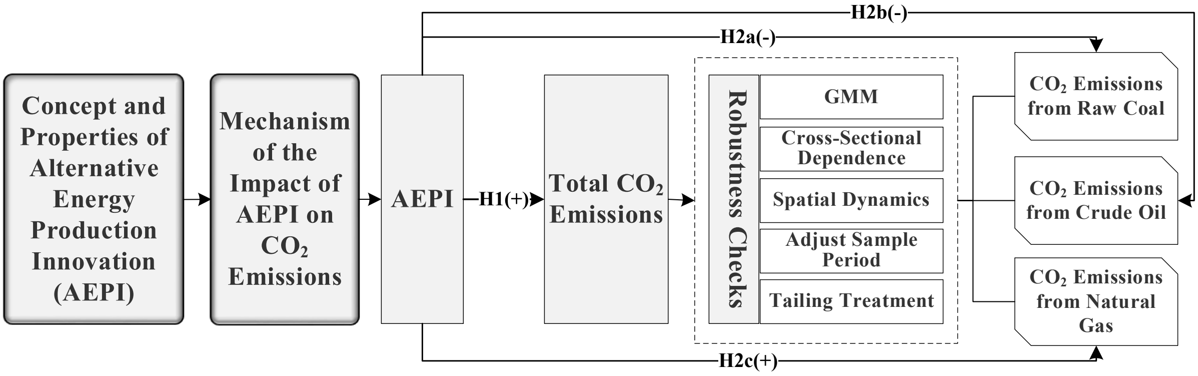
Impacts of Alternative Energy Production Innovation on Reducing CO_2 Emissions: Evidence from China

ABSTRACT: Although environmental economics research explores the impacts of green innovation on reducing CO_2 emissions, most studies ignore these effects in emerging economies. This paper examines how alternative energy production innovation (AEPI) reduces CO_2 emissions. Using a sample of 30 provinces in China during the 1997–2017 period, we find AEPI is negatively related to CO_2 emissions. Specifically, the results show that innovations in raw coal and crude oil are negatively related to CO_2 emissions, while innovations in natural gas are positively related to CO_2 emissions. This study contributes to research on technological innovation and environmental economics. First, we find AEPI as the main driver of all types of green innovation in reducing CO_2 emissions. Second, we explore the heterogeneous effects of different energy sources and deepen our understanding of different reduction mechanisms. Third, this study makes a methodological contribution to research using a series of quantitative analyses.

Keywords: alternative energy production innovation, CO_2 emissions, green innovation, energy structure

Graphical Abstract:



1. Introduction

Energy plays a crucial role in global economic development and growth. However, CO_2 caused by the use of fossil energy lead to global warming, posing a serious challenge to the sustainable development of the global economy [1, 2]. Although COVID-19 has slowed economic growth and reduced energy consumption, researchers argue that energy consumption could increase sharply in the post-COVID-19 period, leading to a sharp increase in CO_2 [3].

Many studies show that technological innovation in energy products is an effective measure to reduce CO_2 [4]. Most of the literature focuses on the impacts of renewable energy technology innovation [5-7], while the effects of alternative energy production innovation (AEPI) are neglected. As a branch of green innovation, AEPI refers to innovation in alternative energy production (AEP) [8]. In addition to renewable energy, AEPI includes new technologies that improve the efficiency of traditional energy sources, which alleviates the environmental hype in terms of economic growth [9].

However, traditional fossil energy sources remain essential for economic growth, particularly in emerging economies. Therefore, it is important to examine the effects of AEPI on reducing CO_2.

In addition, few studies examine the effects of heterogeneity in energy structure. As the substitution is incremental, traditional fossil energy is often used in combination with cleaner alternative energy [10, 11]. Furthermore, the substitution costs for fossil fuels like coal, crude oil and natural gas may differ due to the need to balance commercial costs and environmental protection [12, 13]. Therefore, it remains unclear how the technological improvement of different energy sources affects the reduction of CO_2.

Based on the literature, this study examines the following two research questions: (1) Does AEPI reduce CO_2? (2) Does the energy structure affect the effects of AEPI on CO_2?

To answer the above two questions, we choose China as the research context. As an emerging economy, China has been the world's largest energy consumer for several consecutive years [14-16]. Faced with pressure from the public to reduce CO_2 and economic growth, China has accelerated its development of alternative energy sources [17-19]. However, considering the conflicts between economic growth and sustainable development, China may face an incremental transition process with a heterogeneous energy consumption structure [2, 4]. More importantly, innovations in China would lead to a further spill-over effect since most developing economies employ Chinese technological know-how. For example, Deng et al. (2020) found that China has technology spillover effects from trade and investment with other emerging countries [20]. Therefore, we conduct our study in the context of China.

This study contributes to research on technological innovation and environmental economics in several aspects. First, AEPI is based on the general definition of green innovation, and its effects on reducing CO_2 are confirmed by our results, proving that AEPI is the main driver of all types of green innovation. Second, this study explores the heterogeneous effects of different energy sources, deepening our understanding of different reduction mechanisms. Third, this study makes a methodological contribution to research. Specifically, a series of quantitative analyses are conducted, including GMM models, cross-sectional and spatial dynamic analyses to verify the robustness of our main regression results.

The rest of the paper is structured as follows. Section 2 introduces the theoretical framework of the study and develops the hypotheses. Section 3 presents the research method. Section 4 reports the main results and those of the robustness checks. Section 4 discusses the results. Finally, Section 5 concludes the study and offers policy implications.

2. Theoretical framework and hypothesis development

2.1. Alternative energy production innovation (AEPI)

AEPI refers to innovation in AEP derived from green innovation [8]. As an important subcategory of Green Inventory in International Patent Classification (IPC), AEP patents are defined as innovations aimed at developing or promoting the utility efficiency of alternative energy sources. AEPI includes new energy technology inventions and improvements in the use of traditional energy sources [21]. Figure 1 shows the composition of green patents, with specific numbers and percentages for each type of green innovation, in the years of 1997 and 2017, respectively. AEPI was ranked fourth among all innovations in the green invention patent system in terms of weight in China in 2017, behind waste management invention patents, energy conservation invention patents and administrative, regulatory or design invention patents (Fig. 1). Compared with waste management patents, which ranked first in the Green Innovation Index and focus on reducing polluting emissions, AEPI has a greater effect on inputs that produce CO_2 emissions, thereby reducing emissions.

