** (−8.78)	−0.2706*** (−12.95)	−0.2360*** (−11.41)
ES	−0.2602*** (−21.15)	−0.2751*** (−22.46)	−0.2954*** (−24.58)	−0.2888*** (−24.22)
MS	−0.0552*** (−50.83)	−0.0541*** (−50.02)	−0.0540*** (−51.01)	−0.0529*** (−50.28)
_cons	1.1394*** (59.46)	1.1652*** (61.03)	1.1355*** (60.81)	1.0855*** (58.40)
TFE	Yes	Yes	Yes	Yes
Overall R^2	0.3816	0.3995	0.4071	0.4184
F−statistic	4465.89***	4000.80***	4302.19***	4407.42***
RSE	0.3184 (d.f.=406.80)	0.2926 (d.f.=356.82)	0.3240 (d.f.=418.90)	0.3231 (d.f.=400.32)
N	28,040	28,040	28,040	28,040

Note: t values are in parentheses; ***, **, and * denote 1%, 5%, and 10% significance levels, respectively; TFE indicates time fixed effect; RSE represents the residual standard error.

industrial output are adjusted to constant prices in 2000 on the basis of fixed asset investment and industrial producer price indices published by the National Bureau of Statistics of China. The data on energy consumption are from the China Energy Statistical Yearbook for 2000−2019 and converted into standard coal equivalent. Among them, any missing data for the *CEE* calculation are determined using the average annual growth rate and the interpolation method.

The data for complementary technological linkages and regional technological capabilities use patent text data of listed companies in China National Knowledge Infrastructure patent database from 2000 to 2019. Each patent text contains information such as patent code, patent applicant, patent address, application time, and other relevant data. The co-occurrence of patent applicants and patent codes, respectively determines the number of interregional linkages and related technology fields.

The data for control variables are collected from the China Statistical Yearbook for 2000−2019. The descriptive statistics of all the variables in this study are presented in Table 2.

Empirical analysis

Unit root and cointegration tests

The Fisher−Phillips−Perron (PP) test that addresses the problem of the unit root in a heterogeneous panel is used to test the unit root of each variable to determine the stationarity. The results are presented in Table 3, revealing that all variable series are stable at a 1% significance level.

Benchmark regression

Column (1) of Table 4 presents the benchmark model regression results. The first-order coefficient of complementary technological linkages is significantly positive at a 1% significance level, while its square coefficient is significantly negative. This indicates that the impact of complementary technological linkages on industrial CEE is an inverted U shape, and either too much or too little complementary technological linkage will hamper the improvement of industrial CEE. The primary term coefficient of the number of interregional linkages is significantly negative, but its secondary term coefficient is significantly positive, indicating that the influence of the number of interregional linkages on industrial CEE is U-shaped. When the number of interregional linkages has not reached the threshold, increased interregional linkages inhibit the enhancement of industrial CEE. When interregional linkages exceed the threshold, this accelerates the pace of industrial CEE. As for control variables, the coefficients of industrial, energy, and ownership structure are significantly negative at the 1% level. The results indicate that an increased proportion of secondary industry, coal consumption, and state-owned enterprises significantly weaken industrial CEE, which aligns with the research of Wei et al. (2008). Column (2) of Table 4 indicates that the interaction of regional technological capabilities and complementary technological linkages has a positive effect on industrial CEE, demonstrating that the combination of regional technological capabilities and complementary technological linkages benefit industrial CEE. Columns (3) and (4) of Table 4 indicate that the coefficient of the interaction of related technological diversification and complementary technological linkages on industrial CEE is positive and larger than that of unrelated technological diversification. Significant differences in the impact of different types of technological diversification are confirmed, while the effect of related technological diversification is stronger than that of unrelated technological diversification.

Endogeneity tests

Instrumental variable method

This study adopts the instrumental variable method combined with two-stage least squares (2SLS) to conduct the endogeneity test. We use *CL* and *NL* lagged with one period as the instrumental variables of *CL* and *NL* with no lag, while *RE* and *UN* with two periods lagged are taken as instrumental variables to replace *CL* and *NL* in the

Table 5
Instrumental variable test results.

