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RESEARCH ARTICLE

Technology innovations impact on carbon emission in Chinese cities: exploring the mediating role of economic growth and industrial structure transformation

Lijuan Su[1] · Tao Ji[1] · Fayyaz Ahmad[1] · Abbas Ali Chandio[2] · Munir Ahmad[3] · Gul Jabeen[4] · Abdul Rehman[5]

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Abstract
China seems ambitious to achieve a "carbon emissions peak" before 2030 and "carbon neutrality" before 2060. To deal with this emissions mitigation plan, technology innovations are regarded as a crucial factor. However, considering its rebound effect (CO_2 emissions driving effect) through economic growth, technology innovations might not prove a promising contributor to CO_2 reduction. Therefore, there is a need to investigate further the nexus between technology innovations and CO_2 emissions for conclusive debate. Based on the data of 215 cities in China, this paper uses mediating effects model to investigate the direct and indirect impacts (through economic growth and industrial structure transformation) of technology innovations on CO_2 emissions from a microeconomic perspective. The main results suggest that technology innovations generally increase CO_2 emissions in China both directly and indirectly. The impact of technology innovations and economic growth on CO_2 emissions indicated the EKC characteristics. Furthermore, the contributions of technology innovations to CO_2 emissions are distinguished in different regions. Thus, there is an urgent need for China to promote innovations in "clean technology" and to transform industrial structure to the tertiary industry to achieve the targets of carbon neutrality and emissions peaking.

Keywords CO_2 emissions · Technology innovations · Mediating effect · Industrial structure · Economic growth · Prefecture-level cities

Introduction

As of September 22, 2020, President Xi has made a statement at the General Debate of the 75th Session of UNGA that China would achieve a "carbon emissions peak" before 2030 and "carbon neutrality" before 2060. As one of the fastest-growing countries, China is the largest producer of CO_2 globally, which nearly discharged 10.17 billion tons of CO_2 in 2019 and accounted for 30.56% of overall CO_2 emissions. Apparently, it is quite a big sacrifice for China to

Responsible Editor: Ilhan Ozturk

✉ Fayyaz Ahmad
fayyaz@lzu.edu.cn

Lijuan Su
sulj@lzu.edu.cn

Tao Ji
jit19@lzu.edu.cn

Abbas Ali Chandio
alichandio@sicau.edu.cn

Munir Ahmad
munirahmad@zju.edu.cn

Gul Jabeen
guljabeen@ncepu.edu.cn

Abdul Rehman
abdrehman@henau.edu.cn

1 School of Economics, Lanzhou University, Lanzhou 730000, Gansu, China

2 College of Economics, Sichuan Agricultural University, Chengdu 611130, China

3 School of Economics, Zhejiang University, Hangzhou 310058, China

4 School of Economics and Management, North China Electric Power University, Beijing 102206, China

5 College of Economics and Management, Henan Agricultural University, Zhengzhou 450002, China

cut down such a massive amount of CO_2 emissions since the CO_2 emissions right is commonly viewed as the opportunity for economic development (Holtz-Eakin and Selden 1992). In 2019, annual CO_2 emissions in China, the USA, Germany, and Japan were 10.17, 5.28, 0.7, and 1.1 billion tons, respectively. And annual average person CO_2 emissions in China, the USA, Germany, and Japan were 7.1, 16.06, 8.4, and 8.72 tons, respectively. Although China ranks first in total CO_2 emissions, their average person CO_2 emission is lower than most developed countries. From Fig. 1, we can also see that there is a gap between average person CO_2 emissions and total CO_2 emissions, so it is an adverse requirement for China to cut down its total CO_2 emissions rather than average person CO_2 emissions.

China is a developing country with an income level far behind developed countries. The constraints of total CO_2 emissions as "CO_2 emissions peak" and "CO_2 emissions neutrality" destine that China cannot attain the same average person CO_2 emissions level as the USA, Germany, and Japan, which poses massive challenges to Chinese economic growth and development. Therefore, the nexus between economic growth and CO_2 emissions brings about a dilemma for the Chinese economy, making it urgent to discuss factors influencing total CO_2 emissions than average person CO_2 emissions, considering the CO_2 emissions neutrality goal. Concerning the solution to the stated dilemma, previous studies (Zhou et al. 2018; Shan et al. 2021; Iqbal et al. 2021; Yue et al. 2021) regarded technology innovations as the crucial role player because it has been reported to decrease CO_2 emissions intensity by promoting the transformation of industrial structure or improving energy efficiency. However, technology is also an essential contributor to economic growth, which may indirectly increase CO_2 emissions. Along these lines, the impact of technology innovations on CO_2 emissions is not entirely as expected since many researchers (Shen et al. 2012; Zheng et al. 2012; Danish et al. 2018) found that technology innovations generally increase total CO_2 emissions or CO_2 emissions intensity. Such controversial findings could be because of the application of heterogeneous datasets and techniques employed. It might also be due to the construction of technology innovations variable. In this regard, the previous studies used macro-level data such as province-level, industry-level, and country-level data, which might be the major contributor to conflicting results. Further, the indicators for technology innovations are distinguished, such as total factor productivity (TFP) based on DEA-Malmquist, patents approved, and research and development (R&D) expenditures, causing conflicting results (Demena and Afesorgbor 2020). Therefore, the nexus between technology innovations and CO_2 emissions requires further examination.

This study aims to analyze the direct and indirect impacts of technology innovations on CO_2 emissions across China's 215 prefecture-level cities in the presence of other important determinants of those emissions. More specifically, it contributes to the present body of knowledge in the following terms: Firstly, this study investigates the impact of technology innovations from a relatively micro perspective based on the most recent city-level data. Secondly, it applies the mediating effect model to estimate technology innovations' direct and indirect influence (through economic growth, structural transformation) on CO_2 emissions. For this purpose, an EKC