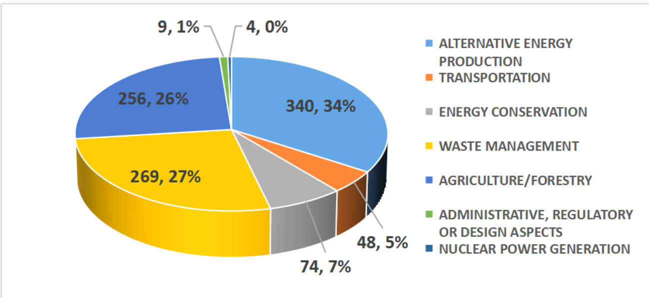


Fig. 1a. Composition of green invention patents, 1997

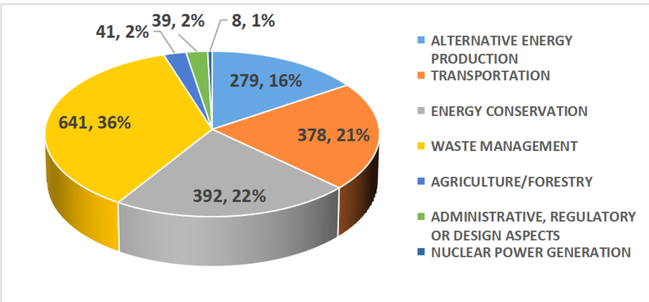


Fig. 1b. Composition of green utility model patents, 1997

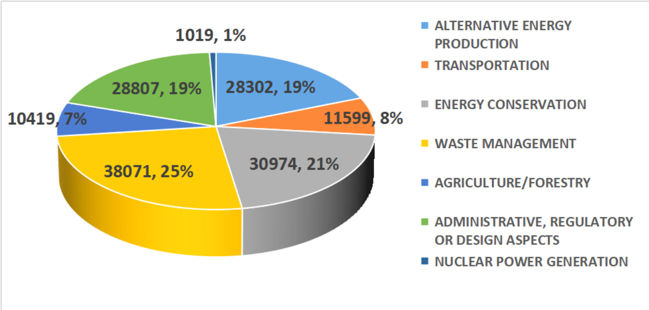


Fig. 1c. Composition of green invention patents, 2017

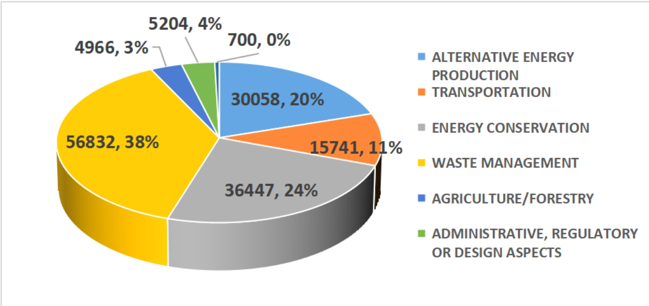


Fig. 1d. Composition of green utility model patents, 2017

Fig. 1. Composition of green patents

Although no studies examine the effects of AEPI on CO_2 emissions separately from its important role in green innovation, the impacts of green innovation on CO_2 emissions are widely explored [22-24]. Most studies examine the direct effects of green innovation on CO_2 emissions and confirm the role of green innovation in reducing CO_2 emissions [25-27]. However, the conclusions are far from consistent [28]. In addition, scholars argue that green innovation acts as a means of low-carbon energy transformation and thus exerts intermediate effects on reducing CO_2 emissions [29-31].

These inconsistent results may be due to a lack of consideration of the heterogeneity of green innovation patents and their possible impacts on CO_2 emissions. Green innovation is a concept with rich connotations and includes various innovations related to environmental improvement. The objectives, characteristics and functions of different types of green innovation vary widely [32, 33]. The patents in the IPC Green

Inventory are divided into seven categories, covering alternative energy production, transportation, energy conservation, waste management, agriculture/forestry, administrative, regulatory or design aspects, and nuclear power generation (see Table 1). As Table 1 shows, different types of innovation have different mechanisms and pathways of impact on reducing CO_2 emissions [9, 34].

Table 1

Seven categories of the IPC Green Inventory

Abbreviation	Category Name	Subclasses
AEPP	Alternative energy production patents	Biofuels; integrated gasification combined cycle (IGCC); fuel cells; pyrolysis or gasification of biomass; harnessing energy from man-made waste; hydro energy; ocean thermal energy conversion (OTEC); wind energy; solar energy; geothermal energy; other production or use of heat not derived from combustion, e.g., natural heat; use of waste heat; devices for producing mechanical power from muscle energy
TSP	Transportation patents	Vehicles in general; vehicles other than rail vehicles; rail vehicles; marine vessel propulsion; cosmonautic vehicles using solar energy
ECP	Energy conservation patents	Storage of electrical energy; power supply circuitry; measurement of electricity consumption; storage of thermal energy; low energy lighting; recovery of mechanical energy
WMP	Waste management patents	Waste disposal; waste treatment; consumption of waste by combustion; reuse of waste materials; pollution control
A/FP	Agriculture/forestry patents	Forestry techniques; alternative irrigation techniques; pesticide alternatives; soil improvement
ARDP	Administrative, regulatory or design patents	Commuting, e.g., teleworking; CO_2 emissions trading, e.g., pollution credits; static structural design
NPGP	Nuclear power generation patents	Nuclear engineering

Source: https://www.wipo.int/classifications/ipc/green-inventory

Although research results may be affected by factors such as research time, purpose and level of economic development [35], we believe that these inconsistent findings are due to a lack of attention to the heterogeneity among the types of green innovation [36]. For example, energy substitution innovations may effectively reduce CO_2 emissions by promoting the low-carbon transformation of energy. In contrast, waste treatment innovations focus on reducing other types of pollution and thus have little effect on CO_2 emissions [37, 38]. Therefore, it is crucial to separate AEPI from green innovation to investigate its impacts on reducing CO_2 emissions.

2.2. Hypothesis development

2.2.1. AEPI and its reduction effect on CO_2 emissions

The development of alternative energy innovation is not only driven by the demand for environmental protection but, more importantly, by concern over the depletion of natural resources. Although new energy sources are being actively promoted and developed by all countries, 80–95% of the world's energy still comes from fossil fuels. Moreover, as fossil energy is not renewable in the short term, it is likely to run out soon [39]. Therefore, AEPI may contribute to reducing CO_2 emissions by finding alternative energy sources or improving the efficiency of current energy use [40].

