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Article

Effects of Primary Energy Consumption and Alternative Energy Patents on CO₂ Emissions in China Using Canonical Correlation Analysis

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Abstract: This study analyzes the effects of primary energy consumption and alternative energy patents on CO₂ emission intensity and CO₂ emissions per capita, and their relationship using canonical correlation analysis. Our results are as follows. First, CO₂ emissions from natural gas and liquefied petroleum gas have positive effects, while CO₂ emissions from gasoline, fuel oil, diesel, and kerosene have negative effects on CO₂ emission intensity. Second, patents for devices for producing mechanical power from muscle energy have large positive effects. Finally, the more the patents use waste heat, geothermal energy, hydro energy, and wind energy, the higher the CO₂ emissions from liquefied petroleum gas, gasoline, and crude oil and the lower the CO₂ emissions from diesel, which are conducive to controlling CO₂ emissions. Therefore, energy policies will be more effective based on the CO₂ “emissions” level from primary energy consumption and the “control” degree of CO₂ emissions by alternative energy.

Keywords: CO₂ emissions; Primary energy consumption; Alternative energy patent; Multiple linear regression; Canonical correlation analysis

1. Introduction

Since 2006, China has been the world’s largest CO₂ emitter [1,2]. It is predicted that the country’s economic growth and urbanization will continue to increase its CO₂ emissions [3] by more than 50% during 2015–2030 [4]. Therefore, China is under significant pressure from international climate negotiations [5]. Rigorously controlling CO₂ emissions in China is thus important for addressing global climate challenges [6].

Compared with major developed countries or regions, China’s CO₂ emission development history has its particularities. Although some developed countries such as the United States, the United Kingdom, and France have reached their peaks of CO₂ emissions [7], the Chinese government’s commitment to reach carbon peaking by 2030 is based on a different circumstance.

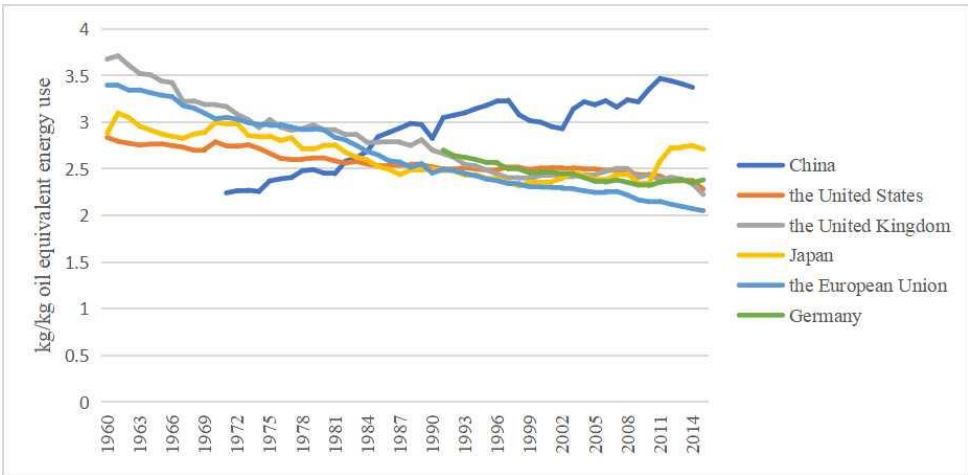


Figure 1. Comparison of CO₂ emission intensity among major developed countries or regions during 1960–2014.

Figure 1 shows the development of CO₂ emission intensity in China compared to the United States, the United Kingdom, Japan, the European Union, and Germany from 1960 to 2014. First, while CO₂ emission intensity decreased in other countries and regions, China was the only country with a significant increase in CO₂ emission intensity. Second, the CO₂ emission intensity curves of China and other countries or regions crossed from 1982 to 1984. Third, China’s CO₂ emission intensity dropped significantly in 1990, 1996–2002, and 2011–2013.

In addition, China’s CO₂ emissions per capita are significantly lower than those of many developed countries or regions. Figure 2 shows the development of CO₂ emissions per capita in China compared to the United States, the United Kingdom, Japan, the European Union, and Germany from 1960 to 2016. First, China’s CO₂ emissions per capita were lower than those in other countries or regions before 2011. Second, China’s CO₂ emissions per capita increased year by year; however, the increase was smaller before 2002 and more obvious from 2002 to 2011. Third, China’s CO₂ emissions per capita were still generally at a low level.

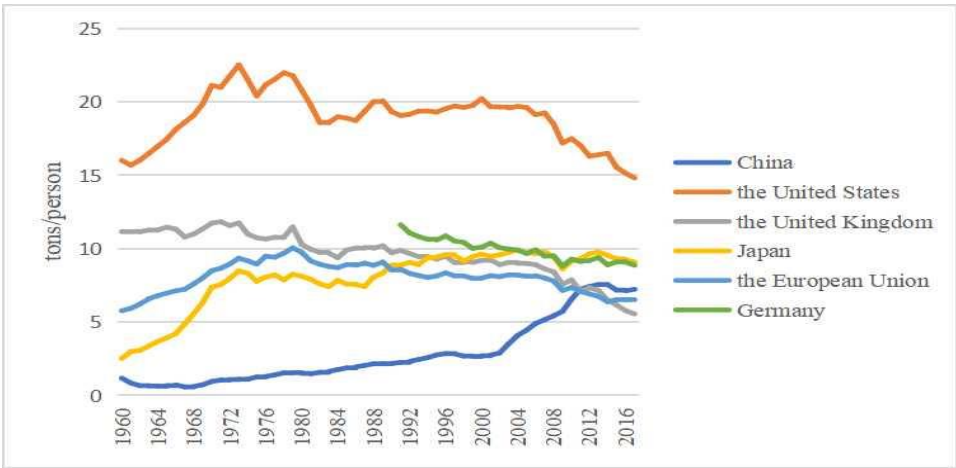


Figure 2. Comparison of CO₂ emissions per capita in major developed countries or regions during 1960–2016.

