Title page

# Does the green technology progress has a significant impact on carbon dioxide emissions?

Shihong Zeng [a,b,c], Tengfei Li [a,c,*], Shaomin Wu [d], Weijun Gao[b,e], Gen Li [a,c]

[a]Applied Economics Department, College of Economics & Management, Beijing University of Technology, Beijing 100124, China

[b]Faculty of Environmental Engineering, the University of Kitakyushu, Kitakyushu 8080135, Japan

[c]Finance and Economics Development Research Center, College of Economics & Management, Beijing University of Technology, Beijing 100124, China

[d]Kent Business School, University of Kent, Canterbury, Kent CT2 7FS, UK

[e]iSMART, Qingdao University of Technology, Qingdao 266033, China

***Corresponding authors**

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## Abstract

Structural, economic and technological effects are the three key factors in the change of carbon dioxide ($CO_2$) emissions under the environmental Kuznets curve hypothesis. Given the infeasibility of curbing economic growth and the limited impact of structural changes in the economy, while ensuring basic well-being, green technology progress (GTP) is considered an effective path to achieve carbon reduction targets. However, existing research is incomplete in exploring how GTP affects $CO_2$ emissions. Therefore, we employ the spatial Durbin model (SDM) to conduct an in-depth examination of the mechanism underpinning GTP with regard to its impact on CO2 emissions based on 2008-2019 panel data on 30 Chinese provinces. The results show that: first, GTP shows an evident "technological dividend", which significantly inhibits local $CO_2$ emissions, while the spatial spillover effect of GTP is not remarkable due to insufficient technological spillover and mismatch of acceptability; second, this paper identifies three potential transmission channels—the industrial structure, the energy structure, and energy efficiency—of the effect of GTP on $CO_2$ emissions based on a mediation model; third, the substantial regional disparity exists in the influence of GTP on $CO_2$ emissions, with the eastern region experiencing a notable reduction in carbon emissions due to GTP, whereas not significantly in the central and western regions. The innovation environment is a possible cause of regional heterogeneity: improving the human capital level and expanding the scale of technology market development have significant effects on the emission reduction effect of GTP, while the marginal emission reduction effect of government technology support is not significant. The findings presented in this study carry significant implications for fostering the

transition towards green and low-carbon economic development, as well as for attaining the ambitious objective of carbon neutrality.

**Keywords:** Green Technology Progress; Carbon Dioxide Emissions; Transmission Mechanism; Regional Heterogeneity

## 1. Introduction

Climate change has brought human beings immeasurable harm such as intensified dry seasons, melting polar ice, and abnormal weather (Khan et al., 2020; Shahbaz et al., 2020; Sarkodie and Owusu, 2021; Többelmann and Wendler, 2020; Wang et al., 2018). Extensive literature attributes carbon dioxide ($CO_2$) emissions as a primary driver of climate change (Adedoyin et al., 2020; Cosmas et al., 2019; Hoang et al., 2022; Oreskes, 2004; Umar and Safi, 2023). China, propelled by its rapid economic growth, stands as the world's largest emitter of $CO_2$ (Xu et al., 2021; Zhang and Liu, 2022). According to BP's Statistical Review of World Energy (BP, 2021), China's $CO_2$ emissions soared to 9,899 million tons in 2020, accounting for approximately 31% of the global total. Confronting the dual pressures of domestic environmental degradation and international climate negotiations, the Chinese government has proactively initiated measures to curtail $CO_2$ emissions and has made a series of ambitious commitments in this regard (Gao et al., 2020; Li et al., 2021; Zhang and Liu, 2022). For instance, during the United Nations General Assembly in September 2020, China unveiled its target to "strive to peak by 2030 and achieve carbon neutrality by 2060," based on the nation's baseline conditions.

Nevertheless, China confronts a time-sensitive and arduous endeavor in its pursuit of carbon neutrality. The magnitude of emission reduction necessary for China to attain carbon neutrality surpasses that of other economies. Moreover, the time span between the attainment of carbon peak and carbon neutrality in developed nations extends beyond 40 years or even 70 years, in stark contrast to China's comparatively limited timeframe of approximately 30 years. This discrepancy renders China's objective significantly more arduous to accomplish in comparison to developed countries. In addition, the process of achieving emission reduction targets will inevitably have a negative impact on economic development. Therefore, the conundrum on how to solve the dilemma of environmental protection and economic growth and to achieve green economic growth has drawn considerable attention from researchers (Fan et al., 2015; Xu et al., 2021). Structural, economic and technological effects are the three drivers of changes in $CO_2$ emissions, according to the Kuznets curve hypothesis (Grossman, 1995). Given the infeasibility of curbing economic growth and the limited impact of structural changes in the economy while ensuring basic well-being, technology progress is considered a key factor for green growth (Danish and Ulucak, 2020; Sarkodie and Owusu, 2021; Su and Moaniba, 2017). But not all technology progress leads to improvement of environmental quality, and technologies are classified into gray and green technologies (Acemoglu et al., 2012), while green technologies, which are more ecologically oriented, are the key elements of the "economic-environmental" system. Currently, China is in a critical period of carbon neutrality, can green technology progress (GTP) become a key force to reduce $CO_2$ emissions? What are the specific impact mechanisms? Answering these questions satisfactorily will have a significant implication in achieving China's $CO_2$ emission reduction target.

The influence of GTP on $CO_2$ emissions has been the subject of investigation within the existing literature. However, differences in the indicators chosen and the models constructed mean that no consistent conclusion can be drawn regarding the impact of GTP on $CO_2$ emissions (Xu et al., 2021; Weina et al., 2015; Khan et al., 2020; Mongo et al., 2021). Few papers have attempted to investigate the actual induced mechanisms of GTP affecting $CO_2$ emissions. Moreover, such effects may vary according to specific social or economic conditions (Du et al., 2019; International Energy Agency (IEA), 2015; Xu et al., 2021). China's economy has the characteristics of a large country economy, and different regions have significant differences in terms of the economic scale, green technology level, and resource endowment. If these objective regional differences are ignored, the conclusions obtained from studies at the overall national level are hardly applicable to the need for emission reduction in different regions. Finally, analysis of the potential causes of regional heterogeneity in the emission reduction effects of GTP is quite sparse. Thus, how GTP affects $CO_2$ emissions remains understudied.

This paper aims to tackle the above challenges and makes the following contributions. First, it examines the spatial implication of GTP on $CO_2$ emissions from a spatial linkage perspective, considering the fact that $CO_2$ easily transports between neighboring regions due to the natural flow of the atmosphere. Second, it explores the transmission channels---including the industrial structure, the energy structure, and energy efficiency--of the impact of GTP on $CO_2$ emissions. Third, it discusses the regional disparities in the influence of GTP on $CO_2$ emissions, considering the different levels of economic development and green technology among regions in China.

Finally, this paper incorporates the innovation environment into the research framework of the emission reduction effect of GTP and analyzes the potential causes of regional heterogeneity from three levels: human capital level, technology market development, and governmental support for science and technology.

The subsequent sections of the paper are structured as follows: Section 2 encompasses a comprehensive literature review and the formulation of theoretical hypotheses. Section 3 offers an intricate account of the research methodology employed and outlines the dataset utilized. Section 4 furnishes an in-depth empirical analysis accompanied by a comprehensive discussion. Section 5 concludes by summarizing the study's key findings and proposing pertinent recommendations for future action.

## 2. Literature review and theoretical hypotheses

### *2.1 Literature review*

Although GTP is often considered a key factor in balancing economic and environmental governance, its impact on environmental governance has been controversial due to the rebound effect (Braungardt et al., 2016). The effect of GTP on CO2 emissions under different conditions may be a promoting effect or an inhibitory effect (Weina et al., 2015; Xu et al., 2021; Paramati et al., 2021). Alternatively, it may be influenced by various factors, such as income (Du et al., 2019) and environmental regulations (Du et al., 2021). Shan et al. (2021) investigated the link between GTP and $CO_2$ emissions in Türkiye using the STIRPAT model, and the results showed that GTP can reduce $CO_2$ emissions. Paramati et al. (2021) and Khan et al. (2020) reached the same conclusion in their studies on different economies. However, Weina et al. (2015) found that GTP increased Italy's environmental productivity but cannot curb $CO_2$ emissions. The relationship between GTP and $CO_2$ emissions has also been explored based on multiple dimensions. Su and Moaniba (2017) observed that GTP demonstrated a positive correlation with the rise in $CO_2$ emissions resulting from natural gas and liquid fuel consumption, but exhibited a negative association with the increase in $CO_2$ emissions attributed to solid fuel consumption. Du et al. (2019) found that $CO_2$ emission effect of GTP is affected by the income level and GTP is only effective in reducing $CO_2$ emissions when the income level exceeds a threshold. Mongo et al. (2021) employed an autoregressive distributional lag model to examine the impact of GTP on $CO_2$ emissions across 15 European countries. Their findings revealed a twofold effect of GTP: while it exhibited a beneficial long-term impact in reducing $CO_2$ emissions, in the short run, it yielded the opposite effect. Khattak et al. (2022) found that the positive shocks of GTP mitigated $CO_2$ emissions during economic booms; however, its adverse shocks increased $CO_2$ emissions during economic downturns. Dong et al., (2022) also indicated that financial development can enhance the impact of GTP on $CO_2$ emission reduction.