AEPI may also contribute to reducing CO_2 emissions by improving the efficiency of widely used new energy sources [41]. The emergence of alternative energy sources can increase the overall energy supply and provide more choices to the market [42]. Increasing the efficiency of alternative energy sources can directly reduce their cost of use [6, 7], which may reduce the cost of AEP in the market. Reducing the cost of AEP may lead to an increase in consumer demand for AEP. This demand comes from several aspects, as shown in Fig. 3. First is the power generation link. Indeed, the main demand for alternative energy sources comes from electricity production [43]. According to the *2020 China Renewable Energy Development Report*, renewable energy generated more than 2.2 trillion kilowatt hours, accounting for about 30% of China's total power generation. Alternative energy sources account for less than 5% of total energy consumption (Fig. 2). Lowering the cost of AEP may facilitate its wider use for power generation. Second, some alternative energy sources can be directly used in industrial production [44]. For example, geothermal energy can be used directly in industrial boilers without being converted into electricity. Third, the reduction in the cost of AEP has increased Chinese residents' demand for AEP for daily use [45]. Geothermal energy mining technology has been widely used for heating systems[46-48]. Recently, rooftop solar equipment providing residents with hot water and lighting has become popular in China[49-51]. In addition, due to the increase in the proportion of low-cost AEP in electricity, electricity is likely to gain popularity in the context of environmental regulations to reduce CO_2 emissions. Innovation may contribute to electric heating [52], thereby increasing the demand for AEP, which may indirectly reduce CO_2 emissions.

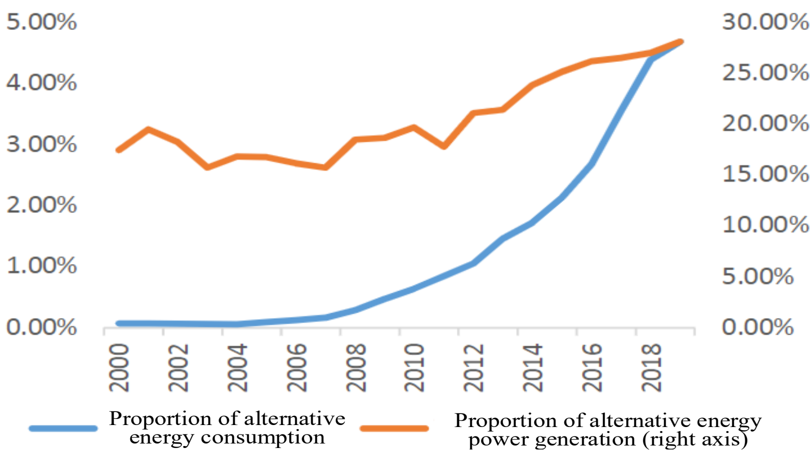


Fig. 2. Alternative energy consumption in China, 2000–2020

It is widely acknowledged that using new energy sources to replace fossil fuels is a way to reduce CO_2 emissions while facilitating economic growth [53-55]. Alternative energy sources include solar, hydropower, wind, biomass, wave, tidal, ocean temperature difference and geothermal energy [56]. Compared with traditional fossil energy sources, alternative energy sources generate less CO_2 emissions in the power/thermal generation process. They can also be technologically recycled, leading to their description as inexhaustible 'green power' [57]. While AEPI can improve production efficiency, diversifying AEP can facilitate the reduction of CO_2 emissions. Some types of AEPI aim to reduce the efficiency and level of CO_2 emissions in the process of AEP factory construction, equipment production and equipment processing. Therefore, although the relationship between AEP consumption and CO_2 emissions may be positive [58], the effects of AEPI on CO_2 emissions are still believed to be generally negative. Thus, the following hypothesis is proposed:

Hypothesis 1. AEPI is negatively related to CO_2 emissions.

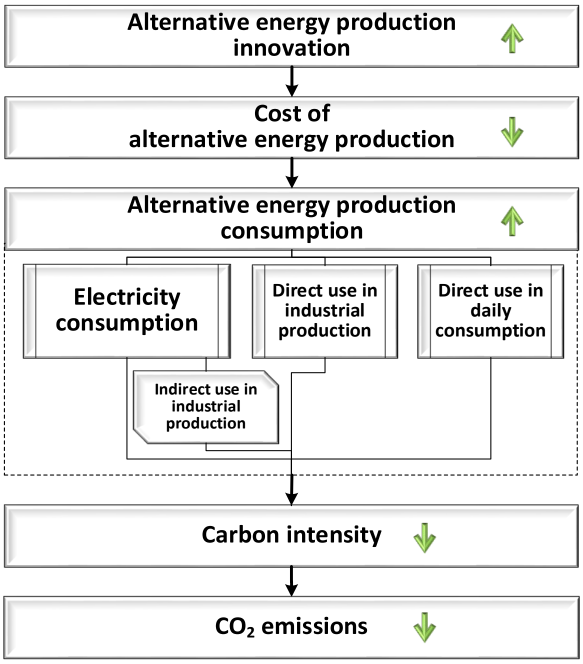


Fig. 3. Impact of AEP cost reduction on AEP consumer demand

2.2.2. Heterogeneous effects of AEPI on CO_2 emissions based on different energy sources

There is also heterogeneity in the mechanism of AEPI on CO_2 emissions based on different energy resources. AEPI includes not only innovation for AEP but also improvements in the efficiency of existing energy sources, which can reduce CO_2 emissions. Governments generally restrict the total volume of CO_2 emissions without regulating the specific source/type of energy used [59]. Thus, firms may prefer to adopt strategies to meet these regulations at the lowest cost, considering both the cost of energy and CO_2 emissions. Therefore, developing technologies to improve the efficiency of traditional energy sources and reduce CO_2 emissions could be a rational strategy for firms in practice.

Regarding the positive relationship between energy use and economic growth, it is undesirable to reduce energy consumption to achieve the CO_2 emissions reduction targets set by governments [60]. Adopting AEP may be one of the best solutions for firms to meet environmental regulations. Due to the great differences between energy sources, there is an order of priority in the process of energy substitution that meets environmental regulations. In general, low-cost alternative fossil energy sources are the first to replace low-carbon energy sources [61]. Among the three most commonly used fossil energy sources in China (i.e., coal, crude oil and natural gas), the replacement cost of coal is the lowest, followed by crude oil and natural gas [42].