For China to achieve its goals of carbon peaking and carbon neutrality by 2030 and 2060, it is essential to study the factors that influence its CO₂ emission intensity and CO₂ emissions per capita. As the consumption of primary energy¹ is the largest source of CO₂ emissions, replacing the coal-dominated energy structure with a green energy structure is crucial for most countries to reduce CO₂ emissions. Alternative energy technology is integral to green energy technology. The development of alternative energy is thus one of the main options to change the coal-dominated energy structure. Alternative energy patents are an important indicator of the innovation capability of this technological field, as they are closely related to energy technology research and development (R&D) expenditure [8]. Therefore, studying the effects of primary energy consumption and alternative energy technology patents on CO₂ emission intensity and CO₂ emissions per capita is important for China to achieve its carbon peaking and neutrality goals.

The literature analyzed the effects of primary energy or alternative energy technologies on CO₂ emissions. Some scholars studied the effects of economic development, industrial structure, population size, urbanization, energy structure, technology, and R&D on CO₂ emissions; meanwhile, others studied the relationship between primary energy consumption and CO₂ emissions and the one between green patents and CO₂ emissions. In addition, some scholars focused on the relationship between alternative energy technology and CO₂ emissions. However, only a few studies analyzed the effects of primary energy consumption and alternative energy technology patents on CO₂ emissions. Thus, this study attempts to identify the effects of the CO₂ “emissions” of primary energy

¹ In this study, primary energy sources include natural gas, fuel oil, coke, liquefied petroleum gas, kerosene, coal, crude oil, gasoline, and diesel.

consumption and the “control” of alternative energy technology patents on CO₂ emissions to contribute to China’s carbon peaking and carbon neutrality goals.

Compared with the literature, this study makes three contributions to the research on controlling CO₂ emissions. First, CO₂ emission intensity was significantly affected by the CO₂ emissions from natural gas, gasoline, liquefied petroleum gas, fuel oil, diesel, and kerosene, as well as by patents related to devices that produce mechanical power via muscle energy, ocean thermal energy conversion, pyrolysis, hydro energy, and harnessing energy from manmade waste. Second, CO₂ emissions per capita were significantly affected by the emissions from liquefied petroleum gas, gasoline, diesel, fuel oil, and kerosene; patents for ocean thermal energy conversion; and devices for producing mechanical power from muscle energy. Thirdly, the more the patents in the technological fields used waste heat, geothermal energy, hydro energy, and wind energy, the more the CO₂ was produced by the consumption of liquefied petroleum gas, gasoline, and crude oil, and the less the CO₂ was produced by the consumption of diesel, which is more conducive to the control of CO₂ emissions.

The remainder of the paper is organized as follows. Section 2 provides a comprehensive review of the relevant literature. Section 2 reviews the relevant literature. We describe the methodology and data in Section 3. In Section 4, we analyze the effects of CO₂ emissions from primary energy consumption and alternative energy technology patents on CO₂ emission intensity, CO₂ emissions per capita, and total CO₂ emissions using multiple linear regression (MLR). We also explore the relationship between CO₂ emissions from primary energy consumption and alternative energy patents using canonical correlation analysis (CCA). Finally, Section 5 provides the conclusion and policy implications.

2. Literature Review

2.1. Primary Energy Consumption and CO₂ Emissions

China is currently one of the countries that consume the most primary energy and produce the most CO₂ emissions [9]; It is also a major producer of coal, oil, and natural gas. The country pledged to peak its CO₂ emissions and increase its non-fossil share of primary energy to 20% by 2030 [10]. Some scholars studied the relationship between primary energy consumption and CO₂ emissions. For example, Siitonen et al. [11] found that energy-saving investments in individual industrial processes may have different effects on primary energy consumption and CO₂ emissions. Valadkhani et al. [12] studied the CO₂ emissions from different types of primary energy and used annual data from 60 countries to examine the effects of various types of primary energy consumption on CO₂ emissions. They found that all countries, except for the highest-income ones, can reduce CO₂ emissions by replacing oil or coal with natural gas. In addition, some scholars studied the effects of specific fuels of primary energy on CO₂ emissions. Liu et al. [13] contend that the Chinese government recognizes its dependence on fossil fuels and the consequent rise in CO₂ emissions. Shao et al. [14] found that China’s consumption structure of coal-dominated energy causes massive CO₂ emissions. Additionally, Zhang et al. [15] found that China’s fossil fuel combustion for electricity generation accounts for more than 40% of the global CO₂ emissions, which is why reducing the use of fossil fuels is significant for controlling CO₂ emissions. Moreover, the consumption of fossil energy has gradually increased, resulting in the emission of a large amount of CO₂ [16,17]. Therefore, primary energy consumption has significant effects on CO₂ emissions. However, the literature rarely systematically studied the differences in the contribution of primary energy consumption to CO₂ emissions.