Moreover, the existing literature mostly uses the number of patents as a proxy for GTP (Du et al., 2019; Xu et al., 2021). Nevertheless, given the fact that patents are often considered knowledge, they may not be applicable in practice and data on patent applications are often difficult to refine at the provincial level (Du and Li, 2019). Therefore, researchers have attempted to measure GTP with green total factor productivity based on a production framework. Existing studies generally use the SBM-ML approach to measuring GTP (Jie, 2021; Li and Chen, 2021), but the ML model suffers from the problem of no feasible solution to linear programming. For this reason, we refer to the study of Oh (2010) and construct the GML index based on the SBM model to solve this problem. Therefore, based on the SBM-GML model for GTP indicators, this study investigates how GTP affects $CO_2$ emissions and its transmission mechanism.

### *2.2 Theoretical hypotheses*

#### *2.2.1. The mechanism of the impact of GTP on $CO_2$ emissions*

Clapp (2014) pointed out that many new technologies have a typical "dirty" character, i.e., gray technology (Acemoglu et al., 2012), which mainly aim at increasing the scale and efficiency of production and can cause an increasing consumption of fossil energy and environmental resources. Acemoglu et al. (2012) pointed out that green technologies can be not only a key tool for achieving sustainable economic development (Danish and Ulucak, 2020; Jiao et al., 2020; Mongo et al., 2021) but also an important factor in curbing $CO_2$ emissions (Garrone and Grilli, 2010; Shan et al., 2021; Shahbaz et al., 2020). GTP mitigates the high consumption and high greenhouse gas emissions that characterize traditional energy technology through carbon reduction technology. It breaks the lock-in effect of traditional fossil energy and reduces $CO_2$ emissions (Wang et al., 2012). Furthermore, GTP promotes $CO_2$ capture and storage or even recycling through decarbonization technologies, such as carbon capture, utilization and storage (CCUS) technology, to directly reduce $CO_2$ emissions in the atmosphere (Xu et al., 2021). We therefore propose Hypothesis 1.

Hypothesis 1: *GTP is a key means of improving environmental quality and can significantly contribute to the reduction of $CO_2$ emissions.*

GTP exhibits indirect effects on $CO_2$ emissions through three distinct transmission channels. First, GTP facilitates a reduction in $CO_2$ emissions by driving the upgrading of the industrial structure. GTP can transform traditional energy-intensive industries, make products and production processes energy-efficient and clean, and promote the optimization and upgrading of traditional industries to decrease $CO_2$ emissions (Xie et al., 2021; Tian et al., 2014). Furthermore, the implementation of GTP not only fosters the advancement of emerging environmentally friendly sectors, exemplified by the new energy automobile industry but also instigates the emergence of novel methodologies and goods such as clean production technology and recycled products (You and Zhang, 2022). Consequently, this facilitates the establishment of fresh industrial growth centers, specifically within the realm of environmental industries, thereby propelling the rapid and transformative evolution of the industrial structure (López and Montalvo, 2015; Du et al., 2019). Second, GTP has an impact on $CO_2$ emissions through the optimization of the energy structure. By reducing the cost of clean energy and driving energy structure reforms, GTP facilitates a departure from the prevailing structural reliance on traditional energy resources, effectively challenging resource endowments and traditional energy monopolies. This transition paves the way for the development and utilization of clean energy sources, such as solar, geothermal, and photovoltaic energy. Consequently, "high-carbon" energy is gradually being replaced by "low-carbon energy", achieving energy cleanliness (Huang et al.,

2022) and thus reducing $CO_2$ emissions (Dauda et al., 2021; Du and Li, 2019; Li and Lin, 2016). Finally, GTP indirectly affects $CO_2$ emissions by improving energy efficiency and increases the marginal productivity of factors by improving and upgrading production equipment in equal proportion to increase total output, which means that energy efficiency is improved with the same input factors (the same amount of output can still be obtained by reducing energy inputs) and therefore reduce $CO_2$ emissions (Cheng et al., 2018; Du and Li, 2019; Yang et al., 2014). We therefore propose Hypothesis 2.

Hypothesis 2: *GTP can help reduce $CO_2$ emissions by promoting industrial structure upgrading, optimizing the energy structure, and improving energy efficiency*.

#### *2.2.2. The mechanism of the impact of the innovation environment on the emission reduction effect of GTP*

The innovation environment not only affects the diffusion behavior of technology but also determines the degree of technology progress enhancement (Wang et al., 2015). According to previous studies (Buesa et al., 2006; Li, 2009; Lu and Huang, 2012; Wang et al., 2015), the human capital level, technology market development, and government technology support are important indicators of the innovation environment.

The enhancement of environmental quality cannot be achieved without technological progress and human capital accumulation that change the structure of factor endowments. Josef Schumpeter was the first to propose that technological progress primarily originates from research and development activities and the learning-by-doing effect. The core of "learning-by-doing" refers to the externality of knowledge accumulation, primarily reflected in the accumulation of human capital. Consequently, the accumulation of human capital represents a fundamental component of technological progress (Acemoglu and Autor, 2012; Oyinlola et al., 2021; Song et al., 2018; Tan and Yan, 2021). In accordance with the theory of technology choice within the factor endowment structure, the specific technological framework must align with the input structure of factors, necessitating technological progress to correspond with elevated levels of human capital, particularly in the context of green technology. Extant studies have demonstrated that a higher level of human capital facilitates the optimization of domestic emission-reduction technologies (Ai et al., 2015). Advancing the level of human capital can foster the industrialization and commercialization of green technology, thereby facilitating the diffusion and application of such environmentally friendly innovations. Consequently, we put forth Hypothesis 3.

Hypothesis 3: *The level of human capital is directly proportional to the emission reduction effect of GTP.*

The technology market plays a crucial role in facilitating the transformation of GTP accomplishments. The market mechanism can regulate the supply and demand of green technology, help promote the free flow of factors and the improvement in factor allocation efficiency and thus promote the transformation, application, and diffusion of GTP achievements (Wang et al., 2022). With the continuous development of the technology market, the number of green technology supply and demand subjects in the market has increased, and there have been increasing technology transactions, therefore reducing information asymmetry and transaction costs, increasing the yield of innovation achievements, making green progress subjects more motivated to carry out technology progress activities, and further elevating the level of GTP (Lichtenthaler, 2013; Yin et al., 2022). In addition, when the technology market reaches a certain scale, GTP subjects can understand the market demand for green technology achievements through price signals in a timely manner and integrate various resources for green technology improvement and innovation based on the specific requirements of the technology demand side to make some technical achievements targeted, transformed in a timely manner and applied to actual production. We therefore propose Hypothesis 4.

Hypothesis 4: *A high-level technology market can promote the transformation, applications, and diffusion of green technologies, and facilitate them to reduce emissions.*

Government technology support is an important guarantee for the successful implementation of GTP activities. Existing studies have found that government support helps stimulate technology progress activities (Jugend et al., 2018; Montmartin and Herrera, 2015; Cano-Kollmann et al., 2017;). GTP is a high-investment, high-risk and high-reward economic activity. Without government support, firms usually lack the motivation to undertake green technology activities and to use green technology. Therefore, the government invests in GTP activities through financial support and thus addresses market failures and creates a positive environment for technological development (Jugend et al., 2018), which promotes the advancement, application and promotion of green technologies. We therefore propose Hypothesis 5.