The Chinese government has set its targets for CO_2 emissions reduction by 2030 and carbon neutrality by 2060, which has imposed strict environmental regulations on the market and thus shaped the behaviour of firms. As mentioned, the cost of energy substitution varies. When the supply of new energy products cannot fully satisfy the demand for traditional fossil energy substitution, the market may first choose fossil energy products with a comparatively low substitution cost, which may increase CO_2 emissions from that type of energy source [62]. Compared with natural gas, coal and crude oil are the first to be replaced by AEP due to their low cost of substitution and high CO_2 emissions. Although AEP has developed rapidly in recent decades, there is still a large gap between demand and supply in the market, with the supply of AEP falling short of its demand. Therefore, as an equivalent of AEP, natural gas remains one of the most important energy sources with low CO_2 emissions on the market. AEPI aimed at lowering the cost of using natural gas may lead to an increase in the total consumption of natural gas, which will increase CO_2 emissions. Thus, CO_2 emissions may increase as natural gas consumption increases due to the development of AEPI.

In addition, under institutional pressure to reduce CO_2 emissions quickly, firms may prioritise improving technologies on energies which generate high CO_2 emissions but are more cost-effective in economics. The investment in AEPI may flow to coal and crude oil rather than natural gas. Thus the quantity, depth and quality of innovations in coal and crude oil may significantly exceed those in natural gas. As a result, the innovation for reducing CO_2 emissions in coal and oil could be far more effective than that in natural gas. In other words, if the constraints on reducing CO_2 emissions reach a certain threshold, the AEPI in coal and crude oil may exert a crowding-out effect, leading to a decrease in innovation in natural gas, which may have a negative impact on CO_2 emission reduction from natural gas. Thus, the following hypotheses are proposed:

Hypothesis 2a. AEPI is negatively related to CO_2 emissions from raw coal.

Hypothesis 2b. AEPI is negatively related to CO_2 emissions from crude oil.

Hypothesis 2c. AEPI is positively related to CO_2 emissions from natural gas.

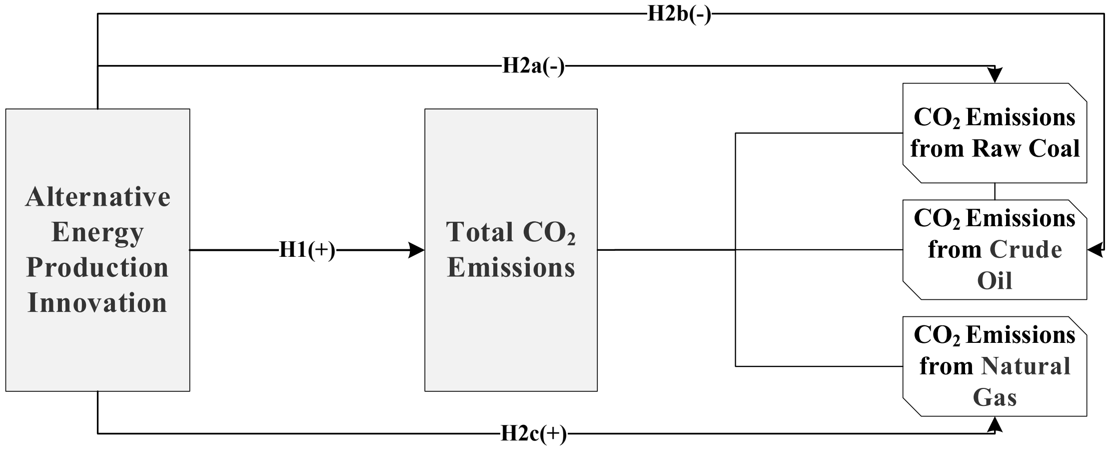


Fig. 4. The theoretical framework of the effects of AEPI on CO_2 emissions

3. Research methods

3.1. Sample and data

Table 2 presents the description of the sample. The panel data come from 30 Chinese provinces from 1997 to 2017 (Tibet, Hong Kong, Macao and Taiwan are excluded due to limited data availability). For our data analysis, the final sample includes 584 observations.

Table 2

Descriptive statistics of the sample

VARIABLE	(1) N	(2) Mean	(3) SD	(4) min	(5) p25	(6) p50	(7) p75	(8) max
ERC	584	187.4	199.7	0	61.11	130.1	235.2	1,527
ECO	584	37.43	46.73	0	4.792	24.50	48.06	353.0
ENG	584	6.088	7.497	0	0.643	3.750	8.552	49.69
TCE	584	245.2	229.8	0.814	92.12	176.4	317.5	1,552
IS	584	46.01	7.887	19.01	42.10	47.40	51.60	61.50
EC	584	1,164	1,082	34.60	449.1	812.2	1,460	5,959
PGDP	584	26,328	22,717	2,048	8,610	19,636	37,312	118,198
POP	584	42.40	26.13	4.960	24.09	37.82	58.08	111.7
FE	584	217.9	227.2	3.363	44.46	128.5	334.6	1,504
ES	584	0.963	0.374	0	0.728	0.902	1.119	2.345
AEPI	584	528.3	1,005	0	37.50	147	551.5	9,170
URB	584	0.489	0.154	0.196	0.381	0.472	0.566	0.896
IER	584	203.9	167.9	28.36	132.0	170.2	235.6	2,368

We set the sample period as 1997–2017 due to data availability. Specifically, the data for the main explanatory variable (i.e., green innovation) were first published in 1997, while the latest provincial data for the dependent variable (i.e., CO_2 emissions) were updated in 2017.

The data on CO_2 emissions are obtained from the Carbon Emission Accounts and Datasets (CEADs, https://www.ceads.net/). The data provided by CEADS are based on the results of research funded by the National Natural Science Foundation of China, the Ministry of Science and Technology of China and the British Research Council. This is an official website that provides the public with accurate and up-to-date data on CO_2 emissions and socio-economic trade in China. CEADs is also one of the most authoritative and reliable databases for research on climate change and carbon neutrality issues in emerging economies [63]. Patent data are obtained from the database of the State Intellectual Property Office of China. We also use other sources, including *China Statistical Yearbooks*, *Energy Statistics Yearbooks* and *Financial Statistics Yearbooks*. Table 3 presents descriptions of the measures and data sources.