2.2. Alternative Energy and CO₂ Emissions

The development of alternative energy technologies has important effects on CO₂ emissions. It is well known that carbon-free energy technologies such as wind and nuclear power are more effective in reducing CO₂ emissions than fossil fuel technologies such as gas- and coal-fired ones. Chen et al. [18] found that wind and nuclear technologies best reduce CO₂ emissions. Manoli et al. [19] argued that green technologies play a key role in controlling the CO₂ emissions from fossil fuel energy. Additionally, the comprehensive utilization of traditional and alternative energy is not only

economically rational but also conducive to the development of alternative energy [20]. In summary, it is an important measure to reduce CO₂ emissions by using alternative energy. However, the literature rarely systematically studied the role of specific alternative energy in mitigating CO₂ emissions.

2.3. Energy Patents and CO₂ Emissions

Many studies investigated the relationship between energy patents and CO₂ emissions. One literature stream focused on the effects of patents on CO₂ emissions. Some scholars considered that patents are also used to study the effects of technological innovation on CO₂ emissions [21–23]. Li et al. [24] found evidence of an inverse U-shaped relation between patents and CO₂ emissions. Another literature stream studied the relationship between renewable energy patents and CO₂ emissions. Cheng et al. [25] analyzed the difference in the effects of renewable energy patents and environmental technology patents on CO₂ emission reduction. A third literature stream studied the relationship between green patents and CO₂ emissions. Cho and Sohn [26] found that policies aimed at controlling CO₂ emissions can effectively promote green patent applications. Meanwhile, Kwon et al. [27] showed that an increase in CO₂ emissions leads to an increase in green patent applications. Patent data were also used to examine the effect of green technologies [27,28]. Alternative energy technology patents are part of renewable and green technology patents. While the literature studied the effect of renewable energy patents and green technology patents on reducing CO₂ emissions, it rarely focused on the effects of alternative energy patents on reducing CO₂ emissions.

3. Methodology and Data

3.1. Methodology

CCA is an exploratory statistical method utilized to assess correlations between two sets of variables and is used in a wide range of disciplines to analyze the relationship between multiple independent and multiple dependent variables. This method was first described by Hotelling [29] and has been widely used in many academic fields such as coastal engineering by Larson et al. [30], dissolved organic matter fractions and contents by Xujing et al. [31], and the functional diversity of the microbial community and the oxidative stress in earthworms by Zhou [32]. In this study, SPSS v24 was used to run the model.

3.2. Variable Design

3.2.1. Dependent Variables

In MLR, the dependent variables include CO₂ emission intensity, CO₂ emissions per capita, and total CO₂ emissions. CO₂ emission intensity refers to the amount of CO₂ emissions produced by one unit of gross domestic product (GDP) growth, which is mainly used to measure the relationship between a country's economy and CO₂ emissions. CO₂ emission per capita is the annual average of CO₂ emission per person in a certain area. In CCA, the dependent variable is represented by total CO₂ emissions.

3.2.2. Independent Variable

In MLR and CCA, the independent variables include CO₂ emissions from primary energy consumption: CO₂ emissions from kerosene (CEKS); CO₂ emissions from diesel (CEDS); CO₂ emissions from natural gas (CENG); CO₂ emissions from liquefied petroleum gas (CELG); CO₂ emissions from crude oil (CECO); CO₂ emissions from coal (CECL); CO₂ emissions from gasoline (CEGL); CO₂ emissions from fuel oil (CEFO); CO₂ emissions from coke (CECK). Patents for alternative energy technologies: biofuel patents (BFLP); integrated gasification combined cycle patents (IGCP); fuel cell patents (FLCP); pyrolysis or gasification of biomass patents (PGBP); harnessing energy from manmade waste patents (HEMP); hydro energy patents (HDEP); ocean thermal energy conversion patents (OTCP); wind energy patents (WDEP); solar energy patents (SLEP); geothermal energy patents (GTEP); other production or use of heat, not derived from combustion patents (OPHP); using

waste heat patents (UWHP); devices for producing mechanical power from muscle energy patents (DPMP).

3.3. Data

The data on CO₂ emissions for 1998–2021 are from the “Carbon Neutrality” sub-database of the “Economic Research Series” in the China Stock Market & Accounting Research Database (<https://cn.gtadata.com/>; retrieval date: April 6, 2022).

The patent data of the alternative energy² technological fields (see the Appendix for the International Patent Classification (IPC)) for 1995–2018³ in China are from the China National Intellectual Property Administration (<http://pss-system.cponline.cnipa.gov.cn/seniorSearch>; retrieval date: April 8–26, 2022).

3.4. Descriptive Statistics

Table 1 shows the descriptive statistics for CO₂ emission intensity; CO₂ emissions per capita; CO₂ emissions from natural gas, fuel oil, coke, liquefied petroleum gas, kerosene, coal, crude oil, gasoline, and diesel; and patent data of alternative energy technological fields in China.

Table 1. Descriptive statistics.

CO ₂ emissions /Patents	Numb er of cases	Min	Max	Mean	Standard Deviation	Variance
CEIT	717	0.0000	30.0200	4.1644	3.3799	11.424
CEPC	717	0.0000	41.5465	7.36514	5.9093	34.919
CECL	716	0.0000	93118.4044	18716.1945	16904.1429	285750045.400
CECK	713	0.0286	26753.4942	2477.0916	3478.7841	12101939.090
CECO	652	0.0302	39419.2915	3902.5952	4715.4648	22235608.040
CEGL	715	28.5548	4554.3921	752.0542	712.7446	508004.803
CEKS	704	0.0304	2131.0210	159.9756	288.8964	83461.122
CEDS	715	30.2231	5624.0911	1194.9783	1017.6913	1035695.603
CEFO	714	0.0634	14858.3263	468.1455	1180.3048	1393119.376
CELG	180	6.7588	2592.3762	333.1892	431.8124	186461.932
CENG	650	0.0000	5979.6703	753.6010	910.2725	828595.971
BFLP	720	0	15412	437.09	1271.677	1617162.929
IGCP	720	0	327	19.96	38.937	1516.082
FLCP	720	0	1961	68.39	170.042	28914.344
PGBP	720	0	153	9.48	18.586	345.429
HEMP	720	0	346	25.58	45.960	2112.363

² The Green Inventory is published by the World Intellectual Property Organization to identify environmentally sound technologies based on the IPC. It divides green patents into eight categories: alternative energy patents, transportation patents, energy conservation patents, waste management patents, agriculture/forestry patents, administrative patents, regulatory or design aspects patents, and nuclear power generation patents. This study only considers alternative energy technology patents.