Hypothesis 5:*Government technology support can regulate the intensity of the emission reduction effect of green technology.*

## 3. Material and methods

### *3.1 Model construction*

#### *3.1.1. Basic model*

The IPAT framework, initially introduced by Ehrlich and Holdren in 1971, serves as the pioneering model for investigating the repercussions of human endeavors on the ecological ecosystem (Ehrlich and Holdren, 1971). Its significance remains prevalent in contemporary research, particularly within the realm of elucidating the determinants that shape $CO_2$ emissions (Lin and Ma, 2022; Xu et al., 2017), and its general expression is:

$$I = P \times A \times T \tag{1}$$

where $I$ stands for environmental impact, $P$ for population, $A$ for economic development and $T$ for technological development. However, the elasticity coefficients of $P$, $A$, and $T$ with respect to pollution are constant for the model, as the model does not allow parameter estimation and hypothesis testing (Lin and Ma, 2022). Therefore, Dietz and Rosa (1997) improved the form of the IPAT identity and constructed the STIRPAT model. The specific expression is:

$$I_i = \beta_0 P_i^{\beta_1} A_i^{\beta_2} T_i^{\beta_3} \varepsilon_i \tag{2}$$

where $\beta_0$, $\beta_1$, $\beta_2$, and $\beta_3$ are estimable parameters, and $\varepsilon_i$ is the residual term. Finally, taking logarithms on both sides of the equation, a linear model is obtained as in equation (3).

$$\ln I_i = \beta_0 + \beta_1 \ln P_i + \beta_2 \ln A_i + \beta_3 \ln T_i + \varepsilon_i \tag{3}$$

To investigate the influence of GTP on $CO_2$ emissions, the aforementioned model is adapted into a panel framework.

$$\ln CE_{it} = \alpha_0 + \alpha_1 GTP_{it} + \alpha_2 X + \mu_i + \gamma_t + \varepsilon_{it} \tag{4}$$

where *t* denotes time and *i* represents the ith region. *CE* is $CO_2$ emissions, which is a logarithmic function for eliminating the effect of heteroskedasticity. $\alpha$ is a series of parameters to be estimated, GTP is green technology progress , *X* is a series of control variables, $\mu_i$ represents individual fixed effects, $\gamma_t$ represents time fixed effects.

*3.1.2. Spatial Durbin model*

(1) Taking into account the mobility of $CO_2$ emissions across regions, it is essential to recognize that the level of $CO_2$ emissions in a particular region can be influenced by the $CO_2$ emissions generated in neighboring regions (Wu et al., 2021), and therefore, there may be some spatial dependence of $CO_2$ emissions across regions. As pointed out by Zheng (2014), ignoring spatial correlation may produce estimation bias. Hence, we introduce a spatial weight matrix constructs a spatial Durbin model (SDM) based on Equation (4) to examine the relationship between GTP and $CO_2$ emissions from a spatial perspective. The model is expressed as follows.

$$\ln CE_{it} = b_0 + \rho \sum_{j=1}^{N} w_{ij} \ln CE_{jt} + b_1 GTP_{it} + b_2 X_{it} + \sum_{j=1}^{N} w_{ij} GTP_{jt} b_3 + \sum_{j=1}^{N} w_{ij} X_{jt} b_4 + \mu_i + \gamma_t + \varepsilon_{it} \tag{5}$$

where $w_{ij}$ is the spatial weight matrix, and we construct three spatial weight matrices: adjacency ($W_1$), geographical ($W_2$), and economic geographical ($W_3$) weight matrices. $\rho$ is the spatial autoregressive coefficient, and $b$ is a series of estimable parameters.

(2) To explore the mediating effects of industrial structure upgrading, energy structure optimization and energy efficiency improvement in the process of $CO_2$ reduction by GTP, we apply the stepwise test method for verification based on equation (5), referring to the studies of Baron and Kenny (1986) and Hao et al., (2023), and set the following model.

$$MV_{it} = l_0 + \rho\sum_{j=1}^{N} w_{ij}MV_{jt} + l_1 GTP_{it} + l_2 X_{it} + \sum_{j=1}^{N} w_{ij}GTP_{jt}l_3 + \sum_{j=1}^{N} w_{ij}X_{jt}l_4 + \mu_i + \gamma_t + \varepsilon_{it} \tag{6}$$

$$\ln CE_{it} = q_0 + \rho\sum_{j=1}^{N} w_{ij}\ln CE_{jt} + q_1 GTP_{it} + q_2 MV_{it} + q_3 X_{it} + \sum_{j=1}^{N} w_{ij}GTP_{jt}q_4 + \sum_{j=1}^{N} w_{ij}MV_{jt}q_5 + \sum_{j=1}^{N} w_{ij}X_{jt}q_6 + \mu_i + \gamma_t + \varepsilon_{it} \tag{7}$$

where $MV$ is the mediating variable, $l$ and $q$ are a set of parameters to be estimated.

(3) To explore the moderating effect of the innovation environment in the process through which GTP affects $CO_2$ reduction, referring to Wu et al., (2021), Lin and Li (2022), we add the interaction term between the innovation environment and GTP in the models and then establish the following econometric panel models.

$$\ln CE_{it} = \varphi_0 + \rho\sum_{j=1}^{N} w_{ij}\ln CE_{jt} + \varphi_1 GTP_{it} + \varphi_2 GTP_{it}RV_{it} + \varphi_3 X_{it} + \sum_{j=1}^{N} w_{ij}GTP_{jt}\varphi_4 + \sum_{j=1}^{N} w_{ij}GTP_{jt}D_{jt}\varphi_5 + \sum_{j=1}^{N} w_{ij}X_{jt}\varphi_6 + \mu_i + \gamma_t + \varepsilon_{it} \tag{8}$$

where $\phi$ is a set of parameters to be estimated and $RV$ represents the moderating variable.

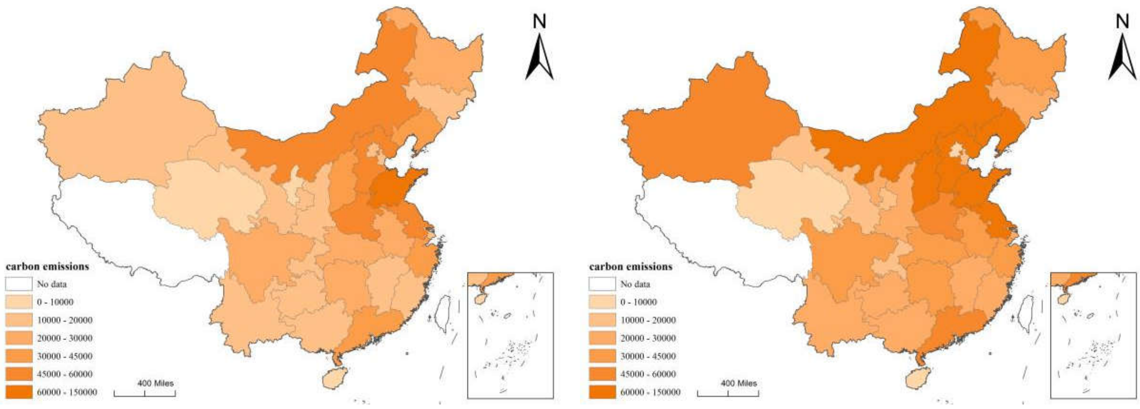
### *3.2 Variable description*

(1) The explained variable is carbon dioxide emissions *(CE)*. Currently, most scholars use the method of IPCC to account for regional $CO_2$ emissions, which is a top-down accounting method of calculating the sum of $CO_2$ produced by each type of energy consumption.

This method is closer to the real value. In this paper, we refer to the IPCC and existing relevant studies on accounting for $CO_2$ emissions to calculate the $CO_2$ emissions of each province, city, and autonomous region in China with the following equation (IPCC, 2006; Wang et al., 2018; Wen et al., 2021).

$$CE = \sum_{i=1}^{n} E_i \times NCV_i \times CEF_i \times COF_i \times 44/12 \tag{9}$$

where $E_i$ denotes the physical quantity of the ith energy source consumed, including the consumption of eight energy sources: coal, diesel, gasoline, kerosene, crude oil, fuel oil, coke, and natural gas. $NCV_i \times CEF_i \times COF_i$ is the carbon emission factor. Finally, 44/12 represents the molecular mass ratio of $CO_2$ to carbon. Based on the $CO_2$ emission calculation results, we illustrate the interprovincial distribution of $CO_2$ emissions in China in 2008 and 2019 in Fig. 1.




(a) 2008 (b) 2019

**Fig. 1.** Interprovincial distribution of $CO_2$ emissions in China, 2008 and 2019

As we can see, the darker areas gradually increase over time, which indicates that the total $CO_2$ emissions in China increased significantly during the period examined. From the regional perspective, all provinces, except Beijing, Chongqing, Qinghai, Henan, Gansu and Hainan, show significant increases in $CO_2$ emissions to different degrees, and Beijing is the only province showing a significant decrease in $CO_2$ emissions. In terms of the distribution characteristics, $CO_2$ emissions show a certain spatial agglomeration, and the regions emitting more $CO_2$ are mainly concentrated in North China, Central China, and East China.