Table 3

Measures and data sources

	Variable	Measure	Unit	Data source
Dependent variables	TCE	Total CO_2 emissions	Metric tons (t)	CEADs, https://www.ceads.net/
	ERC	CO_2 emissions from raw coal	Metric tons (t)	
	ECO	CO_2 emissions from crude oil	Metric tons (t)	
	ENG	CO_2 emissions from nature gas	Metric tons (t)	
Independent variable	AEPI	Alternative energy production innovation		IPC Green Inventory, https://www.wipo.int/classifications/ipc/en/green_inventory/index.html Incopat, https://www.incopat.com

Control variables	ED	Economic development level		*China Statistical Yearbooks*
	IS	Industry structure	Percentage	
	POP	Population	Million	
	UR	Urbanisation rate	Percentage	
	EC	Electricity consumption	Billion kwh	*China Energy Statistical Yearbooks*
	ES	Energy structure	Percentage	
	FE	Fiscal expenditure	Billion yuan	*Almanac of China's Finance and Banking*
	IER	Intensity of environmental regulations	10,000 per t	*China Statistical Yearbooks on Environment*

3.2. Variables and measures

(1) Dependent variables

In this study, we use four dependent variables, namely total CO_2 emissions (*TCE*), CO_2 emissions from raw coal (*ERC*), CO_2 emissions from crude oil (*ECO*) and CO_2 emissions from natural gas (*ENG*).

(2) Independent variable

The independent variable is *AEPI*, which is measured by the total number of patent applications related to AEP.

(3) Control variables

Eight control variables are included in the study: level of economic development (*ED*), industry structure (*IS*), population (*POP*), urbanisation rate (*URB*), electricity consumption (*EC*), energy structure (*ES*), government fiscal expenditure (*FE*) and intensity of environmental regulations (*IER*). ED is measured by the gross domestic product (*GDP*) per capita *(PGDP*). According to the Kuznets curve, environmental pollution has an inverse relationship with per capita income and regional development [64, 65]. *IS* is measured by the proportion of manufacturing industries in GDP. Industry structure is shown to have a significant impact on CO_2 emissions [66], though the results of previous studies remain inconsistent [1, 57, 67]. *POP* is measured by the population of a province [68]. The size of a population is generally positively correlated with CO_2 emissions [69]. *UR* is measured by the ratio of the urban population to the total population of an area. Studies show that CO_2 emissions are positively related to the urbanisation rate [70]. *EC* is measured by the volume of electricity consumption. *EC* is chosen to replace energy consumption as a control variable, as is commonly done in previous studies [71, 72]. *ES* is measured by the proportion of coal consumption in total energy consumption. Studies show that the energy structure is positively related to CO_2 emissions [73]. *FE* is measured by a provincial government's fiscal expenditure in a year. This measure reflects the intensity of government environmental regulations [74], which is negatively related to CO_2 emissions. Finally, *IER* is measured by the cost of polluting discharges per unit of emissions. Scholars generally argue that environmental regulations and CO_2 emissions are negatively correlated [75].

3.3. Empirical models

Multiple regressions are adopted to analyse the panel data at the provincial level in China for the 1997–2017 period. The regressions are run using STATA MP version 17.0.

According to the results of Hausman test for the models (p=0.6761), we adopt fixed-effects models for the regressions. Because of the serious problem of sequential collinearity, time fixed effects are not included in the models. Model 1 is used to test Hypothesis 1. Models 2, 3 and 4 are used to test Hypotheses 2a, 2b and 2c, respectively. The specific models are as follows:

$$TCE_{ij} = \beta_1 AEPI_{ij} + \beta_2 \mathrm{I.S.}_{ij} + \beta_3 \mathrm{E.C.}_{ij} + \beta_4 \mathrm{PGDP}_{ij} + \beta_5 \mathrm{F.E.}_{ij} + \beta_6 \mathrm{POP}_{ij} + \beta_7 \mathrm{E.S.}_{ij} + \beta_8 \mathrm{IER}_{ij} + \beta_9 \mathrm{URB}_{ij} \tag{1}$$

$$ERC_{ij} = \beta_1 AEPI_{ij} + \beta_2 \mathrm{I.S.}_{ij} + \beta_3 \mathrm{E.C.}_{ij} + \beta_4 \mathrm{PGDP}_{ij} + \beta_5 \mathrm{F.E.}_{ij} + \beta_6 \mathrm{POP}_{ij} + \beta_7 \mathrm{E.S.}_{ij} + \beta_8 \mathrm{IER}_{ij} + \beta_9 \mathrm{URB}_{ij} \tag{2}$$

$$ECO_{ij} = \beta_1 AEPI_{ij} + \beta_2 \mathrm{I.S.}_{ij} + \beta_3 \mathrm{E.C.}_{ij} + \beta_4 \mathrm{PGDP}_{ij} + \beta_5 \mathrm{F.E.}_{ij} + \beta_6 \mathrm{POP}_{ij} + \beta_7 \mathrm{E.S.}_{ij} + \beta_8 \mathrm{IER}_{ij} + \beta_9 \mathrm{URB}_{ij} \tag{3}$$

$$ENG_{ij} = \beta_1 AEPI_{ij} + \beta_2 \mathrm{I.S.}_{ij} + \beta_3 \mathrm{E.C.}_{ij} + \beta_4 \mathrm{PGDP}_{ij} + \beta_5 \mathrm{F.E.}_{ij} + \beta_6 \mathrm{POP}_{ij} + \beta_7 \mathrm{E.S.}_{ij} + \beta_8 \mathrm{IER}_{ij} + \beta_9 \mathrm{URB}_{ij} \tag{4}$$

Note: i signifies the year; j signifies the province/region.

4. Results

4.1. Descriptive statistics

As we adopt fixed-effects models with cross-sectional data, we conduct a variance inflation factor (VIF) test to test for multicollinearity before performing the regression analysis. As shown in Table 4, the result of the VIF test is 3.47, which is less than 10, indicating that there is no multicollinearity issue. All of the models are tested for potential heteroscedasticity issues, which are corrected using robust standard errors where appropriate.

Table 4

Tests for model selection

	Model (1)	Model (2)	Model (3)	Model (4)
VIF test	3.47	3.47	3.47	3.47
Heteroscedasticity test	196.71***	9,353.70***	130.78***	1,614.62***
Robust SD	Yes	Yes	Yes	Yes
Model choice	Fixed effects	Fixed effects	Fixed effects	Fixed effects

Notes: Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5 reports the regression results. In Model (1), the coefficient of *AEPI* is -0.0653, which is significant at the 1% level, indicating that *AEPI* is negatively related to total CO_2 emissions. Therefore, Hypothesis 1 is supported.

The results of model (2) show that the coefficient of *AEPI* for *ERC* (coal) is negative and significant (β = -0.0607, $p < 0.01$), indicating that *AEPI* has a positive impact on reducing CO_2 emissions from coal. Therefore, Hypothesis 2a is supported.