³ CO₂ emission-related data and alternative energy patent-related data in this study are monthly data for 1995–2018 and 1998–2021. The three-year lag is because it generally takes around three years for a patent application to be granted.

HDEP	720	0	494	23.05	52.696	2776.817
OTCP	720	0	48	2.68	5.524	30.512
WDEP	720	0	1600	81.19	194.671	37896.605
SLEP	720	0	3957	225.20	540.133	291743.217
GTEP	720	0	2707	62.02	213.084	45404.760
OPHP	720	0	3224	88.15	248.292	61648.837
UWHP	720	0	3981	209.57	448.556	201202.304
DPMP	720	0	111	7.82	13.216	174.654

b. CO₂ emission intensity: tons/10,000 yuan; b. CO₂ emissions per capita: tons/person; c. CO₂ emissions: 10,000 tons.

From Table 1, the following conclusions can be drawn. First, regarding primary energy consumption, the ratio of the mean of CO₂ emissions from coal to the total mean of CO₂ emissions from primary energy consumption is the highest (65.08%). The ratio of the sum of the means of CO₂ emissions from crude oil, coke, and diesel to the total mean of CO₂ emissions from primary energy consumption is larger (26.34%). Second, among alternative energy patents, the ratio of the mean of biofuel patents to the total mean of alternative energy patents is the largest (34.68%). The ratio of the sum of the mean of solar energy patents and using waste heat patents to the total mean of alternative energy patents is relatively large (34.50%).

4. Results and Discussion

4.1. Effects of Primary Energy Consumption on CO₂ Emission Intensity and CO₂ Emissions Per Capita in China based on MLR

4.1.1. Effects of Primary Energy Consumption on CO₂ Emission Intensity

The MLR method was used to analyze the collected data by taking CO₂ emission intensity as the explained variable and CO₂ emissions from the consumption of natural gas, fuel oil, coke, liquefied petroleum gas, kerosene, coal, crude oil, gasoline, and diesel as the explanatory variable, and the results are shown in Tables 2–4. Table 2 shows that CO₂ emissions from primary energy consumption can explain 65.4% of CO₂ emission intensity. The Durbin–Watson value indicates that the samples are independent and less likely to have autocorrelation. Table 4 shows that the CO₂ emissions produced by other primary energy consumption have significant effects on CO₂ emission intensity, except for CEKS and CEDS. The maximum variance inflation factor (VIF) value indicates that there is no multicollinearity between the independent variables. The regression model is as follows:

$$y_{CEIT} = 2.339 + 0.061x_{CECL} - 0.056x_{CECK} + 0.071x_{CECO} - 1.457x_{CEGL} - 0.140x_{CEKS} - 0.225x_{CEDS} - 0.351x_{CEFO} + 1.039x_{CELG} + 2.339x_{CENG} + \varepsilon, \quad (1)$$

where y_{CEIT} represents CO₂ emission intensity. x_{CECL} , x_{CECK} , x_{CECO} , x_{CEGL} , x_{CEKS} , x_{CEDS} , x_{CEFO} , x_{CELG} , and x_{CENG} represent CO₂ emissions from the consumption of coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, liquefied petroleum gas, and natural gas, respectively. Equation (1) shows that, for every RMB 10,000 increase in GDP, CENG, CELG, CECO, and CECL increase by 2,339 tons, 1,039 tons, 71 tons, and 61 tons, respectively; for every RMB 10,000 increase in GDP, CEGL, CEFO, CEDS, CEKS, and CECK decrease by 1,457 tons, 351 tons, 225 tons, and 140 tons, and 56 tons, respectively.

Therefore, the following three conclusions can be drawn. First, with GDP growth, there have been increases or decreases in CO₂ emissions from different types of primary energy consumption. This phenomenon is partly due to the dependence of economic growth on certain types of primary energy consumption and partly due to the impact of China’s energy adjustment policies on CO₂ emissions. Second, with GDP growth, the increase in CENG and CELG is remarkable. In other words, the contribution of natural gas and liquefied petroleum gas to economic development may currently be difficult to replace using other energy sources. Third, with GDP growth, CEGL decrease

significantly, while CEFO, CEDS, and CEKS decrease only slightly. In other words, with economic development, gasoline will be replaced, and fuel oil, diesel, and kerosene may also be replaced.

Table 2. Model summary. ^b.

Model	R	R Square	Adjusted Square	R Std. Error of the Estimate	Durbin-Watson
1	0.809a	0.654	0.635	0.9977881	1.724

a. predictor variable: (Constant), CECL, CECK, CECO, CEG, CEKS, CEDS, CEFO, CELG, CENG. b. dependent variable: CO₂ emission intensity.

Table 3. Anova. ^a.

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	306.752	9	34.084	34.235	0.000b
	Residual	162.280	163	0.996		
	Total	469.032	172			

Table 4. Coefficients. ^a.