(2) The core explanatory variable is green technology progress *(GTP).* We adopt the SBM-GML model to measure GTP. Regarding the selection of GTP indicators, among the input indicators, the labor force indicator is measured by the number of employed persons in each region, the capital stock is measured by the perpetual inventory method, and the energy input indicator is measured by the total energy consumption in each region. For the output indicators, the gross regional product processed by the base price deflator is used as the desired output indicator, while the undesired output is considered based on the failure of GTP and environmental pollution. Specifically, the year-on-year ratio of nonperforming bank loans is used as a proxy indicator for the failure of GTP, and industrial sulfur dioxide and industrial wastewater chemical oxygen demand (COD) are used to measure environmental pollution.

(3) The mediating variables include the following:

- *Industrial structure upgrading (IS)*. GTP can support the transformation of the industrial structure to achieve decarbonisation (Du et al., 2019).In comparison with the secondary industry, the tertiary industry tends to be more capitalintensive and labour-intensive, and there are more $CO_2$ emissions from the secondary industry (Wu et al., 2021). Therefore, following Wang and Wang (2021), the tertiary value-added/secondary value-added ratio is used as a proxy indicator for IS.

- *Energy structure optimization (ES)*. GTP can drive energy consumption toward cleanliness. The energy structure optimizatio plays an indispensable role in the process of emission reduction (Kahia et al., 2016; Sun and Ren, 2021). Therefore, we characterize energy structure optimization using the share of clean energy. To represent clean energy, we choose primary electricity and natural gas based on Wang and Lee (2022).
- *Energy efficiency improvement (EE)*. GTP can improve energy efficiency (Wurlod and Noailly, 2018). Energy efficiency improvement performs an increasingly essential function in reducing emissions (Brodny and Tutak, 2022; Zhong et al., 2021). Therefore, we measure it as a share of GDP in energy consumption.

(4) The moderating variables: This paper characterizes the innovation environment in terms of three dimensions: human capital, technology market development, and government technology support.

- *Human capital (HC).* Talent is a prerequisite for driving technological progress. Therefore, the human capital level influences GTP both quantitatively and qualitatively (Wen et al., 2022). We follow Wang et al. (2018) in utilizing the average number of years of education as a measure of HC.

- *Technology market development (TD).* The technology market is an important factor market for achieving the transformation of the results of GTP (Wang et al., 2022). In this paper, the ratio of technology market turnover to regional GDP is used to characterize the level of TD.
- *Government technology support (GS).* Government technology support provides a source of funding for GTP activities, thereby alleviating the financing constraints on green technologies (Montmartin and Herrera, 2015). Thus, government technology support is an important driver of firms' GTP activities. We use government spending on technology as a share of total financial expenditure to measure government technology support.

(5) The control variables include the following:

- *Economic Growth (EG).* This paper takes the economic growth rate as a proxy for economic growth. Economic growth is an important factor affecting $CO_2$ emissions. An increase in economic activity translates into more energy consumption, which hurts the environment (Obobisa et al., 2022).
- *Population Scale (PS).* Population size, a control variable, refers to the total population of each area by the end of the year. An expanding population scale increases the consumption of resources, which brings about environmental pollution (Zhang et al., 2018).

- *Trade openness (TO).* There is some controversy regarding the effect of the level of trade openness on $CO_2$ emissions. According to Ahmed et al. (2017), trade openness increases $CO_2$ emissions as it drives the process of energy consumption. It has also been argued that trade openness can promote technology and knowledge spillovers, and thus promote the development of green technology (Chen et al., 2020; Wu et al., 2020). Referring to Haug and Ucal (2019), and Acheampong et al. (2019) , we measure the level of trade openness using the share of total exports and imports in GDP.
- *Government intervention (GI).* In this paper, we use the share of government expenditure on environmental protection in total fiscal expenditure to characterize the level of government intervention. Government intervention plays an important role in solving environmental problems (Sun and Huang, 2020). The government has some positive impact on the environment through its spending on pollution prevention and energy conservation and utilization.
- *Environmental regulation (ER).* Environmental regulation performs a key role in driving carbon emission reductions (Wu et al., 2019). Referring to a previous study (Du et al., 2021), we measure the emissions of various pollutants (sulfur dioxide, wastewater, and soot) by calculating a composite index for each region.

### *3.3 Data sources and descriptive statistics*

We select 30 provinces, municipalities, and autonomous regions in China from 2008 to 2019 as the research objects. Unfortunately, we were unable to collect data on other provinces, which are therefore not included in this study. The data come from the National Bureau of Statistics of China, the China Statistical Yearbook, the statistical yearbooks of provinces, municipalities and autonomous regions, the China Energy Statistical Yearbook, the General Principles for Calculation of Comprehensive Energy Consumption (GB/T2589-2020), the Compilation of Provincial Greenhouse Gas Inventories Guide and the Wind database. Table 1 shows the descriptive statistics of the variables selected in this paper.

**Table 1.** Descriptive statistics of the variables

| | Variable | Variable symbol | Description | Mean | Max. | Min. |
|---|---|---|---|---|---|---|
| Dependent variable | Carbon dioxide emissions | CE | Total carbon dioxide emissions | 33394.100 | 110603.200 | 2387.945 |
| Independent variable | Green technology progress | GTP | Calculated by the SBM-GML method | 1.032 | 1.375 | 0.776 |
| Mediating variables | Industry structure upgrading | IS | Ratio of the value added of the tertiary industry to that of the secondary industry | 1.120 | 5.169 | 0.497 |
| | Energy structure optimization | ES | Proportion of clean energy | 0.221 | 1.969 | 0.107 |
| | Energy efficiency improvement | EE | Ratio of GDP to energy consumption | 1.414 | 4.816 | 0.353 |
| Moderating variable | Human capital | HC | Per capita educational level | 8.975 | 12.782 | 6.764 |
| | Technology market development | TD | Proportion of technology market turnover in GDP | 0.013 | 0.161 | 0.004 |
| | Government technology support | GS | Proportion of technology expenditure in total financial expenditure | 0.020 | 0.072 | 0.003 |
| Control variables | Economic Growth | EG | Economic growth rate | 9.573 | 17.800 | 0.500 |
| | Population Scale | PS | Total population | 4543.506 | 12489 | 554 |
| | Trade openness | TO | Proportion of the import and export volume in GDP | 0.293 | 1.597 | 0.013 |
| | Government intervention | GI | Proportion of government spending on environmental protection | 0.327 | 0.074 | 1.073 |

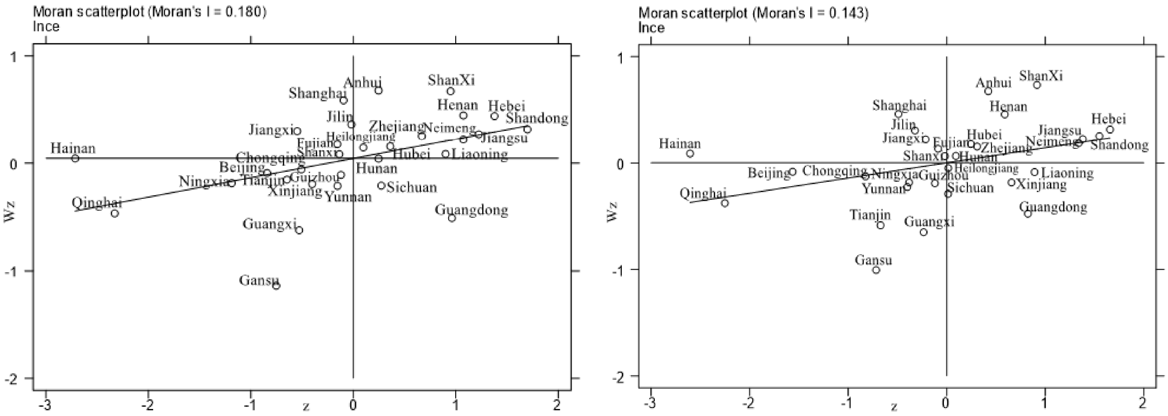
| | | | | | |
|---|---|---|---|---|---|
| Environmental regulation | ER | Measured by calculating a composite index of emissions of various pollutants | 0.532 | 2.585 | 0 |

## 4. Estimation results and discussion

### *4.1 Analysis of the spatial regression results*

In order to ensure the validity of employing spatial econometric models, we have employed the Moran index to assess the spatial correlation of $CO_2$ emissions. The computational outcomes demonstrate that the global Moran index of $CO_2$ emissions during the analyzed timeframe is positive, reaching at least a 10% level of significance. These findings imply that $CO_2$ emissions exhibit a strong spatial correlation rather than being independent across different spatial nodes. Moreover, in order to provide a more visually intuitive representation of the spatial clustering characteristics of $CO_2$ emissions within each province, we have depicted the local Moran scatter plots for the years 2008 and 2019 in Fig. 2. The local spatial clustering patterns of $CO_2$ emissions are clearly discernible, with the trend line falling within the first and third quadrants. During the period spanning from 2008 to 2019, a noticeable decline in the number of provinces situated within the high-high (H-H) agglomeration zone has been observed. The provinces that have predominantly maintained their presence within this zone are primarily located in East China (specifically Shandong, Jiangsu, Zhejiang, and Anhui), Central China (including Henan, Hunan, and Hubei), inland energy-rich provinces (such as Shanxi and Inner Mongolia), and heavy industrial provinces (notably Hebei). Conversely, the low-low (L-L) agglomeration area remains predominantly populated by provinces located in the southwestern and northwestern regions.