Variable	Model1	Model2	Model3	Model4
TD^*lnCL_{it-1}		0.0041***		
		(5.82)		
$RE_{it-2}{}^*lnCL_{it-1}$			0.0064**	
			(2.14)	
$UN_{it-2}{}^*lnCL_{it-1}$				0.0013***
				(3.70)
$lnCL_{it-1}$	0.0955*	0.0985**	−0.1206	0.1018*
	(1.91)	(2.18)	(−0.61)	(1.89)
$lnCL^2{}_{it-1}$	−0.0151***	−0.0155***	−0.0390**	−0.0281***
	(−2.73)	(−3.11)	(−2.02)	(−3.86)
$lnNL_{it-1}$	−1.0062***	−0.6508***	2.3173	−0.2565
	(−6.54)	(−3.83)	(1.50)	(−0.89)
$lnNL^2{}_{it-1}$	0.0879***	0.0546***	−0.2640	0.0100
	(6.39)	(3.40)	(−1.60)	(0.35)
IS	−0.4835	−1.0409**	−7.8632**	−1.5572***
	(−1.29)	(−2.46)	(−2.14)	(−2.91)
ES	−0.7738***	−0.7508***	−1.7969***	−1.0099***
	(−11.41)	(−13.47)	(−3.22)	(−6.14)
MS	−0.0340***	−0.0356***	−0.0815***	−0.0419***
	(−9.25)	(−10.46)	(−3.59)	(−6.80)
_cons	4.0176***	3.3245***	1.4772	3.0056***
	(11.66)	(11.78)	(1.29)	(5.19)
TFE	No	No	No	No
Kleibergen−Paap rk LM	45.823***	38.687***	3.867**	20.540***
Cragg−Donald Wald F	11.519***	7.657***	0.907	4.178***
Kleibergen−Paap rk Wald F	11.498***	7.804***	0.814	4.240***
Hausman test	503.65***	607.83***	605.61***	153.19***
N	10,703	10,703	10,703	10,703

Note: Z values are in parentheses; ***, **, and * denote 1%, 5%, and 10% significance levels, respectively; TFE indicates time fixed effect.

Table 6
SYS-GMM test results.

Variable	Model1	Model2	Model3	Model4
TD^*lnCL		0.0001***		
		(251.12)		
RE^*lnCL			0.00001***	
			(271.24)	
UN^*lnCL				0.00002***
				(636.23)
lnCL	0.0043***	0.0039***	0.0038***	0.0041***
	(193.47)	(446.92)	(463.72)	(923.51)
$lnCL^2$	−0.0004***	−0.0003***	−0.0004***	−0.0006***
	(−131.18)	(−355.79)	(−425.04)	(−810.33)
lnNL	0.0227***	0.0204***	0.0257***	0.0283***
	(110.87)	(474.41)	(683.54)	(889.23)
$lnNL^2$	−0.0014***	−0.0013***	−0.0017***	−0.0020***
	(−101.61)	(−387.55)	(−554.19)	(−854.38)
IS	−0.2942***	−0.2955***	−0.2996***	−0.3049***
	(−539.62)	(−2471.41)	(−2684.02)	(−6864.68)
ES	0.0679***	0.0664***	0.0664***	0.0658***
	(262.05)	(1923.91)	(1180.38)	(1060.58)
MS	−0.0043***	−0.0043***	−0.0045***	−0.0045***
	(−328.80)	(−979.25)	(−959.17)	(−3891.42)
_cons	0.0471***	0.0574***	0.0444***	0.0445***
	(56.93)	(354.43)	(425.40)	(382.21)
TFE	No	No	No	No
AR(1)	0.000	0.000	0.000	0.000
AR(2)	0.313	0.338	0.320	0.253
Hansen test	0.276	0.999	0.998	0.998
N	4136	4136	4136	4136

Note: Z values are in parentheses; ***, **, and * denote 1%, 5%, and 10% significance levels, respectively; TFE indicates time fixed effect.

benchmark model. The second stage regression results of 2SLS are presented in Table 5. In the test of insufficient identification of instrumental variables, the Kleibergen−Paap rk LM statistic passed the significance test at the 1% level, confirming sufficient identification of instrumental variables. In addition, the Kleibergen−Paap rk Wald F statistic is significantly greater than the critical value of the 10% F statistical significance level proposed by Stock & Yogo (2002). This indicates that there are no weak instrumental variables, and the coefficients of TD^*lnCL, RE^*lnCL, and UN^*lnCL are significantly positive, while the coefficient of $\ln CL^2$ is significantly negative, which is basically consistent with our benchmark regression results.