The results of model (3) show that the coefficient of *AEPI* for *ECO* (crude oil) is negative and significant (β = -0.00797, $p < 0.01$) indicating that *AEPI* has a positive impact on reducing CO_2 emissions from crude oil. Therefore, Hypothesis 2b is supported.

The results of model (4) show that the coefficient of *AEPI* for *ENG* (natural gas) is positive and significant ($\beta = 0.00235$, $p < 0.01$), indicating that *AEPI* increases CO_2 emissions from natural gas. Therefore, Hypothesis 2c is supported.

Table 5

Regression results for CO_2 emissions

	Model (1)	Model (2)	Model (3)	Model (4)
VARIABLE	TCE	ERC	ECO	ENG
AEPI	-0.0653***	-0.0607***	-0.00797***	0.00235***
	(0.0122)	(0.0120)	(0.00115)	(0.000317)
IS	-1.575	-2.238**	0.465**	0.00741
	(0.984)	(0.810)	(0.215)	(0.0270)
EC	0.166***	0.129***	0.0324***	0.000306
	(0.00859)	(0.00886)	(0.00371)	(0.000457)
PGDP	0.00121***	0.000949***	0.000417***	4.79e-05***
	(0.000321)	(0.000318)	(0.000102)	(1.12e-05)
FE	-0.0599	-0.0874**	0.00651	0.0152***
	(0.0609)	(0.0419)	(0.0193)	(0.00396)
POP	0.806**	0.726**	-0.0813**	-0.0279***
	(0.328)	(0.299)	(0.0372)	(0.00826)
ES	255.6***	282.6***	-23.85***	-0.434
	(44.53)	(43.65)	(1.405)	(0.641)
IER	-0.0329	-0.000327	-0.0328***	-0.00168*
	(0.0537)	(0.0499)	(0.00924)	(0.000827)
URB	115.7**	88.66*	30.51***	-3.732***
	(54.54)	(48.96)	(9.615)	(1.217)
Constant	-190.0***	-179.6***	-11.74	3.352***
	(41.33)	(43.50)	(7.558)	(0.793)
Observations	584	584	584	584
R-squared	0.672	0.638	0.443	0.424

Notes: Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

4.2. Robustness checks and additional tests

4.2.1. Robustness checks

A series of robustness tests are conducted to test the robustness of our main results. To begin with, GMM estimation is adopted to check for possible endogeneity in the original analysis. This study may be affected by potential endogeneity caused by bidirectional causality between CO_2 and AEPI. The increase in CO_2 emissions may generate additional costs for firms. Therefore, firms may increase AEPI to achieve the energy transition, thereby reducing CO_2 emissions to reduce costs.

To determine whether there is a bidirectional causal relationship between CO_2 emissions and AEPI, GMM analysis is conducted. The results show that there is indeed a problem of endogeneity between the dependent and independent variables.

Following previous studies [76-78], we find that a region's unit sunshine temperature is related to its CO_2 emissions (greenhouse gases are well known to increase the temperature). At the same time, it has no direct impact on AEPI. Therefore, the unit sunshine temperature is adopted as the main instrumental variable for the study. Through a series of tests on the instrumental variable, we find that the unit sunshine temperature with 1-2 lags [L(1/2).T_S], AEPI with 1–3 lags [L(1/3). AEPI] and the fiscal expenditure with 1–2 lags [L(1/2). FE] are the most appropriate ones.

The system GMM method takes the estimation as an equation system that integrates difference GMM with horizontal GMM. It solves the issue brought by the missing errors in difference GMM and has the advantage of improving estimation efficiency [79]. Therefore, we use the system GMM method for model re-estimation on the sample based on the above instrumental variables [80-83]. A fixed-effect model with two-step estimation is adopted as the analysis is based on panel data. We use nonrobust and cluster-robust methods for the two sets of regressions, respectively. The results are consistent with our main results (see Table 6).

We conduct several post-estimation tests for the validity of GMM estimation results. First, an under identification test is conducted to check whether the number of independent variables is less than the number of endogenous explanatory variables. The results show that the p-values of Anderson LM statistic (0.0000) and Kleibergen-Paaprk LM statistic (0.0001) are both significant, which reject the null hypothesis of "insufficient identification of instrumental variables" at the 1% level, indicating that there is no issue of under identification. Second, an over identification test of all instruments is conducted to exclude endogenous problems of instrumental variables. The results show that the p-value of the Sargan statistic is 0.1665 and the Hansen J's is 0.1660, indicating that the null hypothesis that all instrumental variables were exogenous could not be rejected at the 10% level. Therefore, it could be concluded that there is no over identification problem. Third, a weak identification test is conducted based on the correlation between instrumental and endogenous variables. The results show that the F value of the Cragg-Donald Wald statistic is 15.134, which is larger than the 10% maximal IV relative bias of Stock-Yogo weak ID test critical values (11.29). Thus, it rejects the null hypothesis as an instrumental variable is weak, indicating that the model does not have a weak instrumental variable issue. In summary, it is concluded that the instrumental variables of the model are reasonable (Due to space limitation, the process of these tests is available upon request).

In addition, to avoid the cross-sectional dependence problem caused by the choice of sample, we conduct a cross-sectional dependence test on the benchmark models [84]. The results show cross-sectional dependence; however, the coefficient obtained with the corrected regression is -0.0780208 ($p = 0.002$), which is close to the benchmark model and significant at the 1% level. This indicates that the results of the benchmark regression are still robust in the presence of cross-sectional dependence (see Table 7).

Furthermore, we remove all extreme values using 1% bilateral tailing for all variables and rerun the regression. This method is a common robustness test, which can eliminate the influence of extreme values on the regression [85, 86] (see Table 7). The results are consistent with the original measurement.

Besides, the sample period is changed to the 2000–2017 period, as 2000 is the year that Chinese government adjusted statistics criteria in environmental regulations and thus widely used to analyse CO_2 emissions in China [87, 88]. This method is also a commonly used robustness test [85, 89] (see Table 7). The results are also consistent with the original measurement.