Modes	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			TOL	VIF
(Constant)	2.339	0.224		10.446	0.000		
CECL	0.061	0.005	0.786	11.404	0.000	0.446	2.240
CECK	-0.056	0.022	-0.161	-2.572	0.011	0.541	1.848
CECO	0.071	0.023	0.281	3.128	0.002	0.262	3.814
CEGL	-1.457	0.238	-0.767	-6.120	0.000	0.135	7.392
CEKS	-0.140	0.263	-0.035	-0.533	0.595	0.492	2.032
CEDS	-0.225	0.217	-0.138	-1.038	0.301	0.120	8.304
CEFO	-0.351	0.068	-0.420	-5.190	0.000	0.324	3.089
CELG	1.039	0.351	0.275	2.961	0.004	0.246	4.067
CENG	2.339	0.224	0.102	10.446	0.000	0.484	2.066

a. dependent variable: CO₂ emission intensity.

4.1.2. Effects of Primary Energy Consumption on CO₂ Emissions Per Capita

The MLR method was used to analyze the data by taking CO₂ emissions per capita as the explained variable and CO₂ emissions from the consumption of natural gas, fuel oil, coke, liquefied petroleum gas, kerosene, coal, crude oil, gasoline, and diesel as the explanatory variable,. The results are shown in Tables 5–7. Table 5 indicates that CO₂ emissions from primary energy consumption can explain 62.2% of CO₂ emissions per capita. The Durbin–Watson value indicates that the samples are independent and less likely to show autocorrelation. Table 5 also proves that the CO₂ produced by alternative energy sources has significant effects on CO₂ emissions per capita, except for CEKS and CENG. The maximum VIF value indicates no multicollinearity between the independent variables. The regression model is as follows:

$$y_{CEPC} = 10.022 + 0.326x_{CECL} - 0.339x_{CECK} + 0.561x_{CECO} - 4.008x_{CEGL} + 1.442x_{CEKS} - 3.598x_{CEDS} - 1.579x_{CEFO} + 4.639x_{CELG} + 0.520x_{CENG} + \varepsilon, \tag{2}$$

where y_{CEPC} represents CO₂ emissions per capita. x_{CECL} , x_{CECK} , x_{CECO} , x_{CEGL} , x_{CEKS} , x_{CEDS} , x_{CEFO} , x_{CELG} , and x_{CENG} represent CO₂ emissions from the consumption of coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, liquefied petroleum gas, and natural gas, respectively. Equation (2) shows that for a 1-ton increase in CO₂ emissions per capita, CELG, CEKS, CECO, CENG, and CECL increase by 4,639 tons, 1,442 tons, 561 tons, 520 tons, and 326 tons, respectively. For a 1-

ton increase in CO₂ emissions per capita, CEGL, CEDS, CEFO, and CECK decrease by 4,008 tons, 3,597 tons, 1,579 tons, and 339 tons, respectively.

Therefore, the following three conclusions can be drawn. First, there have been increases or decreases in CO₂ emissions per capita for different types of primary energy over the past 20 years. The reason for this may be the comprehensive effect of population, economic, technological, and energy policy development. Second, the growth of CELG per capita has been remarkable and that of CEKS per capita has also been relatively remarkable over the past 20 years. In other words, even after considering population growth, the CO₂ emissions produced by the consumption of liquefied petroleum gas and kerosene show a relatively large increase, indicating the difficulty to replace the two primary energy sources with other sources. Third, CEGL per capita and CEDS per capita have decreased significantly, while CEFO per capita have decreased relatively obviously over the past 20 years. In other words, if population growth is considered, CO₂ emissions from the consumption of gasoline, diesel, and fuel oil drop significantly, indicating that these three primary energy sources have been largely replaced by other sources.

Table 5. Model summary. ^b.

Model	R	R Square	Adjusted Square	R Std. Error of the Estimate	Durbin-Watson
1	0.789a	0.622	0.601	4.7926981	1.945

a. predictor variable: (Constant), CECL, CECK, CECO, CEGL, CEKS, CEDS, CEFO, CELG, CENG. b. dependent variable: CO₂ emissions per capita.

Table 6. Anova.^a.

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6167.771	9	685.308	29.835	0.000b
	Residual	3744.103	163	22.970		
	Total	9911.873	172			

Table 7. Coefficients. ^a.

Modes	Unstandardized Coefficients		Standardize d Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error				TOL	VIF
(Constant)	10.022	1.075		9.319	0.000		
CECL	0.326	0.026	0.921	12.788	0.000	0.446	2.240
CECK	-0.339	0.105	-0.212	-3.238	0.001	0.541	1.848
CECO	0.561	0.109	0.485	5.160	0.000	0.262	3.814
CEGL	-4.008	1.143	-0.459	-3.506	0.001	0.135	7.392
CEKS	1.442	1.261	0.078	1.143	0.255	0.492	2.032
CEDS	-3.598	1.041	-0.479	-3.456	0.001	0.120	8.304
CEFO	-1.579	0.325	-0.411	-4.861	0.000	0.324	3.089
CELG	4.639	1.685	0.267	2.753	0.007	0.246	4.067
CENG	0.520	0.456	0.079	1.141	0.256	0.484	2.066

a. dependent variable: CO₂ emissions per capita.