Consequently, it is deemed justifiable to employ a spatial econometric model for the purpose of conducting a comprehensive analysis of this phenomenon.




(a) 2008 (b) 2019

**Fig. 2.** Local Moran's I scatter plot for $CO_2$ emissions in each region, 2008 and 2019

### *4.2 Analysis of the impact of GTP on $CO_2$ emissions*

*4.2.1. Analysis of the spatial regression results*

Given the introduction of multiple variables in the paper, potential multicollinearity issues arise. To address this, a thorough examination of inter-variable correlations was conducted, with specific outcomes reported in Table 2. Notably, with the exception of variables PS and ER displaying a correlation coefficient of 0.622, all other variable pairs demonstrated correlations below 0.5, suggesting a weak association between them. Meanwhile, the maximum variance inflation factor (VIF) for each variable remained below 2, indicating the absence of severe multicollinearity concerns. Additionally, to evaluate cross-sectional dependence, three distinct methods—Pesara, Friedman, and Frees—were employed, and their outcomes overwhelmingly rejected the null hypothesis of no cross-sectional correlation, signifying the indispensability of considering such correlation (Bekun et al., 2021). Consequently, the Driscoll-Kraay method, as presented in Table 3, I utilized for estimation. By observing the regression results, GTP has the effect of reducing $CO_2$ emissions. However, as the panel model fails to account for spatial effects, further consideration was given to incorporating the spatial factor.

**Table 2.** Tests of correlation and multicollinearity

| | GTP | EG | PS | TO | GI | ER | VIF |
|---|---|---|---|---|---|---|---|
| GTP | 1 | | | | | | 1.2 |
| EG | -0.099 | 1 | | | | | 1.18 |
| PS | 0.094 | -0.033 | 1 | | | | 1.97 |
| TO | 0.383 | -0.073 | 0.023 | 1 | | | 1.19 |
| GI | 0.045 | -0.314 | -0.44 | -0.053 | 1 | | 1.46 |
| ER | 0.051 | -0.096 | 0.622 | -0.023 | -0.234 | 1 | 1.65 |
| Pesaran | cross sectional independence = 16.574, Pr = 0.0000 | | | | | | |
| Friedman | cross sectional independence = 72.662, Pr = 0.0000 | | | | | | |
| Frees | cross sectional independence = 4.577 | | | | | | |

Meanwhile, this study examines the issue of spatial model selection validity, as demonstrated in Table 3. Primarily, the spatial autocorrelation test conducted on the regression residuals yields p-values below 0.05 for LMlag, Robust-LMlag, LMerror, and Robust-LMerror, thus indicating statistical significance for the construction of a spatial econometric model. Additionally, the LR test and Wald test results establish that the SDM model cannot be reduced to a SAR or SEM model. Lastly, considering the AIC, BIC, and log-likelihood criteria, the SDM outcomes obtained using the adjacency matrix exhibit optimal performance. Consequently, this study proceeds with subsequent analyses utilizing the aforementioned model.

Based on the regression findings, the coefficient for the spatial lag of $CO_2$ emissions exhibits a noteworthy positive association at the 1% significance level. This outcome indicates that provincial-level carbon emissions in China exhibit significant spatial clustering in neighboring areas, consistent with the results of spatial autocorrelation tests. The interplay between atmospheric currents, as well as the close proximity of industrial activities and trade among adjacent regions, contribute to the strong interdependence of local $CO_2$ emissions with those of neighboring regions (Han et al., 2018; Wu et al., 2021). As for the GTP variable, its coefficient demonstrates a significant negative relationship, signifying that GTP has a suppressive effect on CO2 emissions, thus lending support to Hypothesis 1. This conclusion is inconsistent with that reached by Du and Li (2019), which suggests that GTP can only inhibit $CO_2$ emissions in high-income regions. We confirm that GTP shows a very robust "technology dividend" for $CO_2$ emission reduction in China, which demonstrates that focusing on research and development and the improvement of core industrial fields and key technologies is conducive to reducing $CO_2$ emissions. Furthermore, improving green technology has become an important force in driving emission reductions (Jiao et al., 2020; Mongo et al., 2021; Töbelmann and Wendler, 2020; Shahbaz et al., 2020) and has laid a solid technological foundation for achieving $CO_2$ emission reduction targets in the future.

**Table 3.** Regression results

| variable | Driscoll-Kraay | SDM | | |
|---|---|---|---|---|
| | | $W_1$ | $W_2$ | $W_3$ |

| | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. |
|---|---|---|---|---|---|---|---|---|
| GTP | -0.252$^{**}$ | 0.088 | -0.818$^{**}$ | 0.403 | -1.220$^{**}$ | 0.623 | -1.079$^{***}$ | 0.394 |
| EG | 0.003 | 0.003 | 0.031$^{**}$ | 0.014 | 0.017 | 0.018 | -0.031$^{***}$ | 0.012 |
| PS | 0.367 | 0.254 | 0.513$^{***}$ | 0.120 | 0.589$^{***}$ | 0.164 | 0.634$^{***}$ | 0.038 |
| TO | 0.220$^{**}$ | 0.090 | 0.209 | 0.178 | 0.140 | 0.125 | -0.538$^{***}$ | 0.108 |
| GI | -0.147 | 0.092 | -0.408 | 0.338 | -0.130 | 0.435 | 0.382$^{**}$ | 0.157 |
| ER | 0.089$^{***}$ | 0.016 | 0.594$^{***}$ | 0.121 | 0.509$^{***}$ | 0.125 | 0.554$^{***}$ | 0.051 |
| w*GTP | | | -0.145 | 0.419 | 0.203 | 1.130 | -1.381$^{*}$ | 0.826 |
| w*EG | | | -0.056$^{**}$ | 0.031 | -0.096$^{***}$ | 0.027 | 0.019 | 0.019 |
| w*PS | | | -0.482$^{***}$ | 0.170 | -0.387 | 0.253 | -0.069 | 0.085 |
| w*TO | | | -0.763$^{**}$ | 0.357 | -0.202 | 0.304 | 1.054$^{***}$ | 0.155 |
| w*GI | | | 0.193 | 0.486 | 1.212$^{*}$ | 0.381 | 1.003$^{***}$ | 0.260 |
| w*ER | | | 0.476$^{***}$ | 0.173 | 0.448$^{*}$ | 0.259 | 0.188 | 0.119 |
| ρ | | | 0.161$^{***}$ | 0.060 | 0.379$^{***}$ | 0.107 | 0.131$^{*}$ | 0.073$^{*}$ |
| $R^2$ | 0.613 | | 0.827 | | 0.667 | | 0.787 | |
| Log-L | | | -79.285 | | -113.373 | | -124.184 | |
| AIC | | | 186.6 | | 254.7 | | 276.4 | |
| BIC | | | 241.0 | | 309.2 | | 330.8 | |
| Robust-LMlag | 3.367$^{**}$ | | LR-lag | | 20.56$^{***}$ | | | |
| LMlag | 209.838$^{***}$ | | LR-error | | 41.46$^{***}$ | | | |
| Robust-LMerror | 124.091$^{***}$ | | Wald-lag | | 31.70$^{***}$ | | | |
| LMerror | 330.562$^{***}$ | | Wald-error | | 36.25$^{***}$ | | | |

Note: ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Among the control variables, economic growth and population scale have positive effects on $CO_2$ emissions, specifically, each unit increase in economic growth and population scale drives $CO_2$ emissions growth by 0.031 and 0.513 units, respectively, revealing that economic growth and population scale are the key factors driving $CO_2$ emissions growth, which is consistent with the findings of Zhang et al. (2018) and Obobisa et al. (2022). Economic and population growth enhances the consumption of resources, which brings about an increase in $CO_2$ emissions. The regression coefficient of environmental regulation is positive at the 1%

level, apparently contributing to $CO_2$ emissions, resulting in a "green paradox" (Sinn, 2008). One possible reason is the "incomplete implementation" and "race to the bottom" of environmental regulation. In addition, trade openness and government intervention do not play a significant role in reducing $CO_2$ emissions.