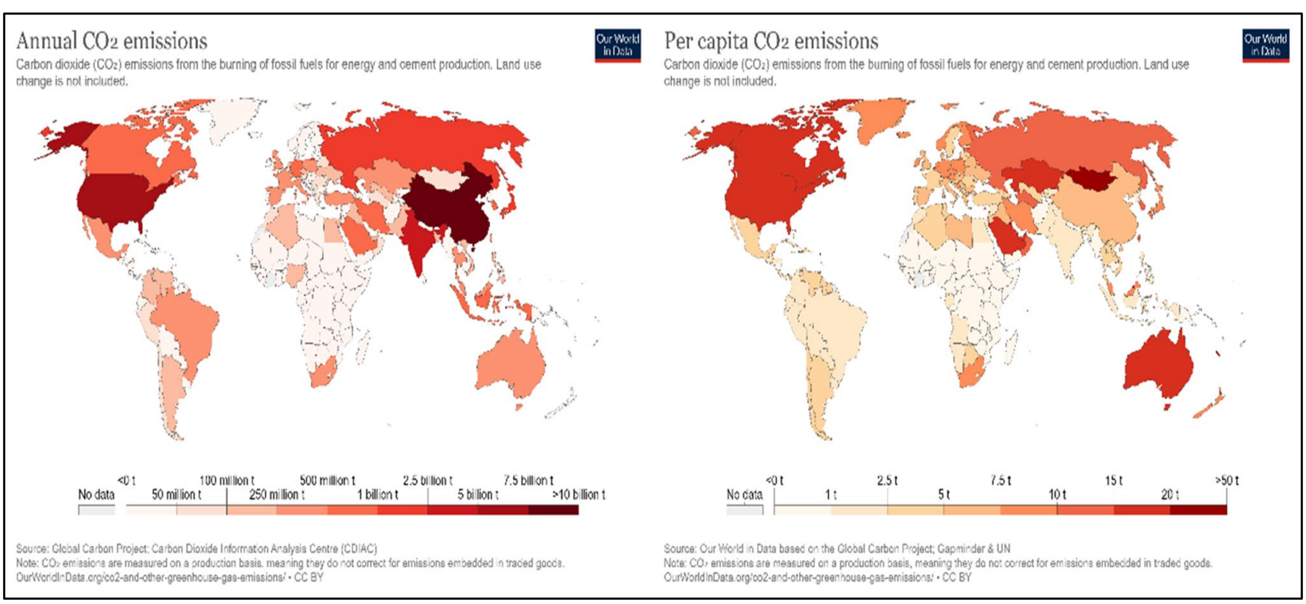

Fig. 1 Trends of annual and per capita CO_2 emissions in China and the rest of the world. Source: https://ourworldindata.org/co2/country/china

hypothesis is to be tested considering the impacts of technology innovations and gross domestic product (GDP) on CO_2 emissions. Thirdly, the study employs several alternative dependent variables, including dust discharge, polluted water discharge, and sulfur dioxide (SO_2) discharge. Further, it also uses the alternative proxies for technology innovations, including TFP, and public science and technology investment, to analyze the robustness of the results.

The remainder of the study is organized as follows: the "Literature preview and research hypothesis" section reviews the related and up-to-date literature on technology innovations—CO_2 emissions nexus and other determinants of CO_2 emissions. The "Data and methodology" section is based on data and methodology. The "Empirical analysis and results" section presents and discusses the empirical results. Finally, the "Conclusion and policy implications" section concludes the study.

Literature preview and research hypothesis

Nexus between technology innovations and CO_2emissions

Generally, researchers have formed a consensus that the increase of each place's GDP growth, population, urbanization, and secondary industry proportion will generally lead to more CO_2 emissions. However, it is rather conflicting about the impact of technology innovations on CO_2 emissions. Acemoglu et al. (2012) and Aghion et al. (2016) found that environmental constraints and non-renewable energy can spur firms to innovate in "clean technology," while more innovations in previous "dirty technology" would lead to more challenging transformation to "clean technology" (Jabeen et al. 2020). Zheng and Zhu (2012) distinguished between productive technology shocks and cleaning technology shocks and used a general equilibrium model to analyze its impact on CO_2 emissions. They found that the increasing effect of CO_2 emissions caused by productive technology shocks is stronger than the emission reduction effect of cleaning technology shocks. Still, the overall impact of technological shocks on CO_2 emissions has not been unambiguous. Shi and Hu (2017) measured the technological contribution of economic growth based on the DEA method and used it as an independent variable to construct a panel VAR model to investigate the impact of technology innovations on CO_2 emissions. They concluded that there was no significant relationship between technology innovations and CO_2 emissions. Zang et al. 2014 also proxied the technology innovations of Chinese provinces based on the DEA method and applied it as a core independent variable to investigate the emissions reduction effects of those technologies. They figured out that the technology innovations generally decreased a province's CO_2 emissions intensity, but the eastern, central, and west regions showed significant regional heterogeneity. Besides, they revealed that the fixed asset output, demographic variables, urbanization, and industrial value had a significant positive impact on CO_2 emissions intensity.

Under the condition of an open economy, Wei and Yang (2010) and Tan and Li (2013) focused on the importing technology and independent technology innovations' impacts on CO_2 emissions and disclosed that both importing technology and independent technology innovations decreased CO_2 emissions in China. However, the impacts of both were not obvious as expected. In their study, Jin et al. (2014) believed that technology innovations might have a double-edged effect on CO_2 emissions. On the one hand, it could increase CO_2 emissions by driving economic growth, and on the other hand, it might reduce those emissions by improving energy efficiency. Further, their regression results showed that technology innovations had generally increased CO_2 emissions, while the emissions reduction effect brought by the improvement of energy efficiency could not outweigh the CO_2 emissions growth effect brought by economic growth driven by technology innovations. In their research, Iqbal et al. (2021) examined the influence of environment-related technology innovations on carbon emissions in the Organization for Economic Cooperation and Development (OECD) nations. They revealed that technology innovations reduced those emissions in the sampled countries. Ahmad et al. (2021c) concluded that energy-industry technology investments in China were found to promote economic growth and associated carbon emissions. However, across the regional samples, the degree of impacts varied significantly.

Most recently, Shan et al. (2021) examined and verified that energy prices and technology innovations in OECD countries were revealed to reduce carbon emissions in the long run. They applied the augmented mean group (AMG) estimator, which is robust to cross-sectional dependence and slope heterogeneity for analysis purposes. Rehman et al. (2021a) employed the asymmetric autoregressive distributed lag (ARDL) model to investigate the technology spillover impact of foreign direct investment (FDI) on carbon emissions in the Pakistani context. They revealed that carbon emissions increased due to increased FDI in the country. Further, Gao et al. (2021) used the panel data of 252 of China's prefecture-level cities to study the influence of land misallocation factors on green technology innovations. They applied the threshold panel regression and found that increased economic development and environmental protection laws reduced the adverse effect of resource misallocation on those innovations. In a different study, Ahmad et al. (2021b) explored the technological spillover impact of foreign investments in Chinese provinces by employed second-generation advanced panel data econometric techniques.