Dynamic panel model

Considering the dynamic continuity of industrial CEE, we also construct a dynamic panel model and use the system generalized method of moments (SYS-GMM) estimation method to test endogeneity. Specifically, the lagged term of the explained variable (*CEEit-1*) and the main explanatory variables (*lnCL, lnNL*, $lnCL^2$, $lnNL^2$, TD^*lnCL, RE^*lnCL, and UN^*lnCL) are regarded as endogenous variables, and the control variables (*IS, ES*, and *MS*) are taken as instrumental variables. The two-step SYS-GMM method is used for regression, and the results are presented in Table 6. In Table 6, the value of the *AR(1) test* approaches 0, while the values of *AR(2)* and *Hansen tests* are greater than 0.05, indicating first-order autocorrelation but no second-order autocorrelation in the residuals. The *Hansen test* confirms that the instrumental variables are valid and all models pass the setting test. The regression results of each explanatory variable in the sys-GMM do not significantly differ from that of benchmark model.

Robustness tests

We conduct three robustness tests; first, displacing the dependent variable by using the ratio of industrial added value to industrial carbon emission (*ECO_ind*) to substitute the dependent variable (*CEE*). The estimated results are presented in Table 7. Second, we replace the independent variable, taking the total import and export trade as a substitution variable for the independent variable (*CL*), and the regression results are presented in Table 8 (Zhu et al., 2017). Third, we substitute the regression method, employing the panel quantile model that has fewer constraints and more tolerance for outliers and heteroskedasticity in comparison to ordinary least squares. Referencing Xie et al. (2021), we select the three quantiles of 25%, 50%, and 75% to represent low, medium, and high industrial CEE, as shown in Table A.1). The three robustness tests are all basically consistent with the benchmark regression, indicating that results of the benchmark regression are robust.

Moderating effect test

The impact of each explanatory variable may differ in terms of regional income levels; therefore, we introduce the economic development level dummy variable (*lnpgdp*). If the economic development level of a region is higher than the median of the whole sample, then *lnpgdp = 1*, otherwise *lnpgdp = 0*. The results of moderating effect analysis are presented in Table 9, and basically coincide with the benchmark regression. In economically developed regions, the impact of complementary technological linkages on industrial CEE presents an inverted U shape, while the number of interregional linkages is U-shaped. The interactive term of regional technological capabilities and complementary technological linkages is significantly negative at a 1% significance level, indicating that the relationship between regional technological capabilities and complementary technological linkages is not complementary but substitutable in regions with high economic levels. The coefficients of $RD^*lnCL^*lnpgdp$ and $UN^*lnCL^*lnpgdp$ are significantly positive at the 1% level. Moreover, the coefficient of $UN^*lnCL^*lnpgdp$ is obviously higher than that of $RD^*lnCL^*lnpgdp$, indicating that unrelated technological diversification has a greater influence on promoting the industrial CEE for high-income regions.

Table 7
Results of robustness tests.