Finally, we examine the impact of spatial correlations as provincial data are used in this study. The existence of spatial correlations is common in data at the sub-regional level of a country [90-92]. We first test the panel data using the Moran's I index (general and partial) based on the regional neighbour weight matrix. The results show that the Moran's I index is not significant, whether general or partial, indicating that there is no spatial correlation between the independent and dependent variables in terms of geographical proximity. Then, we test the sample based on the weight of economic distance and obtain similar results. That is, there is no spatial correlation between the independent and dependent variables in terms of economic distance. Finally, we construct an economic and social weight matrix to analyse the data. The results show that the Moran's I index is negative and significant in this test, indicating that there is a correlation (see Fig. 6).

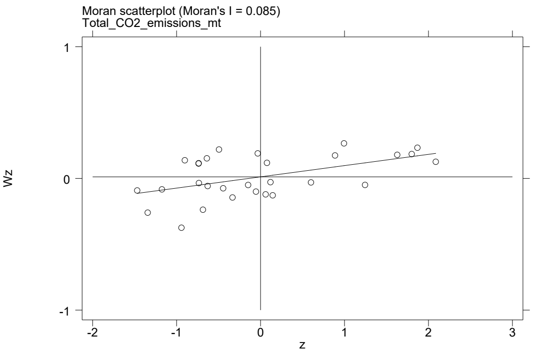


Fig. 6a. Moran's I (1997)

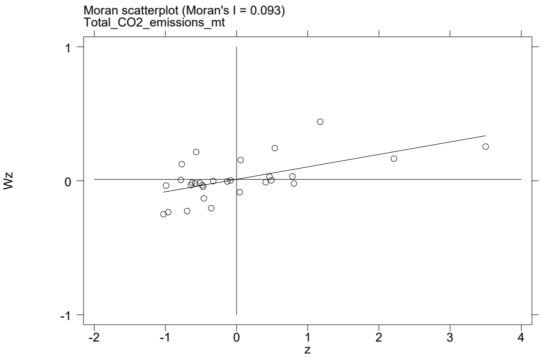


Fig. 6b. Moran's I (2017)

Fig. 6. Local Moran tests based on the economic and social weight matrix

To further examine the impact of spatial correlations, we use the spatial Durbin model (SDM) to test the robustness of the sample [93-95]. The results remain consistent with the original results. Furthermore, the coefficient of AEPI on CO_2 emissions is negative (-0.0564) and significant at the 1% level, indicating that the benchmark model is robust in terms of spatial correlations (see Table 8).

Table 6

Robustness test (R1: System-GMM)

	R1：GMM-nonrobust Model (5)	R1：GMM-cluster-robust Model (6)
VARIABLES	TCE	TCE
AEPI	-0.146***	-0.146***
(AEPI = l (1/2). RT_S L (1/3) . AEPI L(1/2).FE)	(0.0243)	(0.0309)
IS	-0.655	-0.655
	(0.619)	(0.556)
EC	0.0980***	0.0980***
	(0.0134)	(0.0161)
PGDP	0.00475***	0.00475***
	(0.00118)	(0.000987)
FE	0.523***	0.523***

	(0.0920)	(0.109)
POP	-0.560*	-0.560
	(0.319)	(0.363)
ES	260.4***	260.4***
	(21.75)	(30.51)
IER	-0.0458	-0.0458
	(0.0422)	(0.0807)
URB	50.02	50.02
	(44.93)	(43.88)
Observations	253	253
R-squared	0.792	0.792
Number of year	21	21

Notes: Standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 7

Robustness tests (R2: Cross-sectional dependence/R3:Tailing/R4:Years)

VARIABLES	R2: Cross-sectional dependence Model (7)	R3: Tailing Model (8)	R4: Years Model (9)
	TCE	TCE	TCE
AEPI	-0.0780***	-0.0832***	-0.0607***
	(0.0235)	-0.0108	-0.0126
IS	-1.456	-0.925	-1.723
	(2.041)	-0.713	-1.044
EC	0.165***	0.153***	0.159***
	(0.0259)	-0.0075	-0.00916
PGDP	0.00181	0.00164***	0.00104**
	(0.00113)	-0.000308	-0.000428
FE	0.0587	0.116***	-0.0567
	(0.0759)	-0.0339	-0.0654
POP	0.559	0.697***	0.988**
	(0.577)	-0.231	-0.435
ES	257.1***	226.3***	282.5***
	(58.20)	-34.42	-46.29
IER	-0.0316	-0.0486	-0.033
	(0.0542)	-0.043	-0.0613
URB	79.42	74.02*	160.4*
	(83.88)	-37.37	-82.49
Constant	-203.3**	-193.1***	-223.6***
	(79.90)	-30.81	-50.88
Observations	584	584	516
R-squared	0.741	0.734	0.684

Number of years	21	21	18

Notes: Standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 8
Robustness test (R5:SDM)

VARIABLE	Model (10) Main	Model (11) Wx	Model (12) Spatial	Model (13) Variance	Model (14) LR_Direct	Model (15) LR_Indirect	Model (16) LR_Total
AEPI	-0.0564***	-0.216***			-0.0637***	-0.0238	-0.0876***
	(0.0161)	(0.0574)			(0.0117)	(0.0196)	(0.0154)
IS	-4.437***	3.287			-3.448***	3.101*	-0.347
	(1.378)	(5.129)			(0.941)	(1.689)	(1.454)
EC	0.184***	0.550***			0.199***	0.0383	0.237***
	(0.0222)	(0.125)			(0.0147)	(0.0320)	(0.0289)
PGDP	0.000492	-0.000373			0.000339	-0.000369	-3.00e-05
	(0.00100)	(0.00372)			(0.000693)	(0.00132)	(0.00105)
FE	-0.106	0.774*			-0.0316	0.252*	0.221*
	(0.113)	(0.400)			(0.0728)	(0.141)	(0.120)
POP	-5.217*	-22.69			-6.255***	-3.069	-9.324*
	(2.806)	(18.27)			(1.856)	(5.419)	(5.439)
ES	186.6***	26.53			156.4***	-88.99	67.39
	(48.51)	(235.5)			(32.34)	(74.51)	(66.98)
URB	-13.62	-308.1			-36.60	-61.18	-97.78*
	(52.08)	(198.0)			(37.46)	(63.31)	(56.21)
IER	0.0429	-0.0528			0.0325	-0.0377	-0.00521
	(0.0327)	(0.153)			(0.0232)	(0.0486)	(0.0455)
rho			-2.089***				
			(0.340)				
sigma2_e				10,606***			
				(843.4)			
R-squared	0.275	0.275	0.275	0.275	0.275	0.275	0.275

Notes: Standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1.