They concluded with the heterogeneous findings proving pollution halo and pollution haven hypothesis across the Chinese provinces. Anser et al. (2021a) estimated the impact of information and communication technologies (ICTs) on carbon emissions in 26 European nations and found that both variables were complimentary for each other. Thus, carbon emissions increased in those countries because of such technologies. Finally, Rehman et al. (2021b) applied fully modified OLS (FMOLS) and dynamic OLS to estimate the influence of ICTs on economic growth and CO_2 emissions of Pakistan. They found that ICTs had promoted economic growth and those emissions during the sample period.

Hypothesis 1: Technology innovations can effectively reduce CO_2.

Other determinants of CO_2emissions

Among other determinants of CO_2 emissions, Lin and Liu (2010) introduced urbanization into the Kaya equation and used co-integration analysis methods to explore the influencing factors of CO_2 emissions. They revealed that energy intensity, GDP per capita, and urbanization had significant impacts on CO_2 emissions. Wang et al (2010) used the Divisia Exponential Decomposition method to decompose China's CO_2 emissions growth into the weighted contributions of 11 factors. The main driving factors were GDP per capita, total population, and economic structure. Similarly, Li and Zhou (2012) explored the impact of the structural transformation of the primary, secondary, and tertiary industries on the CO_2 intensity of each province. They found that the secondary industry was the main factor affecting each province's CO_2 intensity; however, its impact on the total CO_2 emissions remained unclear. Chen et al. (2018) introduced industrial structure, urbanization, and climate differences into the "stochastic impacts by regression on population, affluence, and technology" model. Their regression results showed that population size, the proportion of the secondary industry, and heating demand had significantly increased the city-based CO_2 emissions. Further, Li and Li (2010) investigated the relationship between CO_2 emissions, population, economy, and technology using a dynamic panel model of 30 provinces in China. They found that the impact of population on CO_2 emissions in the east, middle, and western regions were heterogeneous. In this regard, economic growth had significantly increased each province's CO_2 emissions, while technology innovations decreased those emissions.

Among the most recent works, Ahmad et al. (2021, a, b, c, d, e, f) studied the influence of renewable energy consumption and the service sector on carbon emissions of ASEAN5 nations. They disclosed that both factors significantly contributed to carbon emissions reduction in the region; however, the degree of impacts varied across the sampled countries. Likewise, Chandio et al. (2021) analyzed the influence of renewable and non-renewable energy consumption on China's carbon emissions by employing the ARDL model. They found that renewable energy improved the environmental quality, while non-renewable energy use deteriorated it. Jabeen et al. (2021a) employed a partial least squares method and found that the adoption and diffusion of renewable energy solutions were effective in reducing environmental degradation in Pakistan. In a similar way, Anser et al. (2021b) conducted research to find the renewable energy nexus with economic growth and environmental quality. They found that environmental quality was improved due to clean energy use in the South Asian economies. Ahmad et al. (2020) investigated the role of renewable energy in reducing carbon emissions in selected Chinese provinces. They revealed that positive shocks in renewable energy increase carbon emissions in those provinces. Hussain et al. (2021) studied the influence of financial development and economic openness on environmental sustainability. They found that both variables significantly drove a sustainable environment. Fatima et al. (2019) investigated the influence of aggregated energy use and human capital on environmental quality and found the emissions reduction effect of the two variables. Likewise, Jabeen et al. (2019) conducted a consumer-based analysis of renewable technology adoption and found that the acceptance of those technologies helped reduce environmental emissions.

Some of the studies examined the EKC relationship in the context of various samples and diverse methods. In this regard, Işık et al. (2021) applied the common correlated effects mean group approach on 8 OECD nations and confirmed the EKC existence for four countries. Similarly, Jan et al. (2021) investigated the EKC hypothesis for Pakistani time series from 1971 to 2016 and found the EKC valid by employing the dynamic ARDL method. In the same vein, Ahmad et al. (2021d) analyzed the existence of EKC in the developing world and revealed its presence for some countries, while others did not validate this hypothesis. In their study, Alvarado et al. (2021) examined the impact of economic development on non-renewable energy consumption and environmental quality in the OECD nations. They found the existence of EKC for some countries. In different work, Ahmad et al. (2020) examined the effects of natural resources on carbon emissions in China's northwestern provinces. They employed FMOLS methods and did not confirm the presence of EKC in the region. In another work, Işık et al. (2020) examined the EKC hypothesis for G-7 economies by employing an AMG estimator and found its existence only for France. Chandio et al. (2020) applied FMOLS and ARDL methods to investigate the environmental nexus for forestry, energy consumption, and agriculture. They did not verify the existence of the EKC hypothesis in the time series of China. Finally, Ahmad et al.

(2021a) used AMG and Dumitrescu-Hurlin causality methods to investigate the EKC across China's provinces in the presence of urbanization, energy intensity, and economic growth. They validated the EKC hypothesis in the sampled provinces.

Hypothesis 2: Technology innovations are conducive to promoting industry structure and further reducing CO_2.
Hypothesis 3: Technology innovations can effectively reduce CO_2 in an inverted U-shaped curve.

Summary of literature gaps

In view of the above-discussed literature, several scholars have conducted studies on the influencing factors on CO_2 emissions. Most scholars thought that economic growth, population, urbanization, and capital stock were positively correlated with CO_2 emissions, and economic growth was the major driving force of CO_2 emissions. But, most importantly, there existed a controversy about the impact of technology innovations on CO_2 emissions. The following reasons might have caused the differences in empirical results: Firstly, since technology innovation is not an actual input like labor or capital, the measurement of this variable is somewhat different. Some studies employ TFP as its indicator, while some others use public science and technology budgets, annually approved patents, and so on. Secondly, the chosen datasets were largely different. For instance, most scholars derive provincial CO_2 emissions data from the consumption of coal, oil, and natural gas, which could leave some measurement differences. Additionally, the regression results obtained from the provincial panel data cannot be considered rich enough to provide better outcomes. Finally, previous studies ignored the transformation of industrial structure caused by technology innovations, which might generate a mediating impact on CO_2 emissions. The present study fills these gaps by investigating the impact of technology innovations from a relatively micro perspective using the prefecture-level city data of China.