Variable	(1)	(2)	(3)	(4)
*TD*lnCL*		0.0013***		
		(6.92)		
*RE*lnCL*			0.0012***	
			(25.04)	
*UN*lnCL*				0.0014***
				(39.94)
lnCL	0.0898***	0.0792***	0.0940***	0.1055***
	(10.46)	(9.10)	(11.07)	(12.63)
lnCL²	−0.0107***	−0.0103***	−0.0202***	−0.0284***
	(−10.40)	(−9.96)	(−18.55)	(−25.89)
lnNL	−1.9705***	−1.9670***	−1.8319***	−1.7158***
	(−79.03)	(−78.94)	(−72.49)	(−68.42)
lnNL²	0.2084***	0.2071***	0.1910***	0.1778***
	(94.56)	(93.69)	(83.46)	(78.15)
IS	−4.1155***	−4.124***	−4.3768***	−4.3405***
	(−43.64)	(−43.76)	(−46.64)	(−47.23)
ES	−2.1069***	−2.1314***	−2.2094***	−2.2237***
	(−38.73)	(−39.13)	(−40.94)	(−41.95)
MS	−0.1784***	−0.1766***	−0.1749***	−0.1691***
	(−37.14)	(−36.72)	(−36.79)	(−36.13)
_cons	8.0951***	8.1374***	8.0837***	7.8748***
	(95.50)	(95.83)	(96.42)	(95.30)
TFE	Yes	Yes	Yes	Yes
Overall R^2	0.6364	0.6357	0.6461	0.6562
F−statistic	6465.66***	5672.89***	5862.25***	6178.89***
RSE	0.1592	0.1700	0.1551	0.1536
	(d.f.= 68.48)	(d.f.= 70.72)	(d.f.= 59.67)	(d.f.= 64.48)
N	28,040	28,040	28,040	28,040

Note: t values are in parentheses; ***, **, and * denote 1%, 5%, and 10% significance levels, respectively. TFE indicates time fixed effect; RSE represents the residual standard error.

Table 8
Results of robustness tests.

Variable	(1)	(2)	(3)	(4)
*TD*OPEN*		0.0008***		
		(4.84)		
*RE*OPEN*			0.0020***	
			(21.30)	
*UN*OPEN*				0.0024***
				(35.13)
OPEN	1.2295***	1.2266***	1.0729***	0.9730***
	(114.84)	(114.46)	(83.07)	(76.20)
OPEN²	−0.4382***	−0.4399***	−0.4188***	−0.4122***
	(−65.32)	(−65.51)	(−62.34)	(−62.37)
lnNL	−0.3375***	−0.3376***	−0.2920***	−0.2578***
	(−75.52)	(−75.57)	(−59.32)	(−52.31)
lnNL²	0.0301***	0.0301***	0.0250***	0.0208***
	(78.58)	(78.55)	(55.33)	(45.37)
IS	0.0860***	0.0831***	0.1115***	0.1852***
	(4.72)	(4.56)	(6.15)	(10.25)
ES	0.1673***	0.1643***	0.0817***	0.0378***
	(17.43)	(17.08)	(7.90)	(3.75)
MS	−0.0217***	−0.0216***	−0.0209***	−0.0197***
	(−25.99)	(−25.92)	(−25.17)	(−24.04)
Constant	1.0238***	1.0280***	0.9821***	0.9176***
	(71.79)	(71.98)	(68.76)	(64.25)
TFE	Yes	Yes	Yes	Yes
Overall R^2	0.6976	0.6973	0.7183	0.2387
F−statistic	11,392.33***	9979.22***	10,186.02***	10,561.44***
RSE	0.4430	0.4467	0.3091	0.2387
	(d.f.=127.00)	(d.f.= 128.21)	(d.f.= 69.02)	(d.f.= 68.18)
N	28,040	28,040	28,040	28,040

Note: T values are in parentheses; ***, ** and * denote 1%,5% and 10% significance levels, respectively; TFE indicates time fixed effect; RSE represents the residual standard error.

Table 9
Results of moderating effect analysis.