4.2.2. Additional tests

In accordance with the standards of the Patent Office of China, general patents can be further divided into three subcategories, namely invention patents (i.e., the most original innovation in terms of method/technology), utility patents (i.e., application innovation or improvement of technology based on the original innovation) and design patents (i.e., improvement of the outlook and appearance of a product). Compared with design patents, invention and utility patents represent an essential innovation in terms of improving technology and functionality. Therefore, we further test the impacts of invention patents (IP) and utility patents (UP) on CO_2 emissions. The standards for invention patents are higher than those for utility patents, indicating greater innovation efficiency [96, 97]. The results show that the coefficients of IP and UP are negative and significant. However, the negative effects of UP on CO_2 emissions are greater than those of IP. Specifically, the coefficient of IP is -0.0822 ($p < 0.01$), while the coefficient of UP is -0.151 ($p < 0.01$) (See Table 9).

Table 9

Additional tests

VARIABLES	TCE	TCE	TCE	TCE
AEPI	-0.0653***			
	(0.0122)			
IS	-1.575	-1.497	-1.223	-1.452
	(0.984)	(1.004)	(0.994)	(1.033)
EC	0.166***	0.155***	0.178***	0.160***
	(0.00859)	(0.00835)	(0.00970)	(0.00817)
PGDP	0.00121***	0.000864**	0.00111***	0.00115***
	(0.000321)	(0.000320)	(0.000253)	(0.000301)
FE	-0.0599	-0.134**	-0.0498	0.0374
	(0.0609)	(0.0562)	(0.0539)	(0.0642)
POP	0.806**	1.015***	0.638*	0.693**
	(0.328)	(0.348)	(0.306)	(0.306)
ES	255.6***	259.6***	250.6***	254.6***
	(44.53)	(45.50)	(43.85)	(44.16)
IER	-0.0329	-0.0355	-0.0311	-0.0331
	(0.0537)	(0.0551)	(0.0527)	(0.0528)
URB	115.7**	141.9**	93.86*	100.1*
	(54.54)	(58.27)	(51.12)	(53.81)
GCP				
IP		-0.0822***		

		(0.0143)		
UP			-0.151***	
			(0.0295)	
GI				-0.0145***
				(0.00284)
Constant	-190.0***	-192.2***	-194.3***	-195.4***
	(41.33)	(43.47)	(41.67)	(39.61)
Observations	584	584	584	584
R-squared	0.672	0.664	0.679	0.676
Number of year	21	21	21	21

Notes: Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5. Discussion

Hypothesis 1 is supported, indicating the significant reduction effects of AEPI on CO_2 emissions. First, our results confirm that AEPI, as a branch of green innovation, contributes to reducing CO_2 emissions, which echoes the results of previous studies [4, 27]. Second, our research supports the argument that green innovation can improve the efficiency of using traditional energy sources by promoting energy substitution [30]. We further compare the effects of general green innovation and AEPI on CO_2 emissions. The results indicate that the reduction effects of AEPI on CO_2 emissions are stronger than those of general green innovation without classification. The coefficients of GI and AEPI are -0.0145 and -0.0653 (both significant at the 1% level), respectively (see Table 9). Third, our study provides empirical evidence that different types of green innovation have different effects on CO_2 emissions [36]. This explains why some studies find that the effects of green innovation on CO_2 emissions are unstable [28].

The results also show that the reduction effects of utility patents on CO_2 emissions are stronger than those of invention patents. According to innovation theory, a high level of technological innovation leads to a strong impact on CO_2

emissions [98]. Invention patents are generally considered to be more innovative than utility patents; however, our empirical results show the opposite regarding their impact on CO_2 emissions. One possible reason for this finding is that utility patents are more directly related to practical application, which reduces CO_2 emissions more directly. In contrast, applying a new technology associated with an invention patent may take much longer.

Hypotheses 2a, 2b and 2c are supported and demonstrate the different effects of AEPI on reducing CO_2 emissions through different energy sources. The results further imply that AEPI can lead to a low-carbon energy transition. This indicates that AEPI can respond better to environmental regulations than other types of innovation. Furthermore, the results for Hypothesis 2 imply that the current supply of new energy sources cannot fully support the task of energy substitution in China. Theoretically, with the development of AEPI, CO_2 emissions from traditional petrochemical energy sources should be reduced. Although the impacts of AEPI on CO_2 emissions from various traditional petrochemical energy sources may be heterogeneous, AEPI is still expected to reduce CO_2 emissions. However, our empirical results show that AEPI is positively related to CO_2 emissions from natural gas. This implies that new energy sources have not yet filled the shortage caused by the reduced use of coal and crude oil. There is still a demand for traditional low-carbon petrochemical energy represented by natural gas in the market. Furthermore, AEPI may include some innovations related to improving the efficiency of the use of natural gas. As a result, although AEPI reduces the CO_2

intensity of natural gas, it may increase the demand for natural gas, which ultimately leads to a positive correlation between AEPI and CO_2 emissions from natural gas.

6. Conclusions, policy implications and future research

This paper examines the relationship between AEPI and CO_2 emissions using multiple regression analysis on panel data from China at the provincial level during the 1997–2017 period. Our results suggest that AEPI has a positive effect on reducing CO_2 emissions. Compared with invention patents, utility patents have a stronger impact on reducing CO_2 emissions. Furthermore, our results show that the reduction mechanism varies across different energy sources, which implies that AEPI actively responds to environmental regulations. Our study contributes to research on technological innovation and environmental economics. First, we find AEPI as the main driver of all types of green innovation in reducing CO_2 emissions. Second, we explore the heterogeneous effects of different energy sources and deepen our understanding of different reduction mechanisms. Third, this study makes a methodological contribution to research using a series of quantitative analyses.

The findings of this paper have two practical implications for policymakers. First, the government should further support green innovation by encouraging AEPI, as it is the main driver for reducing CO_2 emissions in green innovation. The government could issue supportive policies such as fiscal subsidies, reward systems and tax reductions. Second, it is important to improve the efficiency of the patent review system, especially for AEPI. The reduction of CO_2 emissions could benefit from a shorter patent application time and a lower application cost.

This study has two main limitations which provide the direction of future research. First, as the study is conducted in China, the findings may not apply to other emerging economies because of China's uniqueness in terms of economic size and institutions. Further studies are needed in other emerging economies to determine the generalisability of our findings. Due to data availability, a second limitation comes from the sub-country level of the study. Future research could adopt firm-level studies that focus on the innovation process of firms. This complementary research level would allow a better understanding of firms' role in the innovation process.

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