Data and methodology

Data description

This study uses the total CO_2 emissions (dependent variable) of China's 215 prefecture-level cities. It uses the annual patents approved, GDP, the proportion of the secondary industry, and GDP per capita to measure the technology innovations, economic growth, industrial structure, and income level, respectively. Variables such as house investment, FDI, capital stock, population, labor stock, dust discharge, polluted water discharge, SO_2 discharge, and public funds for science and technology are considered for further investigations. This is noteworthy that we remove the appearance design patents from annual patents approved to make sure it truly reflects the technology innovations. Next, the FDI and capital stock are calculated by Perpetual Inventory Method. The monetary variables are calculated at the constant price in 2008 to avoid nominal effects. Except for the proportion of the secondary industry, all other variables are processed with logarithmic function. The descriptive statistic of the variables is reported in Table 1.

This study cites the data calculated by Yuli Shan (2020), which covers most cities' CO_2 emissions in China and merges them into a city-level dataset. The data demonstrated above is extracted from the CEI database and different provincial Chinese yearbooks. Finally, the study uses dust, polluted water, and SO_2 discharge for the robust test part, and they also collected from various yearbooks of each province.

Theoretical framework and methods

The influence of technology innovations on CO_2emissions

According to Restuccia et al. (2008) and Acemoglu (2009), technology innovations displayed bias depending on the investment market. If the investment in "dirty technology" is more profitable than "clean technology," such innovations in energy and environmental protection are anticipated to trigger the path dependency of innovations in "dirty technology" that would cause more CO_2 emissions. Therefore, besides the indirect effect of technology innovations on GDP and industrial structure, it can also cause damage to the environment directly. This study defines industrial structure transformation as the decreasing proportion of secondary industry. This is because the proportion of the primary industry is relatively stable, then the decreasing proportion of secondary industry can be seen as the increasing proportion of tertiary industry. Therefore, this study illustrates two indirect impact paths of technology innovations (economic growth and structural change) on CO_2 emissions by extending the framework of rebound effect (RE) proposed by Zhou and Lin (2007) as follows:

$$\mathrm{RE} = \frac{Y_{t+1}^{A}\mathrm{CI}_w}{Y_{t+1}\left(S_t - S_{t+1}\right)CI_s} = \frac{Y_{t+1}^{A}}{Y_{t+1}} \times \frac{1}{\left(S_{t+1} - S_t\right)} \times \beta \tag{1}$$

where Y_{t+1}^{A} is the economic growth driven by technology innovations and Y_{t+1} is the overall economic growth, CI_w and CI_s are respectively the carbon intensity of GDP and the carbon intensity of secondary industry, and S_t is the proportion of secondary industry value-added. Therefore, $Y_{t+1}^{A}CI_w$ means CO_2 emissions caused by economic growth, which is driven by technology innovation, and $Y_{t+1}(S_t - S_{t+1})\mathrm{CI}_s$ means potential CO_2 emissions reduction caused by industrial structure transformation. Technically, if RE is more than 1 (vice versa), it means that technology innovations generally cause more CO_2 emissions indirectly. Since the

Table 1 Descriptive statistic

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Unit	Numbers	Mean	Stand error	Minimum	Maximum
CO_2 emission *(lnco2)*	Million tons	2160	30.99	28.49	2.265	230.7
Annual patents approved *(lnpat)*	Unit	2376	3270	8143	5	106,089
GDP *(lngdp)*	10 thousand yuan	2337	1.263e+07	2.617e+07	352,861	2.625e+08
Proportion of secondary industry *(str)*	%	2365	49.38	10.95	13.51	83.40
GDP per capita (*lngdp_p*)	Yuan	2304	55,458	112,789	5728	5.265e+06
House investment (*lnhou*)	10 thousand yuan	2318	2.024e+06	4.128e+06	9919	3.599e+07
Population (*lnpop*)	10 thousand	2286	1.243e+06	1.691e+06	109,056	1.729e+07
Dust discharge *(lndus)*	Tons	2365	31,012	90,883	34	3.154e+06
Polluted water discharge *(lnplw)*	Tons	2365	7501	9162	7	110,763
SO_2 discharge *(lnso2)*	Tons	2365	58,198	89,819	2	1.526e+06
Labor stock *(lnlab)*	millions	2364	190.9	282.5	1.042	2430
Capital stock *(lncap)*	10 Thousand	2365	5.136e+07	5.881e+07	1.198e+06	5.434e+08
Public funds for science and technology *(lntechin)*	10 Thousand	2087	61,093	254,525	125.9	3.361e+06
Number of cities	215					

direct effect of technology innovations on CO_2 emissions is unclear, the study employs the mediating model to do empirical analysis in order to explore the direct and indirect impact of technology on CO_2 emissions.

The mediation model

Based on the methodology of mediating model, the study builds the model as 1 to 4. Corner marks i and t represent cities and years in China. Model 1 tests whether there is a significant correlation between CO_2 emissions and technology innovations ($lnPAT_{it}$). Models 2 to 3 tests whether there is an actual impact from the technology innovation to intermediary variables-economic growth and industrial structure. Model 4 tests the effect of technology innovations on CO_2 emissions with controlling economic growth and industrial structure. Technically, the study can calculate the direct and indirect impact of technology innovations on CO_2 emissions by multiplying variables' coefficients. γ_1 can be referred to as the direct impact of technology innovations on CO_2 emissions. $\beta_1 \times \gamma_2$ can be referred to as the indirect impact through technology innovations on economic growth. $\eta_1 \times \gamma_3$ can be referred to as the indirect impact through technology innovations on industrial structure.

$$lnCO2_{it} = \alpha_0 + \alpha_1 lnPAT_{it} + \alpha_2 X_{it} + v_{it} \tag{2}$$

$$lnGDP_{it} = \beta_0 + \beta_1 lnPAT_{it} + \beta_2 STR_{it} + \beta_3 lnX_{it} + v_{it} \tag{3}$$

$$STR_{it} = \eta_0 + \eta_1 lnPAT_{it} + \eta_2 lnX_{it} + v_{it} \tag{4}$$

$$lnCO2_{it} = \gamma_0 + \gamma_1 lnPAT_{it} + \gamma_2 lnGDP_{it} + \gamma_3 STR_{it} + v_{it} \tag{5}$$

Further investigation

After investigating the impact of the technology innovations, this study builds two additional models to test further whether there are inverted "U-shaped" relations between CO_2 emissions, technology, and GDP. Therefore, the study adds the squared terms of technology innovations and GDP as dependent variables, respectively. Besides, this study also introduces CO_2 emissions intensity as CO_2 emissions per GDP ($lnCO2\_e_{it}$) to explore the impact of technology innovations on "CO_2 emissions efficiency."