Variable	Model1	Model2	Model3	Model4
*TD*lnCL*lnpgdp*		−0.0002***		
		(−8.90)		
*RD*lnCL*lnpgdp*			0.00003***	
			(2.95)	
*UN*lnCL*lnpgdp*				0.0001***
				(11.95)
*lnCL*lnpgdp*	0.0092***	0.0125***	0.0093***	0.0105***
	(6.03)	(13.13)	(6.13)	(6.91)
*lnCL²*lnpgdp*	−0.0010***	−0.0012***	−0.0012***	−0.0021***
	(−5.57)	(−6.56)	(−6.29)	(−10.59)
*lnNL*lnpgdp*	−0.5665***	−0.5676***	−0.5640***	−0.5501***
	(−88.02)	(−88.34)	(−86.93)	(−83.85)
*lnNL²*lnpgdp*	0.0524***	0.0525***	0.0522***	0.0508***
	(101.95)	(102.23)	(99.89)	(95.97)
lnpgdp	1.3375***	1.3408***	1.3341***	1.3070***
	(64.56)	(64.83)	(64.32)	(62.82)
IS	1.9546***	1.9633***	1.9491***	1.9048***
	(60.99)	(61.34)	(60.73)	(59.13)
ES	−0.4890***	−0.4834***	−0.4906***	−0.4845***
	(−42.57)	(−42.09)	(−42.67)	(−42.29)
MS	−0.0031***	−0.0031***	−0.0031***	−0.0031***
	(−5.20)	(−5.18)	(−5.07)	(−5.09)
_cons	−0.3171***	−0.3211***	−0.3132***	−0.2914***
	(−14.11)	(−14.31)	(−13.91)	(−12.95)
TFE	Yes	Yes	Yes	Yes
Overall R^2	0.0004	0.0012	0.0002	0.0004
F−statistic	907.20***	880.72***	875.41***	885.51***
RSE	0.9249	0.9260	0.9246	0.9234
	(d.f.= 12.45)	(d.f.=12.50)	(d.f.=12.15)	(d.f.=12.09)
N	28,040	28,040	28,040	28,040

Note: t values are in parentheses; ***, **, and * denote 1%, 5%, and 10% significance levels, respectively; TFE indicates time fixed effect; RSE represents the residual standard error.

Discussion

Carbon mitigation is a long-term endeavor that requires identifying effective approaches to improve CEE. It has been clearly demonstrated that technology innovation has made an outstanding contribution to carbon mitigation (Gu, 2022; He et al., 2021). Nevertheless, technological innovation is risky and requires considerable expenditure. Accessing more effective and necessary technology has become important for each region. In this study, we provide insights into complementary technological linkages and examine their effect on CEE.

First, the effect of complementary technological linkages on industrial CEE presents an inverted U shape. Furthermore, the number of interregional linkages has a U-shaped impact on industrial CEE. This is somewhat inconsistent with research that found the impact of technological linkages to be positive. For examples, Bahar et al. (2014) pointed out that a region that equipped a neighbor with comparative advantage has a higher growth of exports. Boschma (2017) demonstrated that regions are more likely to breed new export industry that their neighbors have specialized in and have similar export structure to their neighbors. Whittle, Lengyel, & Kogler (2020) found that the inflowing knowledge from neighbors is important to enhance regions' existing knowledge capabilities. In contrast to these studies, this study not only confirms the positive impact of complementary technological linkages, but also determines that only moderate external technological linkages are good for long-term regional development.

Second, combined regional technological capabilities, and complementary technological linkages indeed have the positive influence on industrial CEE. This finding aligns with Balland & Boschma (2021), who found a positive interactive effect of smart specialization technology density and complementary interregional linkages. In addition, this study stresses that complementary technological linkages advance regional technological diversification with superior impact on industrial CEE, and related technological diversification has a more obvious positive effect on industrial CEE, in comparison to unrelated technological diversification. This confirms previous studies demonstrating the importance of related diversification on regional economic growth compared to unrelated diversification (Frenken et al., 2007; Balland et al., 2018). The reason may be that related diversification is easier to achieve due to existing technological capabilities, while unrelated diversification involves uncertainty, risk, and expenditure (Saviotti & Frenken, 2008).

Third, compared with low-income regions, both regional technological capabilities, and complementary technological linkages have a mutually negative impact on industrial CEE in high-income regions, where unrelated technological diversification cooperates more effectively with complementary technological linkages than related technological diversification. Boschma & Capone (2016) also demonstrated this difference in Europe, finding that western European regions were inclined to diversify into new industries that are unrelated to existing industries, whereas eastern European regions were more likely to develop new industry that was related existing industries. In addition, Petralia et al. (2017) demonstrated that high-income countries are more likely to diversify into unrelated technology fields, but low-income countries are the opposite. This means that high-income regions tend to choose unrelated technological diversification and low-income regions prefer diversification in related technological fields.