We further decompose the impact of GTP on CO2 emissions into direct and spillover effects. The empirical findings, as displayed in Table 4, demonstrate that the direct effect of GTP exhibits a negative association at a significance level of 5%. However, the spillover effect fails to attain statistical significance, thereby contradicting the results reported by Xu et al. (2021) and Liu et al. (2022). We believe that there are two reasons for the insignificant spillover effect of GTP. First, protectionism in various regions seriously hinders the cross-regional flow of innovation factors, which fundamentally weakens the spillover effect of technological progress. Second, the actual effect of technological spillover also depends on the learning, imitation and absorption ability of the technology absorber, and the obvious differences in the level of socioeconomic development in various regions of China may reduce the actual effect of technology spillover, so the mismatch between the lack of technology spillover and the acceptance of the abilities of technology makes the effect of GTP on reducing $CO_2$ emissions in spatially related regions not obvious.

**Table 4.** Estimation results of the decomposition effects

| variable | LR_Direct | | LR_Indirect | | LR_Total | |
|---|---|---|---|---|---|---|
| | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. |
| GTP | -0.815** | 0.408 | -0.331 | 0.473 | -1.146** | 0.520 |
| EG | 0.028** | 0.013 | -0.057* | 0.033 | -0.029 | 0.0312 |

| | | | | | | |
|---|---|---|---|---|---|---|
| PS | 0.5094*** | 0.113 | -0.458** | 0.180 | 0.051 | 0.197 |
| TO | 0.180 | 0.165 | -0.810** | 0.382 | -0.630* | 0.351 |
| GI | -0.391 | 0.346 | 0.194 | 0.559 | -0.198 | 0.737 |
| ER | 0.609*** | 0.111 | 0.667*** | 0.211 | 1.276*** | 0.226 |

Note: ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

*4.2.2.Robustness test*

To ensure the validity and robustness of the estimation results, we conduct robustness tests with three methods: replacing the model, replacing the explanatory variables, and reducing the sample period (Table 5). In terms of replacing the model (model 1). Since the SAR model assumes that the dependent variable can affect neighboring regions based on spatial interactions, which is consistent with the assumption of spatial spillover effects, we adopt the SAR model to investigate the relationship between GTP and $CO_2$ emissions. In terms of replacing the explanatory variables (model 2), we refer to the study of Du et al. (2019), Weina et al. (2015) and Paramati et al.(2021), the number of green patents is used to measure GTP to examine the relationship between the two. In terms of reducing the sample period (model 3), the financial crisis that broke out in 2008 might cause a certain impact on the indicators. As such, we exclude the data of 2008 and take 2009-2019 as the sample period for the study. Based on the regression model results, the signs and significance of GTP for all models are consistent with the original model, indicating that the effect of GTP on $CO_2$ emissions is robust.

**Table 5.** Tests of robustness

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. |
| GTP | -0.259** | 0.116 | -0.013*** | 0.003 | -0.676* | 0.359 |
| EG | -0.012*** | 0.002 | 0.015 | 0.011 | 0.027** | 0.011 |

| | | | | | | |
|---|---|---|---|---|---|---|
| PS | 0.822*** | 0.189 | 0.610*** | 0.036 | 0.509*** | 0.036 |
| TO | 0.223*** | 0.082 | 0.194** | 0.090 | 0.173** | 0.079 |
| GI | -0.007 | 0.068 | 0.062 | 0.167 | -0.428*** | 0.147 |
| ER | 0.093*** | 0.031 | 0.536*** | 0.046 | 0.594*** | 0.044 |
| ρ | | | 0.397*** | 0.083 | 0.127* | 0.068 |

Note: ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

### *4.2.3. Endogeneity test*

Although we control for relevant variables, important variables may still be omitted and lead to endogeneity problems. In addition, there may be a reciprocal causal relationship between GTP and $CO_2$ emissions, which is one of the sources of the endogeneity problem in this paper. Therefore, to avoid bias in the estimation results due to the endogeneity problem, we adopt the method of taking one period lag of the core explanatory variables for the endogeneity test, as shown in Table 6. Wooldridge (2010) indicates that if the error term of the model is only related to the disturbance term in the current period, a one-period lag of the endogenous variable can be taken as the current period value to solve the endogeneity problem. Hence, we re-estimated the parameters by taking the GTP with a one-period lag and applying the SDM under the three spatial weight matrices of adjacency, geography, and economic geography, and the regression results showed that the GTP exhibits a significant emission reduction effect, which is consistent with the regression results of the original model and proves the validity of the estimation results.

**Table 6.** Tests of endogeneity

| | $W_1$ | | $W_2$ | | $W_3$ | |
|---|---|---|---|---|---|---|
| | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. |
| GTP | -0.209* | 0.123 | -0.255** | 0.123 | -0.788* | 0.405 |

| | | | | | | |
|---|---|---|---|---|---|---|
| EG | -0.001 | 0.004 | -0.006 | 0.004 | -0.031*** | 0.012 |
| PS | 0.792*** | 0.089 | 0.626** | 0.252 | 0.628*** | 0.038 |
| TO | 0.372*** | 0.083 | 0.272*** | 0.089 | -0.563*** | 0.109 |
| GI | -0.019 | 0.073 | -0.019 | 0.072 | 0.351** | 0.156 |
| ER | 0.081* | 0.033 | 0.098*** | 0.032 | 0.556*** | 0.051 |
| ρ | 0.544*** | 0.050 | 0.572*** | 0.064 | 0.137* | 0.073 |

Note: ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

### *4.3 Analysis of the transmission mechanism*

To elucidate the transmission mechanism underlying the impact of GTP on $CO_2$ emissions, we employ a stepwise testing approach to validate the mediating influences of industrial structure upgrading, energy structure optimization, and energy efficiency improvement. The initial regression analysis of the GTP variable demonstrates a noteworthy impact on $CO_2$ emissions, thus establishing a foundation for subsequent testing. Detailed regression outcomes are presented in Table 7.

Drawing on the transmission mechanism governing the upgrading of industrial structure, the impact of GTP on industrial structure upgrading is found to be remarkably positive. A mere 1% increase in GTP yields a corresponding 0.352% rise in the industrial structure upgrading index. Concurrently, industrial structure upgrading exerts a mitigating effect on $CO_2$ emissions. At this point, the indirect impact of GTP on $CO_2$ emissions is found to be significantly negative when industrial structure upgrading serves as a mediator. Specifically, a 1% enhancement in GTP results in a reduction of $CO_2$ emissions by 0.049% (calculated as the product of 0.352 and 0.139) through the pathway of industrial structure upgrading. This outcome underscores the substantial mediating role played by industrial structure upgrading in the emission reduction effect of GTP. Through the facilitation of cleaner production processes and the advancement of novel environmentally friendly and green industries, GTP propels the industrial structure towards a low-carbon trajectory, thereby effectively diminishing $CO_2$ emissions (Du et al., 2019; Xie et al., 2021).

**Table 7.** Regression results of the mediating effects of industrial structure upgrading, energy structure optimization and energy efficiency improvement

| | Industrial structure upgrading | | | | Energy structure optimization | | | | Energy efficiency improvement | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | IS | | CE | | ES | | CE | | EE | | CE | |
| | Coef. | Std. | Coef. | Std. | Coef. | Std. | Coef. | Std. | Coef. | Std. | Coef. | Std. |
| GT | $0.352^{**}$ | 0.15 | $-0.235^{**}$ | 0.11 | $0.084^{***}$ | 0.02 | -0.190 | 0.11 | $0.866^{***}$ | 0.17 | 0.068 | 0.10 |
| IS | — | — | - | 0.03 | — | — | — | — | — | — | — | — |
| ES | — | — | — | — | — | — | - | 0.31 | — | — | — | — |
| EE | — | — | — | — | — | — | — | — | — | — | - | 0.03 |
| EG | 0.007 | 0.00 | 0.002 | 0.00 | $-0.001^{*}$ | — | -0.001 | 0.00 | 0.010 | 0.00 | 0.005 | 0.00 |
| PS | - | 0.32 | $0.483^{**}$ | 0.23 | $0.114^{***}$ | 0.04 | $0.839^{***}$ | 0.23 | -0.388 | 0.35 | $0.546^{***}$ | 0.20 |
| TO | - | 0.11 | $0.308^{***}$ | 0.08 | - | 0.01 | $0.278^{***}$ | 0.09 | - | 0.13 | -0.048 | 0.08 |
| GI | 0.087 | 0.09 | -0.019 | 0.07 | $0.030^{**}$ | 0.01 | -0.046 | 0.07 | $0.200^{*}$ | 0.10 | 0.023 | 0.06 |
| ER | -0.035 | 0.04 | $0.052^{*}$ | 0.03 | 0.005 | 0.00 | $0.067^{**}$ | 0.03 | $-0.090^{*}$ | 0.04 | 0.031 | 0.02 |
| ρ | $0.384^{***}$ | 0.05 | $0.543^{***}$ | 0.05 | $0.469^{***}$ | 0.05 | $0.512^{***}$ | 0.05 | $0.559^{***}$ | 0.04 | $0.571^{***}$ | 0.04 |