$$lnCO2_{it} = \gamma_0 + \gamma_1 lnPAT_{it} + \gamma_2 (lnPAT_{it})^2 + \gamma_3 lnGDP_{it} + \gamma_4 STR_{it} + v_{it} \tag{6}$$

$$lnCO2_{it} = \gamma_0 + \gamma_1 lnPAT_{it} + \gamma_2 lnGDP_{it} + \gamma_3 (lnGDP_{it})^2 + \gamma_4 STR_{it} + v_{it} \tag{7}$$

$$lnCO2\_e_{it} = \gamma_0 + \gamma_1 lnPAT_{it} + \gamma_2 (lnPAT_{it})^2 + \gamma_3 lnGDP_{it} + \gamma_4 STR_{it} + v_{it} \tag{8}$$

The model for heterogeneity analysis

Apparently, by using the panel data, this study expects that the locations of cities, economic development, the economic scale, and the industrial structure of cities can affect the impact of technology innovations on CO_2 emissions. Therefore, in the heterogeneity analysis, this study constructed two models (8) and (9): one adds two cross variables which are $ln(PAT \times GDP_{it})$ and $ln(PAT \times STR_{it})$, another divides the dataset into three parts by the regions of cities—the East, the Middle, and the West. It is necessary to distinguish between the mediating effect and moderating effect in case of being confused. Mediation discusses problems with the causal-steps procedure, whether a consequential relationship between the antecedent and the outcome. Additionally, the moderator acts upon the relationship between two variables and changes its direction or strength, which is outside the causal chain (Aguinis et al. 2017). Technically, moderation is a tool for analyzing heterogeneity regarding categorization of continuous variables. In this research, cross variables represent how the impact of patents approved changes with different sizes of GDP and industrial structure.

$$lnCO2_{it} = \gamma_0 + \gamma_1 lnPAT_{it} + \gamma_2 lnGDP_{it} + \gamma_3 STR_{it} + \gamma_4 ln(PAT * GDP_{it}) + \gamma_5 ln(PAT * STR_{it}) + v_{it} \quad (9)$$

$$lnCO2_{it} = \gamma_0 + \gamma_1 lnPAT_{it} + \gamma_2 lnGDP_{it} + \gamma_3 STR_{it} + v_{it}(\text{if region is the East, the Middle, the West}) \quad (10)$$

Empirical analysis and results

Correlation and unit root test

The correlation analysis is conducted, and the results are presented in Table 2. The CO_2 emissions show the highest correlation with lncap (74.7%), followed by its correlation with lnpat (68.4%) and lnhou (67.1%). They present a positive correlation, whereas CO_2 emissions are found least correlated with str (10.8%), presenting a negative correlation between the two variables. Among other variables, lngdp exhibits the highest correlation with lnhou (88.2%), while lngdp_p and str are revealed least correlated (13.9%) across the sample, indicating the presence of positive correlation among these variables.

The unit root test results are presented in Table 3. According to different test methods, CO_2 emissions, technology innovations, economic growth, and industrial structure are stationary without difference or at 1st difference. And the results indicate four variables are integrated at $I(0)$ or $I(1)$, which states that there might exist a long-term relationship.

Baseline regression

The mediating effect of technology innovations

Table 4 shows the baseline regression result, which is grounded on the methodology of mediating effect. The regression is applied by excluding economic growth and industrial structure transformation and including GDP per capita, house investment, fixed capital stock, population, and foreign direct investment as controlling variables. The regression results indicate that controlling variables such as income level, population, and capital stock generally increase cities' CO_2 emissions, consistent with previous research (Lin and Liu 2010; Verbič et al. 2021; Chen et al. 2018; Li and Zhou 2012). FDI has no significant influence on CO_2 emissions, supporting the findings of previous studies that the "Pollution Haven Hypothesis" did not hold in China (Demana and Afesorgbor 2020; Song et al. 2011; Zhan et al. 2021). Principally, the technology innovations

Table 2 Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) lnco2	1.000							
(2) lnpat	0.684	1.000						
(3) lngdp	0.658	0.822	1.000					
(4) lngdp_p	0.412	0.585	0.702	1.000				
(5) str	−0.108	−0.153	−0.064	0.139	1.000			
(6) lnpop	0.606	0.710	0.869	0.258	−0.184	1.000		
(7) lncap	0.747	0.880	0.788	0.594	−0.174	0.657	1.000	
(8) lnhou	0.671	0.831	0.882	0.582	−0.198	0.792	0.813	1.000

Table 3 Unit root test

Test	Variables			
	lnco2	lnpat	lngdp	structure
Levin, Lin and Chu	(−23.4198)*	(−21.4398)*	(−27.1477)*	(−24.5839)*
Im, Pesaran and Shin W-stat	(−2.3365)	(−2.3302)	(−2.0906)	(−2.0826)
ADF–Fisher chi-square	(580.3795)*	(762.9622)*	(819.6404)*	(614.0826)*
PP–Fisher chi-square	(329.5596)*	(1021.7645)*	(790.1371)*	(926.1671)*

Numbers in parenthesis are test statistics and * indicates 1st difference increase the cities' CO_2 emissions. This result is inconsistent with Fatima et al. (2021) since they empirically argued that the promotion of renewable energy technology solutions significantly reduced carbon emissions in a developing country of Pakistan. Similarly, Jabeen et al. (2021b) also negated this finding by revealing that green energy technologies substantially mitigated carbon emissions by increasing renewable energy share in the total energy mix. Then we investigate the influence of technology innovations on GDP and industrial structure. And in the case of collinearity, some less relevant variables are removed. Table 4 shows that technology innovations increase both economic growth and the proportion of secondary industry. Besides technology innovations, economic growth is also positively linked with the population, house investment, and the proportion of secondary industry. Further, the proportion of the secondary industry is also positively linked with income level, population, and capital stock. In the following step, the study regresses CO_2 emissions on technology innovations, economic growth, and industrial structure simultaneously. The coefficients of technology innovations and economic growth appear to be positive. From the baseline regression results, the study summarizes as follows:

Firstly, technology innovations increase CO_2 emissions both directly and indirectly. In this regard, it partly increases CO_2 emissions through economic growth. But the proportion of secondary industry cannot increase the CO_2 emissions directly, and verify hypothesis 2. Secondly, multiple transmission mechanisms are given as "technology innovations → proportion of secondary industry → economic growth → CO_2 emissions." It infers that secondary industry is also a crucial factor contributing to CO_2 emissions indirectly from these linking mechanisms, and verify hypothesis 3. Thirdly, since technology innovations increase the proportion of the secondary industry, it infers that the innovation in the "dirty industry" might be responsible for an increase in CO_2 emissions (Acemoglu et al. 2012; Aghion et al. 2016), and dismiss hypothesis 1. This finding is also consistent with the argument of Ali et al. (2021) since they emphasized that the renovation of existing industrial systems will only help carbon emissions promotion in the context of Bangladesh. Lastly, FDI imparts no significant influence on CO_2 emissions, supporting the idea that the "Pollution Heaven Hypothesis" might not hold in China.