4.2. Effects of Alternative Energy Patents on total CO₂ Emissions and CO₂ Emissions per Capita in China Based on MLR

4.2.1. Effects of Alternative Energy Patents on Total CO₂ Emissions

Tables 8–10 show the results of the MLR analysis for the explained variable of total CO₂ emissions and the following explanatory variables: BFLP, IGCP, FLCP, PGBP, HEMP, HDEP, OTCP, WDEP, SLEP, GTEP, OPHP, UWHP, and DPMP. Table 8 shows that alternative energy patents can

explain 48.0% of total CO₂ emissions. The Durbin–Watson value indicates that the sample is independent and unlikely to have autocorrelation. Table 10 indicates that patents from other technological fields have significant effects on total CO₂ emissions, except for BFLP and IGCP. The VIF values of patents in other technological fields are all below 20, except for WDEP, indicating a slight multicollinearity between the independent variables. The regression model is as follows:

$$y_{TCDE} = 18.181 - 0.001x_{BFLP} + 0.083x_{IGCP} - 0.091x_{FLCP} + 0.493x_{PGBP} + 0.112x_{HEMP} + 0.128x_{HDEP} - 1.845x_{OTCP} + 0.098x_{WDEP} - 0.038x_{SLEP} + 0.017x_{GTEP} - 0.040x_{OPHP} + 0.023x_{UWHP} + 0.974x_{DPMP} + \varepsilon, \quad (3)$$

where y_{TCDE} represents total CO₂ emissions. x_{BFLP} , x_{IGCP} , x_{FLCP} , x_{PGBP} , x_{HEMP} , x_{HDEP} , x_{OTCP} , x_{WDEP} , x_{SLEP} , x_{GTEP} , x_{OPHP} , x_{UWHP} , and x_{DPMP} represent patent data for BFLP, IGCP, FLCP, PGBP, HEMP, HDEP, OTCP, WDEP, SLEP, GTEP, OPHP, UWHP, and DPMP, respectively. Equation (3) indicates that for a 10-million-ton increase in total CO₂ emissions, DPMP, PGBP, HDEP, HEMP, WDEP, IGCP, UWHP, and GTEP increase by 974, 493, 128, 112, 98, 83, 23, and 17 patents, respectively; for a 10-million-ton increase in total CO₂ emissions, OTCP, FLCP, SLEP, and BFLP decrease by 1845, 91, 40, 38, and 1 patent, respectively.

Therefore, the following three conclusions can be drawn. First, different types of alternative energy technology patents have positive or negative effects on total CO₂ emissions. This phenomenon may be because the growth rates of total CO₂ emissions are partly higher than the growth rates of alternative energy technology patents and partly lower than the growth rates of alternative energy technology patents. Second, with the growth of total CO₂ emissions, DPMP increase significantly and PGBP increase relatively fast. In other words, although total CO₂ emissions are increasing, the technology of devices for producing mechanical power from muscle energy and the technology of pyrolysis or gasification of biomass, which are used to control CO₂ emissions, are also developing rapidly. Third, as total CO₂ emissions increase, OTCP decrease significantly, while FLCP, SLEP, and BFLP decrease relatively significantly. In other words, compared with the growth rate of CO₂ emissions, the development speed of ocean thermal energy conversion technology has been significantly reduced, and the technology developments of fuel cell, solar energy, biofuel are relatively insignificant.

Table 8. Model Summary. ^b.

Model	R	R2	Adjusted R2	Std. Error of the Estimate	Durbin-Watson
1	0.693a	0.480	0.470	17.5873205	1.408

a. predictor variable: (Constant), BFLP, IGCP, FLCP, PGBP, HEMP, HDEP, OTCP, WDEP, SLEP, GTEP, OPHP, UWHP, DPMP. b. dependent variable: total CO₂ emissions.

Table 9. Anova. ^a.

Model	Sum of Squares	df	Mean Square	F	Sig.
1 Regression	200493.291	13	15422.561	49.861	0.000 ^b
Residual	217447.631	703	309.314		
Total	417940.922	716			

Table 10. Coefficients. ^a.

Modes	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			TOL	VIF
(Constant)	18.181	0.840		21.632	0.000		
BFLP	-0.001	0.002	-0.065	-0.755	0.451	0.101	9.921
IGCP	0.083	0.053	0.134	1.572	0.116	0.102	9.782
FLCP	-0.091	0.013	-0.639	-6.827	0.000	0.085	11.831

PGBP	0.493	0.071	0.380	6.994	0.000	0.251	3.988
HEMP	0.112	0.056	0.213	1.998	0.046	0.065	15.306
HDEP	0.128	0.043	0.280	2.954	0.003	0.082	12.137
OTCP	-1.845	0.345	-0.423	-5.345	0.000	0.118	8.447
WDEP	0.098	0.020	0.787	4.860	0.000	0.028	35.436
SLEP	-0.038	0.004	-0.858	-9.197	0.000	0.085	11.751
GTEP	0.017	0.007	0.154	2.415	0.016	0.182	5.480
OPHP	-0.040	0.005	-0.413	-7.393	0.000	0.237	4.225
UWHP	0.023	0.004	0.435	6.037	0.000	0.143	7.004
DPMP	0.974	0.114	0.533	8.519	0.000	0.189	5.299

a. dependent variable: total CO₂ emissions.