Note: ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

In the context of the transmission mechanism governing energy structure improvement, the coefficient of GTP demonstrates a significant positive association at a confidence level of 1%, which underscores the pivotal role of GTP as a driving force behind the optimization of energy structure. Simultaneously, the optimization of energy structure exhibits considerable potential in curtailing $CO_2$ emissions. Notably, this result means that via the path of energy structure optimization, a 1% improvement in GTP leads to an indirect effect on CO2 emission reduction of approximately 0.074%, highlighting the substantial mediating function of energy structure in the relationship between GTP and $CO_2$ emissions. GTP facilitates the optimization of energy structure, facilitating the gradual replacement of "high-carbon" energy sources with "low-carbon" alternatives, thereby diminishing $CO_2$ emissions (Dauda et al., 2021; Du and Li, 2019; Huang et al., 2022).

With respect to the transmission mechanism of energy efficiency improvement, the effect of GTP on energy efficiency improvement is significant. Improving energy efficiency can have a significant inhibitory effect on $CO_2$ emissions. Hence, the product of the two regression coefficients is negative, i.e., a 1% improvement in GTP reduces $CO_2$ emissions by 0.298% through the path of energy efficiency improvement. This result demonstrates that the effect of energy efficiency improvement as a mediating variable on the explained variable is significant, which implies that green technology can curb $CO_2$ emissions by improving energy efficiency and reducing per unit energy consumption (Cheng et al., 2018; Yang et al., 2014).

To summarize, the emission reduction effect of GTP is significantly mediated by the industrial structure, energy structure, and energy efficiency, which implies that GTP exerts an indirect inhibitory impact on $CO_2$ emissions through three distinct pathways: promoting industrial structure upgrading, optimizing the energy structure, and enhancing energy efficiency. These findings provide support for Hypothesis 2.

### *4.4 Analysis of regional heterogeneity*

The actual impact of GTP on $CO_2$ emissions is subject to variation based on the prevailing socioeconomic environment (Du et al., 2019; International Energy Agency (IEA), 2015; Xu et al., 2021). China's economy embodies the attributes of a large-scale national economy, with discernible dissimilarities observed among different regions pertaining to economic magnitude, proficiency in green technology, and resource endowment. Consequently, we proceed to investigate the regional heterogeneity of GTP's impact on $CO_2$ emissions by stratifying the sample into three regions: eastern, central, and western regions. The regression outcomes, presented in Table 8, reveal notable regional heterogeneity in the influence of GTP on $CO_2$ emissions. Specifically, the coefficient of GTP in the eastern region exhibits a significant negative association at a confidence level of 1%, signifying the substantial role played by GTP in reducing $CO_2$ emissions in this region. However, the emission reduction effect of GTP in the central and western regions is not statistically significant. Upon measuring the GTP levels in each region, we observe that the eastern region possesses significantly higher GTP levels compared to the central and western regions (Fig. 3), which indicates that green technology is not well applied and promoted in these two regions, resulting in a less significant emission reduction effect (Wang et al., 2012).

**Table 8.** Estimation results for different regions of China

| variable | Eastern | | Central | | Western | |
|---|---|---|---|---|---|---|
| | Coef. | Std. | Coef. | Std. | Coef. | Std. |
| GTP | -0.974*** | 0.361 | -0.043 | 0.404 | -0.074 | 0.489 |
| EG | 0.0029 | 0.015 | -0.006 | 0.008 | 0.008 | 0.007 |
| PS | 0.860*** | 0.070 | 0.056 | 0.676 | 4.155*** | 0.429 |
| TO | -0.039 | 0.110 | 0.254 | 0.503 | 0.092*** | 0.021 |
| GI | -0.740*** | 0.200 | 0.343** | 0.171 | -0.078 | 0.126 |

| | | | | | | |
|---|---|---|---|---|---|---|
| ER | 0.172** | 0.076 | 0.155*** | 0.054 | 0.136 | 0.088 |
| w*GTP | -0.720* | 0.379 | 0.057 | 0.523 | -0.511 | 0.663 |
| w*EG | -0.121*** | 0.032 | -0.012 | 0.009 | -0.001 | 0.009 |
| w*PS | -0.775*** | 0.131 | 0.801 | 0.940 | -1.006 | 0.999 |
| w*TO | -0.170 | 0.157 | 0.669 | 0.727 | -0.021 | 0.041 |
| w*GI | 0.424 | 0.319 | -0.034 | 0.231 | -0.139 | 0.210 |
| w*ER | 0.559*** | 0.132 | -0.191** | 0.083 | 0.032 | 0.152 |
| ρ | 0.151* | 0.083 | 0.357*** | 0.090 | 0.703*** | 0.063 |

Note: ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

### *4.5 Analysis of the moderating effect of the innovation environment*

To further clarify the reasons for the influence of GTP on the regional heterogeneity of $CO_2$ emissions, we explore the moderating effect of the innovation environment on the emission reduction effect of GTP at three levels: the human capital level, technology market development, and government technology support. The specific results are shown in Table 9. The coefficient of the interaction term between GTP and the human capital level is -0.072 and significant at the 5% level. This result indicates that the human capital level has a moderating effect on the emission reduction effect of GTP, and the higher the human capital level is, the stronger the effect of GTP on reducing $CO_2$ emissions, which supports Hypothesis 3. Regions with higher levels of human capital have more skilled personnel, and thus promote the application and diffusion of green technologies (Oyinlola et al., 2021; Song et al., 2018). According to Fig. 4, discernible regional disparities in human capital are evident within China, with the eastern region exhibiting markedly higher levels compared to the central and western regions. Consequently, the elevated level of human capital observed in the eastern region has engendered the advancement and implementation of environmentally sustainable technologies, thereby serving as a catalyst for $CO_2$ reduction efforts. Conversely, the limited availability of human capital in the central and western regions has impeded the widespread adoption and dissemination of green technology.

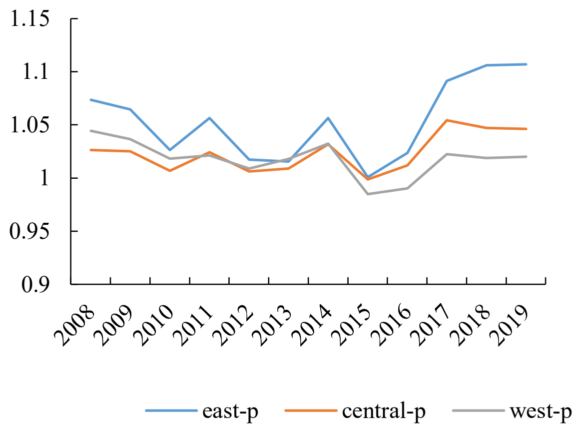



**Fig. 3**. Change trend of GTP.

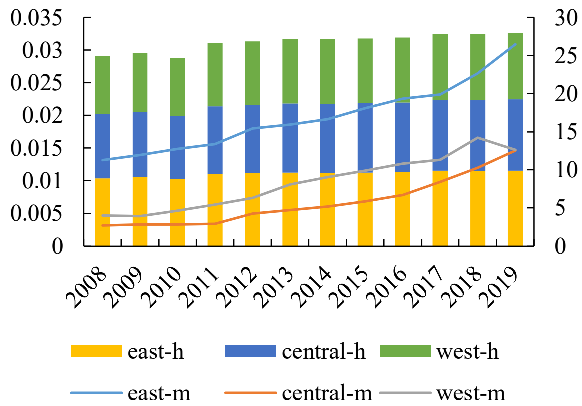



**Fig. 4**. Change trend of human capital and technology market in different regions of China.

The interaction coefficient of GTP and technology market development is negative and significant at the 1% level. This result indicates that technology market development can enhance the emission reduction effect of GTP, supporting Hypothesis 4. The larger the scale of technology market development is, the more obvious the emission reduction effect of GTP. The technology market is an important factor market for realizing the transformation of GTP achievements. The market mechanism is used to adjust technology supply and demand, to realize the optimal allocation of resources and to promote the transformation, application and diffusion of GTP achievements (Wang et al., 2022). According to Fig. 4, the development scale of the technology market in the central and western regions is much lower than that in the eastern region, and an underdeveloped technology market is not conducive to transforming and promoting green technology achievements.