Table 4 Regression results of mediating effect model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	lnco2	lnco2	lnco2	lngdp	structure	lnco2	lnco2
lnpat	0.017*	0.025***	0.016*	0.053***	0.012**	0.024***	0.019**
	(1.92)	(3.15)	(1.79)	(3.06)	(2.15)	(3.14)	(2.07)
lngdp_p	0.107***	0.052***	0.119***		0.120***		
	(3.57)	(2.90)	(4.18)		(5.92)		
lnpop	0.039*	0.038**	0.061***	0.390***	0.076***		
	(1.78)	(2.52)	(2.61)	(3.13)	(5.34)		
lnhou	0.027***	−0.003	0.029***	0.091***	−0.006	−0.003	0.028***
	(2.62)	(−0.37)	(2.87)	(5.99)	(−1.25)	(−0.32)	(2.92)
lncap	0.113***	0.181***	0.106***	0.060	0.040**	0.180***	0.147***
	(6.32)	(4.00)	(6.15)	(1.47)	(2.50)	(4.05)	(7.68)
lnfdi	−0.022	−0.010	−0.014	0.017	0.002	−0.010	−0.011
	(−1.63)	(−0.83)	(−1.10)	(0.83)	(0.27)	(−0.84)	(−0.93)
Structure				1.299***		0.060	0.464***
				(8.95)		(0.87)	(6.84)
lngdp						0.037**	0.044*
						(2.46)	(1.94)
Constant	−0.369	−0.749	−0.592*	9.906***	−1.745***	−0.614	−0.693**
	(−1.29)	(−1.09)	(−1.96)	(10.72)	(−5.53)	(−0.86)	(−2.40)
Observations	2056	2056	2056	2245	2245	2087	2087
R-squared	0.608	0.782	0.607	0.862	0.503	0.785	0.629
Number of city	214	214	214	214	214	214	214
City FE	Yes	Yes	No	Yes	Yes	Yes	No
Year FE	No	Yes	No	Yes	Yes	Yes	No

*, **, and *** indicate robust level of significance of 10%, 5%, and 1%, respectively

Further investigation

The EKC hypothesis by Grossman and Krueger (1991) claims that though the increase of GDP will generally lead to more CO_2 emissions, its impact decreases with the rise in GDP growth. The intuition is that a country with a relatively high economic development level usually has a low-carbon industrial structure, clean and productive technologies, and a more robust environmental protection awareness. In this regard, we construct three additional regression models by adding GDP per capita (lngdp_p), square term of annual patent approved (lnpat_s), and the squared term of GDP (lngdp_s) as new independent variables to investigate the "EKC" impacts of annual patent approved and GDP on CO_2 emissions. Table 5 shows that the coefficients of annual patent approved square term (lnpat_s) are negative and small, indicating that the impact of technology innovations on CO_2 emissions confirms the "EKC" curve. However, China is still far from the turning point that technology innovations would decrease CO_2 emissions. The proportion of secondary industry has a little direct impact on CO_2 emissions. This is because the industrial structure is significantly linked with GDP, and its impact on CO_2 emissions is channeled through the GDP. The coefficient of GDP square term (lngdp_s) is negative, consistent with most previous research that the negative impact of economic growth on CO_2 emissions gradually declines (Danish et al. 2018; Su et al. 2021; Ahmad et al. 2021a; Işık et al. 2021). Considering the CO_2 emissions intensity, coefficients of annual patent approved are positive, implying that technology innovations also increase the CO_2 emissions intensity. And the negative coefficients of the proportion of secondary industry and GDP per capita, along with the higher proportion of secondary industry and income level, indicate that the CO_2 emissions intensity decreases. Based on this analysis, the key results are summarized as follows.

Firstly, the situation that technology innovations lead to more CO_2 emissions is hard to change in the short term. Secondly, the "EKC" curve reveals the new aspects of the significant influence of technology innovations

Table 5 Further regression outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	lnco2	lnco2	lnco2	lnco2	lnco2_e	lnco2_e
lnpat	0.113***	0.145***	0.022***	0.020**	0.158***	0.222***
	(5.81)	(6.58)	(2.85)	(2.25)	(3.60)	(4.20)
lnpat_s	−0.008***	−0.010***			−0.016***	−0.025***
	(−4.69)	(−5.99)			(−4.79)	(−6.65)
lngdp	0.049***	0.051**	0.398**	0.490***		
	(3.20)	(2.26)	(2.49)	(2.90)		
Structure	0.033	0.368***	0.034	0.424***	−1.160***	−0.464**
	(0.53)	(5.35)	(0.50)	(5.76)	(−4.88)	(−2.20)
lnhou	0.002	0.031***	−0.003	0.026**	−0.101***	−0.070***
	(0.19)	(3.10)	(−0.37)	(2.59)	(−5.37)	(−3.71)
lncap	0.143***	0.141***	0.165***	0.150***	0.146**	−0.115***
	(4.02)	(7.55)	(4.01)	(7.72)	(2.47)	(−2.95)
lnfdi	−0.013	−0.020*	−0.011	−0.020	−0.013	−0.035
	(−1.16)	(−1.72)	(−0.98)	(−1.58)	(−0.51)	(−1.32)
lngdp_s			−0.012**	−0.015***		
			(−2.27)	(−2.77)		
lngdp_p					−0.112**	−0.098**
					(−2.47)	(−2.60)
Constant	−0.443	−0.936***	−3.130**	−3.944***	−11.642***	−8.072***
	(−0.77)	(−3.26)	(−2.48)	(−3.04)	(−12.64)	(−16.63)
Observations	2087	2087	2087	2087	2055	2055
R-squared	0.797	0.653	0.788	0.635	0.638	0.572
Number of city	214	214	214	214	214	214
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No

*, **, and *** indicate robust level of significance of 10%, 5%, and 1%, respectively

and economic growth on CO_2 emissions. Thirdly, though the higher proportion of secondary industry indirectly increases CO_2 emissions, it decreases CO_2 emissions intensity.