Conclusions and future research

Our study employs the super-SBM DEA method to evaluate industrial CEE in China, calculating regional technological capabilities, and complementary technological linkages using patent text data. We also investigate the interactive effect of regional technological capabilities and complementary technological linkages on industrial CEE, validating the results with robustness and endogenous tests. Finally, we conduct heterogeneity analysis to compare the regression results in high- and low-income regions. The main findings are summarized below.

First, the impact of complementary technological linkages on industrial CEE presents an inverted U-shaped curve, indicating that when complementary technological linkages have not reached a certain threshold, the increase of complementary technological linkages is beneficial for improving industrial CEE. However, too many complementary technological linkages are harmful for industrial CEE, suggesting that an optimal level of complementary technological linkages is present. In addition, the number of interregional linkages has a U-shaped effect on industrial CEE. When the number of interregional linkages exceeds the threshold, further increase in interregional linkages can boost the industrial CEE.

Second, the interaction of regional technological capabilities and complementary technological linkages have a positive effect on industrial CEE, meaning that the relationship between regional technological capabilities and complementary technological linkages is indeed complementary, not substitutable. Complementary technological linkages can compensate for weak or absent regional technological capabilities, which is an effective way to enrich regional technological capabilities. Furthermore, the interactive coefficient of related technological diversification and complementary technology linkage on industrial CEE is positive and larger than that of unrelated technological diversification. In comparison to low relatedness of regional technological capabilities, high relatedness could combine more effectively with complementary technological linkages and compensate more for weak regional technological capabilities.

Third, in comparison to low-income regions, the interactive term of regional technological capabilities and complementary technological linkages in high-income regions has a negative influence on industrial CEE. Unrelated technological diversification matches better with complementary technological linkages in promoting industrial CEE than related technological diversification for high-income regions. Other variable regression results in high-income regions are basically consistent with the benchmark regression results, indicating that the regional technological capabilities in high-income regions may be strong, and it is difficult for complementary technological linkages to offer new or advanced technology. Therefore, complementary technological linkages may partially substitute for the influence of regional technological capabilities on industrial CEE, while unrelated technological diversification indicates less regional advantaged technologies overlapping with complementary technological linkages and further boosts the industrial CEE.

With the advancement of efficiency measurement methods and green patent data accessibility, future research will be constructed to investigate the issues below. The first is the new trial of CEE measurement. We intent to adopt the stochastic non-smooth envelopment of data model proposed by Kuosmanen & Kortelainen (2012) to calculate industrial CEE. This method is a more efficient than standard DEA and stochastic frontier analysis methods when the distribution of the inefficiency term is incorrectly specified. The second is the measurement of the green technological capabilities and complementary green technological linkages, if green patent text data is accessible, which is more targeted to analyze the impact of complementary green technological linkages on industrial CEE. The third is to regard the city as the research subject. We could investigate the relationship between complementary technological linkages and industrial CEE from a more micro-level perspective, which is beneficial for promoting China's Smart City project.

In addition, CL appears to be a more effective way to transform promising technology into the advantaged technology compared with general technological linkage, and more advantaged technologies are the foundation of technological diversification. Technological diversification promotes industrial diversification, which helps to eliminate the industrial development dilemma, reach green economy transformation, and establish a leading role for a region, which is worth further investigation.

Declaration of Competing Interest

The authors declare no conflicts of interest.

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Appendix A

Table A.1
Results of panel quantile regression.