4.2.2. Effects of Alternative Energy Patents on CO₂ Emissions per Capita

Tables 11–13 present the results of MLR for the explained variable of CO₂ emissions per capita and the following explanatory variables: BFLP, IGCP, FLCP, PGBP, HEMP, HDEP, OTCP, WDEP, SLEP, GTEP, OPHP, UWHP, and DPMP. Table 11 shows that alternative energy patents can explain 17.0% of CO₂ emissions per capita. The Durbin–Watson value indicates that the samples are independent and unlikely to have autocorrelation. Table 13 shows that the patents produced by other technological fields are significantly correlated with CO₂ emissions per capita at the 0.1 level, except for HDEP. The VIF values of patents in other technological fields are all below 20, indicating that there is a slight multicollinearity between the independent variables, except for WDEP. The regression model is as follows:

$$y_{CEPC} = 6.292 - 0.001x_{BFLP} + 0.046x_{IGCP} - 0.016x_{FLCP} + 0.081x_{PGBP} - 0.042x_{HEMP} + 0.005x_{HDEP} - 0.392x_{OTCP} + 0.016x_{WDEP} - 0.002x_{SLEP} - 0.005x_{GTEP} - 0.003x_{OPHP} + 0.007x_{UWHP} + 0.137x_{DPMP} + \varepsilon, \quad (4)$$

where y_{CEPC} represents CO₂ emissions per capita. x_{BFLP} , x_{IGCP} , x_{FLCP} , x_{PGBP} , x_{HEMP} , x_{HDEP} , x_{OTCP} , x_{WDEP} , x_{SLEP} , x_{GTEP} , x_{OPHP} , x_{UWHP} , and x_{DPMP} represent patents of BFLP, IGCP, FLCP, PGBP, HEMP, HDEP, OTCP, WDEP, SLEP, GTEP, OPHP, UWHP, and DPMP, respectively. Equation (4) shows that for a 1-ton increase in CO₂ emissions per capita, DPMP, PGBP, IGCP, WDEP, UWHP, and HDEP increase by 137, 81, 46, 16, 7, and 5 patents, respectively; for a 1-ton increase in CO₂ emissions per capita, OTCP, HEMP, FLCP, GTEP, OPHP, SLEP, and BFLP decrease by 392, 42, 16, 5, 3, 2, and 1 patent, respectively.

Therefore, the following three conclusions can be drawn. First, patents for different types of alternative energy have had positive or negative effects on CO₂ emissions per capita over the past 20 years. The reason for this may be the comprehensive effects of population, economic, technological, and energy policy development. Second, the growth of DPMP has been relatively remarkable over the past 20 years. In other words, even after considering population growth, the patents of devices for producing mechanical power from muscle energy show a relatively large increase, indicating that this technological field has achieved relatively rapid development. Third, OTCP have decreased over the past 20 years. In other words, if population growth is considered, ocean thermal energy conversion patents drop significantly, indicating that the development of this technological field is relatively insignificant.

Table 11. Model Summary. b.

Model	R	R ²	Adjusted R ²	Std. Error of the Estimate	Durbin-Watson
1	0.412a	0.170	0.154	5.4319320	1.116

aa. predictor variable: (Constant), BFLP, IGCP, FLCP, PGBP, HEMP, HDEP, OTCP, WDEP, SLEP, GTEP, OPHP, UWHP, DPMP. b. dependent variable: CO₂ emissions per capita.

Table 12. Anova.^{a.}

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	4234.835	13	325.757	11.040	0.000b
	Residual	20713.132	702	29.506		
	Total	24947.967	715			

Table 13. Coefficients. a.

Modes	Unstandardized Coefficients		Standardize d Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			TOL	VIF
(Constant)	6.292	0.260		24.210	0.000		
BFLP	-0.001	0.001	-0.181	-1.671	0.095	0.101	9.919
IGCP	0.046	0.016	0.304	2.826	0.005	0.102	9.779
FLCP	-0.016	0.004	-0.467	-3.950	0.000	0.085	11.829
PGBP	0.081	0.022	0.257	3.742	0.000	0.251	3.986
HEMP	-0.042	0.017	-0.324	-2.412	0.016	0.065	15.300
HDEP	0.005	0.013	0.049	0.407	0.684	0.082	12.134
OTCP	-0.392	0.107	-0.367	-3.674	0.000	0.118	8.445
WDEP	0.016	0.006	0.545	2.662	0.008	0.028	35.428
SLEP	-0.002	0.001	-0.209	-1.771	0.077	0.085	11.748
GTEP	-0.005	0.002	-0.187	-2.322	0.020	0.182	5.480
OPHP	-0.003	0.002	-0.125	-1.765	0.078	0.237	4.225
UWHP	0.007	0.001	0.556	6.110	0.000	0.143	7.002
DPMP	0.137	0.035	0.307	3.883	0.000	0.189	5.298

a. dependent variable: CO₂ emissions per capita.

4.3. Relationship Between CO₂ Emissions and Alternative Energy Patents in China Based on CCA

Tables 14–17 show the results by analyzing two sets of data on the amount of CO₂ emitted by primary energy consumption and patents for alternative energy sources using CCA by SSPS v24.

Table 14. Canonical correlations.

	Correlation	Eigenvalue	Wilks Statistic	F	Num D.F	Denom D.F.	Sig.
1	0.948	8.911	0.001	13.168	117.000	1044.880	0.000
2	0.888	3.717	0.011	9.308	96.000	946.621	0.000
3	0.820	2.059	0.054	6.922	77.000	846.382	0.000
4	0.736	1.183	0.164	5.111	60.000	743.798	0.000
5	0.658	0.764	0.358	3.664	45.000	638.303	0.000
6	0.429	0.225	0.631	2.197	32.000	528.953	0.000
7	0.378	0.166	0.773	1.846	21.000	414.040	0.013
8	0.278	0.084	0.902	1.279	12.000	290.000	0.230
9	0.150	0.023	0.978	0.670	5.000	146.000	0.647

H0 for Wilks test is that the correlations in the current and following rows are zero.

Table 15. Set 1 Standardized canonical correlation coefficients.