Robustness analysis

Regression analysis with truncated variables

In order to eliminate errors caused by extreme values, the study uses the truncated sample to do further regression. Technically, Table 6 demonstrates the results of cutting 1%, 2.5%, and 5% extreme dependent and independent variables' values. Based on empirical results, the technology innovations are still positive, which means the previous results are robust regarding the extreme values. However, there is a little change in GDP's findings. In this regard, half coefficients of economic growth are insignificant, signifying that the positive link between economic growth and CO_2 emissions is more obvious in large cities than in small cities.

Regression with alternative dependent variables

Besides CO_2 emissions, environmental indicators, including dust discharge, polluted water, and SO_2 emissions, are also vital pollutants that could potentially bring about serious damage to environmental quality. Investigating the impact of technology innovations on these three pollutant emissions may improve the reliability of our results based on CO_2 emissions. Table 7 reports the coefficients of annual patent approved regressed by dust discharge and SO_2 emissions are positive, while the results regressed by polluted water are statistically insignificant. However, this finding is aligned with the channel that the direct impact of technology innovations on pollutant discharge is positive since technology innovations encourage economic growth, thus generating an indirect impact on pollutant discharge. As for the direct impact of technology innovations on polluted water, though its coefficient is not significant, it may indirectly reduce polluted water discharge. It may occur through the channel that since

Table 6 Regression with truncated variables

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	lnco2_w1	lnco2_w2	lnco2_w3	lnco2	lnco2	lnco2
lnpat	0.021***	0.021***	0.022***			
	(3.06)	(3.03)	(3.09)			
lngdp	0.347**	0.364**	0.221	0.252*	0.204	0.076
	(2.19)	(2.02)	(1.38)	(1.75)	(1.28)	(0.42)
lngdp_s	−0.010**	−0.011*	−0.006	−0.007	−0.005	−0.001
	(−1.99)	(−1.84)	(−1.16)	(−1.50)	(−1.03)	(−0.21)
str	0.043	0.048	0.072	0.037	0.035	0.052
	(0.65)	(0.73)	(1.07)	(0.56)	(0.53)	(0.87)
lncap	0.159***	0.157***	0.147***	0.152***	0.146***	0.132***
	(3.94)	(3.81)	(3.72)	(3.85)	(3.69)	(3.89)
lnfdi	−0.003	−0.005	−0.008	−0.012	−0.013	−0.011
	(−0.28)	(−0.59)	(−0.98)	(−1.00)	(−1.06)	(−1.01)
lnhou	−0.007	−0.004	−0.002	−0.002	−0.001	0.003
	(−0.90)	(−0.53)	(−0.26)	(−0.22)	(−0.12)	(0.31)
lnpat_w1				0.019**		
				(2.43)		
lnpat_w2					0.019**	
					(2.33)	
lnpat_w3						0.021**
						(2.59)
Constant	−2.637**	−2.759**	−1.502	−1.780	−1.316	−0.159
	(−2.15)	(−2.03)	(−1.34)	(−1.57)	(−1.04)	(−0.11)
Observations	2046	1980	1875	2046	1989	1883
R-squared	0.811	0.810	0.821	0.787	0.786	0.792
Number of city	212	209	204	214	214	212
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

*, **, and *** indicate robust level of significance of 10%, 5%, and 1%, respectively

technology innovations promote economic growth and economic growth is negative linked with polluted water discharge. From the robustness test, technology innovations mainly lead to air pollution. But since water pollution is relatively a serious and urgent problem, Chinese government has made much effort to control water pollution in previous years (Liao et al. 2021).

Regression with the alternative independent variables

Another major concern is whether annual patent approved is an appropriate indicator for technology innovations. Since technology innovations are not actual inputs like labor and capital, the measurement of technology innovations is rather difficult and ambiguous. So in the case of the errors caused by different indicators for technology innovations, the study substitutes annual patent approved for total factor product (TFP) and each city's public investment for science and technology. TFP is calculated according to the research by Hsieh and Klenow (2009) . As can be seen from Table 8, the coefficients of TFP and public funds for science and technology are still positive and statistically significant. Thus, results regressed by different independent variables indicate that our previous results are robust with two different technology innovations indicators. And three industrial structure coefficients are positive and statistically significant, implying that the proportion of the secondary industry is expected to increase the total CO_2 emissions. Besides, "lngdp" and "lngdp_p" are not included in the regression because TFP is calculated using "lngdp" and there would be strong collinearity between TFP and "lngdp." Moreover, this way can also help estimate the impact of industrial structure transformation on CO_2 emissions without disturbing the economic growth.

Heterogeneity analysis

The moderating effect

To further investigate whether technology innovations have a different impact on CO_2 emissions for different economic growth and industrial structure variables, this study construct two additional cross variables (cro1 = (lnpat) × (lngdp), cro2 = structure × ln(pat)) and added them into the regression model.

Table 9 displays the annual patent approved remained positive and statistically significant. The new variable cro1 is negative and significant, suggesting that technology innovations have less impact on CO_2 emissions in cities with bigger economic scales (GDP). To some extent, this result shows consistency with the findings in the "Regression

Table 7 Regression with different dependent variables

	(1)	(2)	(3)
Variables	lndus	lnplw	lnso2
lnpat	0.195***	−0.037	0.100*
	(2.67)	(−0.79)	(1.93)
lngdp	0.073	−1.980**	4.018***
	(0.06)	(−2.51)	(4.76)
lngdp_s	−0.003	0.067***	−0.129***
	(−0.08)	(2.66)	(−4.81)
Structure	−0.127	0.352	−0.105
	(−0.28)	(0.98)	(−0.25)
lncap	−0.209	−0.162	−0.127
	(−1.14)	(−1.31)	(−0.84)
lnfdi	−0.117	−0.007	−0.009
	(−1.50)	(−0.12)	(−0.14)
lnhou	0.000	0.008	0.002
	(0.01)	(0.19)	(0.04)
Constant	12.839	25.759***	−18.697***
	(1.52)	(4.52)	(−2.87)
Observations	2281	2281	2281
R-squared	0.314	0.380	0.605
Number of city	215	215	215
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