Variable	Model1			Model2			Model3			model4		
	Quantile levels											
	25th	50th	75th	25th	50th	75th	25th	50th	75th	25th	50th	75th
*TD*lnCL*				0.0018^{***}	0.0012^{***}	0.0016^{***}						
				(17.08)	(11.00)	(15.40)						
*RE*lnCL*							0.0006^{***}	0.0004^{***}	0.0005^{***}			
							(43.83)	(22.85)	(17.47)			
*UN*lnCL*										0.0006^{***}	0.0003^{***}	0.0004^{***}
										(65.90)	(47.27)	(26.29)
lnCL	0.0365^{***}	0.0214^{***}	0.0219^{***}	0.0236^{***}	0.0242^{***}	0.0129^{***}	0.0285^{***}	0.0312^{***}	0.0469^{***}	0.0349^{***}	0.0329^{***}	0.0543^{***}
	(9.37)	(9.96)	(7.51)	(11.81)	(11.24)	(5.3100)	(8.24)	(10.40)	(11.96)	(12.82)	(14.99)	(14.94)
$lnCL^2$	-0.0044^{***}	-0.0023^{***}	-0.0025^{***}	-0.0035^{***}	-0.0038^{***}	-0.0024^{***}	-0.0070^{***}	-0.0068^{***}	-0.0093^{***}	-0.0101^{***}	0.0082^{***}	-0.0111^{***}
	(−9.81)	(−8.74)	(−7.69)	(−14.96)	(−12.53)	(−8.73)	(−16.30)	(−17.81)	(−15.58)	(−33.40)	(−30.17)	(−22.54)
lnNL	-0.3250^{***}	-0.4902^{***}	-0.4009^{***}	-0.2799^{***}	-0.4813^{***}	-0.3910^{***}	-0.2617^{***}	−0.4694	-0.3621^{***}	-0.2223^{***}	-0.4362^{***}	-0.3502^{***}
	(−20.21)	(−63.7600)	(−42.10)	(−28.83)	(−51.58)	(−48.46)	(−17.58)	(−52.80)	(−50.67)	(−32.43)	(−43.00)	(−43.38)
$lnNL^2$	0.0362^{***}	0.0515^{***}	0.0425^{***}	0.0312^{***}	0.0507^{***}	0.0415^{***}	0.0287^{***}	0.0482^{***}	0.0384^{***}	0.0247^{***}	0.0451^{***}	0.0369^{***}
	(25.80)	(89.60)	(57.37)	(39.06)	(65.65)	(65.52)	(19.26)	(49.28)	(47.99)	(35.79)	(60.55)	(41.32)
IS	-0.7049^{***}	-0.1980^{***}	0.4927^{***}	-0.5032^{***}	-0.2004^{***}	0.4813^{***}	-0.6038^{***}	-0.4042^{***}	0.4353^{***}	-0.6562^{***}	-0.3493^{***}	0.3355^{***}
	(−20.15)	(−13.82)	(14.72)	(−21.80)	(−10.29)	(16.58)	(−14.15)	(−13.05)	(9.88)	(−17.28)	(−18.58)	(7.47)
ES	0.0488^{***}	-0.1840^{***}	-0.7736^{***}	0.0328^{***}	-0.2016^{***}	-0.8000^{***}	0.0889^{***}	-0.1596^{***}	-0.7942^{***}	0.1587^{***}	-0.1715^{***}	-0.7988^{***}
	(2.83)	(−14.17)	(−50.31)	(3.27)	(−10.48)	(−41.34)	(6.75)	(−7.53)	(−40.12)	(11.40)	(−10.77)	(−34.78)
MS	-0.0447^{***}	-0.0569^{***}	-0.0483^{***}	-0.0410^{***}	-0.0531^{***}	-0.0437^{***}	-0.0523^{***}	-0.0531^{***}	-0.0370^{***}	-0.0453^{***}	-0.0534^{***}	-0.0322^{***}
	(−24.21)	(−15.91)	(−6.30)	(−25.62)	(−23.73)	(−6.76)	(−28.52)	(−37.64)	(−5.79)	(−23.24)	(−36.28)	(−8.08)
_cons	1.3332^{***}	1.8266^{***}	1.7692^{***}	1.1580^{***}	1.8152^{***}	1.7611^{***}	1.1748^{***}	1.9116^{***}	1.7239^{***}	1.0777^{***}	1.8152^{***}	1.7553^{***}
	(27.59)	(64.83)	(48.71)	(34.79)	(68.63)	(64.98)	(25.30)	(63.11)	(74.02)	(38.81)	(44.07)	(77.16)
N	28,040	28,040	28,040	28,040	28,040	28,040	28,040	28,040	28,040	28,040	28,040	28,040

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