**Table 9.** Regression results of the moderating effect of the innovation environment

| | Human capital level | | Technology market | | Government technology | |
|---|---|---|---|---|---|---|
| | Coef. | Std. | Coef. | Std. | Coef. | Std. |
| GTP | 0.431 | 0.317 | -0.074 | 0.1201 | -0.301** | 0.133 |
| GTP*HC | -0.072** | 0.030 | — | — | — | — |
| GTP*TD | — | — | -0.496*** | 0.083 | — | — |
| GTP*GS | — | — | — | — | 0.603 | 1.209 |
| EG | 0.001 | 0.004 | -0.001 | 0.004 | -0.006 | 0.004 |
| PS | 0.564** | 0.244 | 0.679*** | 0.237 | 0.608** | 0.254 |
| TO | 0.194** | 0.088 | 0.120 | 0.087 | 0.262*** | 0.090 |
| GI | -0.033 | 0.070 | -0.062 | 0.070 | -0.020 | 0.072 |
| ER | 0.106*** | 0.031 | 0.078*** | 0.030 | 0.100*** | 0.032 |
| ρ | 0.418*** | 0.077 | 0.583*** | 0.062 | 0.561*** | 0.065 |
| $R^2$ | 0.692 | | 0.636 | | 0.513 | |
| Log(L) | 312.098 | | 316.268 | | 294.459 | |
| AIC | -592.2 | | -600.5 | | -556.9 | |
| BIC | -530.0 | | -538.4 | | -494.7 | |

Note: ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

The interaction term between GTP and government technology support is not significant. This result indicates that the increase in government technology support has not enhanced the emission reduction effect of GTP and that Hypothesis 5 is not valid. One possible reason is that promoting economic development is still the top priority of various regions, and government fiscal expenditures are more inclined toward production-oriented technologies that improve productivity, and thus hinder the application and promotion of green technologies.

In conclusion, a superior innovation environment is conducive to enhancing the emission reduction effect of GTP.

## 5. Conclusions and policy recommendations

This study delved into the influence of GTP on $CO_2$ emissions, as well as the underlying transmission mechanism, employing a comprehensive dataset covering the period from 2008 to 2019 across 30 provinces in China. Recognizing that the actual effect of GTP on $CO_2$ emissions may be contingent upon the particular socioeconomic context, we conducted an analysis of the regional heterogeneity in the impact of GTP on $CO_2$ emissions. Furthermore, we investigated potential factors contributing to this regional heterogeneity from the perspective of the innovation environment.

The key findings and policy implications derived from this research endeavor are summarized as follows.

First, the results of the Moran index show that $CO_2$ emissions exhibit a strong spatial correlation. Driven by both atmospheric flows and trade exchanges, local $CO_2$ emissions are closely related to the $CO_2$ emission levels of neighboring regions. Second, GTP has a significant inhibitory effect on China's $CO_2$ emissions, showing a very robust "technological dividend" effect, but due to insufficient technology spillover and mismatch in receptivity, the spatial spillover effect of GTP is not significant. Third, there are three potential transmission channels for the emission reduction effect of GTP: the industrial structure, the energy structure and energy efficiency. GTP can reduce $CO_2$ emissions by promoting industrial structure upgrading, optimizing the energy structure, and improving energy efficiency. Finally, we found that there is obvious regional heterogeneity in the effect of GTP on $CO_2$ emissions. GTP can significantly suppress $CO_2$ emissions in the eastern region, but the effect is not obvious in the central and western regions. Meanwhile, we explore the potential causes of regional heterogeneity from the perspective of innovation environment. The results show that both the human capital level and technology market development can enhance the effect of GTP on emission reduction; however, the moderating effect of government technology support is not significant.

Based on the empirical evidence presented in this study, we put forth the following policy recommendations.

First, it is imperative to expedite the dissemination of green technologies. The empirical results show that GTP is an important force to promote $CO_2$ emission reduction. Therefore, we should accelerate the promotion of green and low-carbon technologies with high maturity and low emission reduction costs, promote the efficient and clean use of coal and other fossil energy, increase the proportion of clean energy use, and promote the transformation and upgrading of "high-carbon" industries to "low-carbon" industries. Furthermore, the extent of GTP within different regions of China displays variation, warranting the implementation of tailored policy frameworks in each region to enhance green technology proficiency in accordance with their unique circumstances. Particularly, the central and western regions should assimilate and garner insights from the low-carbon development model observed in the frontier region (the eastern region), expediting the transfer, dissemination, and assimilation of green technology across regions, thereby augmenting the overall level of GTP.

Second, we need to improve the human capital level. Findings from research indicate that the proficiency of human capital can significantly augment the $CO_2$ reduction impact of GTP, underscoring its pivotal role in fostering GTP and serving as a vital means to achieve environmentally sustainable and low-carbon economic development. Consequently, Chinese governmental bodies ought to prioritize education as a fundamental developmental strategy across all levels, augment investments in education, and elevate the educational attainment of the populace. Furthermore, they should actively cultivate the enthusiasm and dynamism of all regions to actively engage in the transition towards green and low-carbon practices, bolster societal awareness regarding green and low-carbon environmental preservation, promote green and low-carbon production methodologies and lifestyles, and heighten residents' inclination to invest in green technologies.

Third, it is imperative to foster the growth of a robust and efficient technology market. The technology market is an important platform for promoting the flow of technology resources and the transfer and commercialization of technological achievements, and extensive research substantiates that the technology market plays a formidable role in driving GTP. Presently, despite the rapid advancements witnessed in China's technology market, certain challenges persist, such as regional disparities in development, inadequate market mechanisms, and a dearth of proficient science and technology intermediaries. In less-developed technology market regions, the government should focus on enhancing pertinent policies and regulations while encouraging all relevant entities to actively engage in technology market transactions. In more developed technology market regions, the government should further bolster the expansion of science and technology intermediaries, refine the technology assessment framework, and augment the efficiency of resource allocation within the technology market.

Fourth, we need to optimize government spending structure on technology. The government is the main body supporting technological progress, especially in terms of its strong support for high-level research institutions, which is the main reason that Europe, the United States and other countries dominate the most advanced global technologies (Stiglitz, 2015). Hence, it is imperative to harness the pivotal role of the government in advancing the proficiency of green technology. However, based on our findings, the impact of government-backed technology support on augmenting GTP in terms of emission reduction is not prominently substantial. One plausible explanation for this phenomenon is that government technology expenditures primarily channel towards production-oriented technologies. Therefore, for GTP to better play its role in $CO_2$ reduction, the government should optimize the structure of technology expenditure and increase the subsidies for green technologies, especially for the proliferation and application of existing green technologies.

**Declaration of competing interest**

None.

**Funding**

This research is partially funded by Major projects of China National Social Science Fund

(22&ZD145); the National Natural Science Foundation of China: Research on the Construction of a Carbon Neutral Economic Transformation Model for China (72140001).

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**Abstract**

Structural, economic and technological effects are the three key factors in the change of carbon dioxide ($CO_2$) emissions under the environmental Kuznets curve hypothesis. Given the infeasibility of curbing economic growth and the limited impact of structural changes in the economy, while ensuring basic well-being, green technology progress (GTP) is considered an effective path to achieve carbon reduction targets. However, existing research is incomplete in exploring how GTP affects $CO_2$ emissions. Therefore, we employ the spatial Durbin model (SDM) to conduct an in-depth examination of the mechanism underpinning GTP with regard to its impact on CO2 emissions based on 2008-2019 panel data on 30 Chinese provinces. The results show that: first, GTP shows an evident "technological dividend", which significantly inhibits local $CO_2$ emissions, while the spatial spillover effect of GTP is not remarkable due to insufficient technological spillover and mismatch of acceptability; second, this paper identifies three potential transmission channels—the industrial structure, the energy structure, and energy efficiency—of the effect of GTP on $CO_2$ emissions based on a mediation model; third, the substantial regional disparity exists in the influence of GTP on $CO_2$ emissions, with the eastern region experiencing a notable reduction in carbon emissions due to GTP, whereas not significantly in the central and western regions. The innovation environment is a possible cause of regional heterogeneity: improving the human capital level and expanding the scale of technology market development have significant effects on the emission reduction effect of GTP, while the marginal emission reduction effect of government technology support is not significant. The findings presented in this study carry significant implications for fostering the transition towards green and low-carbon economic development, as well as for attaining the ambitious objective of carbon neutrality.