*, **, and *** indicate robust level of significance of 10%, 5%, and 1%, respectively

Table 8 Regression with different independent variables

	(1)	(2)	(3)	(4)
Variables	lnco2	lnco2	lnco2	lnco2
lntfp	0.041**	0.070***		
	(2.60)	(2.97)		
str	0.069	0.471***	0.121*	0.523***
	(0.99)	(6.83)	(1.86)	(7.67)
lncap	0.197***	0.191***	0.180***	0.191***
	(4.60)	(20.13)	(4.08)	(17.19)
lnlab	0.046**	0.076***	0.015	0.030*
	(2.57)	(3.40)	(1.03)	(1.69)
lntechin			0.008*	0.014**
			(1.76)	(2.26)
Constant	−0.924	−1.328***	−0.371	−0.935***
	(−1.24)	(−5.59)	(−0.50)	(−4.21)
Observations	2106	2106	2072	2072
R-squared	0.784		0.782	
Number of city	214	214	213	213
City FE	Yes	No	Yes	No
Year FE	Yes	No	Yes	No

*, **, and *** indicate robust level of significance of 10%, 5%, and 1%, respectively

analysis with truncated variables" section. It infers that cities with a more prominent economic scale might achieve a more significant scale effect, cultivating productivity and mitigating the negative impact of technology.

Regression for different regions

To investigate whether technology innovations have a different impact on CO_2 emissions in different regions, we divide the data into the east, the middle, and the west regions. Table 10 demonstrates that the CO_2 emissions increment influence of technology innovation is more significant in the middle region. FDI mitigates CO_2 emissions in the east region, advising that reverse technology spillovers might help CO_2 emissions reduction in the east region. Basically, the heterogeneity results reflect that factors influencing CO_2 emissions are distinguished in different regions.

Table 9 Regression of moderating model

	(1)	(2)
Variables	lnco2	lnco2
lnpat	0.368***	0.535**
	(2.92)	(2.15)
lngdp	−0.404	−0.665
	(−1.11)	(−0.87)
lngdp_s	0.019	0.033
	(1.38)	(1.13)
str	0.352	
	(1.55)	
cro1	−0.021**	−0.032*
	(-2.54)	(−1.95)
cro2	−0.054	0.047
	(−1.42)	(1.10)
lncap	0.160***	
	(3.87)	
lnfdi	−0.014	0.006
	(−1.23)	(0.53)
lnhou	−0.003	0.043***
	(−0.33)	(4.14)
Constant	1.972	4.659
	(0.79)	(0.92)
Observations	2087	2097
R-squared	0.795	0.596
Number of city	214	215
City FE	Yes	No
Year FE	Yes	No

*, **, and *** indicate robust level of significance of 10%, 5%, and 1%, respectively

Conclusion and policy implications

This study aimed to examine the direct and indirect impact of technology innovations on CO_2 emissions by employing the mediating model for the micro perspective across the prefecture-level cities of China. The key empirical results suggested that, firstly, the technology innovations in China generally increased cities' total CO_2 emissions and CO_2 emissions per capita both directly and indirectly (through economic growth and industrial structure transformation). Furthermore, an increasing proportion of secondary industry promoted economic growth in China, which indirectly increased the cities' CO_2 emissions. In response to a rise in GDP growth, the positive impact of technology innovations on CO_2 emissions is expected to reduce. But it would take a long time for technology innovations to reduce cities' CO_2 emissions. Secondly, the EKC characteristics are revealed in the impact of technology innovations and economic growth on CO_2 emissions. Thirdly, besides the CO_2 emissions indicator, technology innovations are also expected to increase the cities' dust and SO_2 discharge. Likewise, the positive impact of technology innovations on CO_2 emissions in

Table 10 Regression with different regions

	The east	The middle	The west
Variables	lnco2	lnco2	lnco2
lnpat	0.013	0.041***	−0.017
	(1.28)	(3.12)	(−0.80)
lngdp	0.365*	−0.117	0.296
	(1.87)	(−0.40)	(0.97)
lngdp_s	−0.010	0.006	−0.009
	(−1.66)	(0.67)	(−1.02)
str	−0.004	−0.208**	0.191
	(−0.06)	(−2.62)	(1.01)
lncap	0.202***	0.014	0.193***
	(5.55)	(0.57)	(2.73)
lnfdi	−0.043***	0.010	−0.031
	(−2.88)	(0.87)	(−1.38)
lnhou	0.011	−0.004	0.002
	(1.18)	(−0.44)	(0.06)
Constant	−2.973*	2.649	−2.599
	(−1.79)	(1.18)	(−0.87)
Observations	853	808	426
R-squared	0.811	0.835	0.843
Number of city	87	84	43
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

*, **, and *** indicate robust level of significance of 10%, 5%, and 1%, respectively

the middle region exhibited a rather greater effect than in the east and the west regions. In light of these outcomes, it is noteworthy that technology innovations significantly increase cities' proportion of the secondary industry, and secondary industry emits around 70% of total CO_2 emissions. The increasing impact of technology on CO_2 emissions might be attributed to the path of "dirty innovations," facilitating economic growth and cost efficiency rather than focusing on the adverse environmental effects in China. Therefore, this conclusion is actually not astonishing that technology innovations have worsened CO_2 emissions in China to maintain economic growth. Along these lines, the "carbon neutrality" and "carbon peak" targets of China are expected to face substantial challenges in the days to come.

Based on empirical results, the following policies are drawn: firstly, since technology innovations generally increase CO_2 emissions, facilitating the transition of "clean technology" innovations should be the top priority. The Chinese government should strengthen fiscal and policy support to "clean technology," and draw out its central regulatory power to change relative profit and cost of "clean technology" and "dirty technology." Secondly, the estimated results indicate that the increasing proportion of secondary industry would lead to more CO_2 emissions. Therefore, it is important to facilitate the transformation to tertiary industry. Thirdly, the government needs to give more concern to the middle region to control the negative influence of technology innovations on CO_2 emissions, formulating distinguished policies towards different regions. Finally, small- and medium-sized cities tend to discharge more CO_2 emissions than big cities; consequently, the monitoring and assessment of the negative effects of technology innovations should be ensured in small- and medium-sized cities.

In the next step, based on the complexity of technological innovation, there are many issues that need to be further studied in the follow-up research, such as what is the mechanism of green technology and low-carbon technology on carbon emission reduction, and whether their emission reduction effects are the same, etc.

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