Variable	1	2	3	4	5	6	7	8	9
CECL	-0.158	-0.037	0.275	-0.426	0.106	0.593	-0.867	0.167	-1.188
CECK	0.111	-0.141	-0.077	-0.223	0.188	-1.253	-0.068	-0.099	0.470
CECO	-0.302	-0.208	0.962	-0.839	0.884	0.826	0.273	-0.485	0.504
CEGL	-0.524	-0.899	1.024	1.597	0.669	0.261	-0.782	1.420	0.466
CEKS	0.005	-0.673	-0.586	-0.942	0.306	0.034	0.238	0.176	-0.569

CEDS	0.519	0.556	-0.658	-0.626	-0.355	-0.467	2.368	-0.534	-1.218
CEFO	0.195	-0.046	-0.115	0.541	-1.257	-0.394	-0.108	0.920	0.496
CELG	-0.774	0.815	-0.800	-0.332	-0.098	-0.321	-1.193	-0.279	0.534
CENG	-0.111	-0.006	-0.093	0.333	-0.941	-0.090	-0.011	-1.111	0.094

Table 16. Set 2 Standardized canonical correlation coefficients.

Variable	1	2	3	4	5	6	7	8	9
BFLP	0.434	-0.012	0.353	-0.217	-0.136	-1.216	0.449	-0.017	1.505
IGCP	-0.224	-0.346	-0.056	0.301	-0.780	1.238	-0.539	-1.195	-0.850
FLCP	-0.317	0.281	-0.760	1.435	0.668	1.040	-0.305	-0.511	-0.475
PGBP	0.046	-0.090	-0.008	-0.623	0.034	-1.467	-0.112	0.353	-0.720
HEMP	0.479	-0.520	0.366	0.150	-0.457	-0.603	1.634	1.465	2.843
HDEP	-0.376	0.179	0.766	1.496	-0.691	0.014	1.311	0.162	-2.060
OTCP	0.075	0.075	-0.113	0.091	-0.396	1.470	-0.962	-0.993	-0.382
WDEP	-0.368	0.375	0.771	-1.086	1.582	-1.619	-4.562	-0.159	0.028
SLEP	0.172	-1.088	-1.471	-0.361	-0.153	1.136	1.438	0.781	-0.009
GTEP	-0.411	0.826	-0.517	-0.405	-1.842	-0.107	0.023	-0.079	-0.711
OPHP	0.127	0.311	-0.745	-0.138	-0.329	0.838	0.064	0.560	-0.112
UWHP	-0.436	-0.042	1.068	-0.768	1.091	0.901	0.979	0.207	0.171
DPMP	-0.160	-0.261	0.134	0.094	0.836	-1.772	0.773	-0.446	0.526

Table 17. Proportion of variance explained.

Canonical Variable	Set 1 by Self	Set 1 by Set 2	Set 2 by Self	Set 2 by Set 1
1	0.350	0.315	0.526	0.473
2	0.105	0.083	0.163	0.128
3	0.147	0.099	0.027	0.018
4	0.069	0.037	0.042	0.023
5	0.079	0.034	0.032	0.014
6	0.096	0.018	0.009	0.002
7	0.043	0.006	0.016	0.002
8	0.056	0.004	0.044	0.003
9	0.055	0.001	0.022	0.000

4.3.1. Canonical Correlations Sets

Canonical correlations sets: set 1 includes CECL, CECK, CECO, CEGl, CEKS, CEDS, CEFO, CELG, and CENG; set 2 includes BFLP, IGCP, FLCP, PGBP, HEMP, HDEP, OTCP, WDEP, SLEP, GTEP, OPHP, UWHP, and DPMP. This section studies the correlation between sets 1 and 2.

4.3.2. Canonical Correlations

Table 14 shows the results of 9 groups of data in set 1 and 13 groups of data in set 2; these are significantly correlated based on CCA, and the correlation coefficients are 0.948, 0.888, 0.820, 0.736, 0.658, 0.429, 0.378, respectively. The regression results of the other two sets of data were not significant. These correlation coefficients indicate a strong correlation between the amount of CO₂ emitted by primary energy consumption and patents for alternative energy.

4.3.3. Correlation Coefficients and Models for CO₂ Emissions from Primary Energy Consumption

Table 15 shows that the coefficients on CECL, CECK, CECO, CEGl, CEKS, CEDS, CEFO, CELG, and CENG in the first pair of typical variable equations in set 1 are -0.158, 0.111, -0.302, -0.524, 0.005, 0.519, 0.195, -0.774, and -0.111, respectively. According to this, the typical variable 1 equation of set 1 can be written as follows:

$$CX_1 = -0.158 \times CECL + 0.111 \times CECK - 0.302 \times CECO - 0.524 \times CEG L + 0.005 \times CEKS \\ + 0.519 \times CEDS + 0.195 \times CEFO - 0.774 \times CELG - 0.111 \times CENG, (5)$$

Equation (5) shows that CELG, CEG L, CEDS, CECO, CEFO, CECL, CENG, and CECK have relatively large effects on CO₂ emissions from primary energy consumption, with CEDS, CEFO, and CECK having positive effects and CELG, CEG L, CECO, CECL, and CENG, negative effects. For information on the remaining groups in set 1, see Table 15.

4.3.4. Correlation Coefficients and Models for Alternative Energy Patents

Table 16 shows that the coefficients on BFLP, IGCP, FLCP, PGBP, HEMP, HDEP, OTCP, WDEP, SLEP, GTEP, OPHP, UWHP, and DPMP in the first pair of the canonical variable equations in set 2 are 0.434, -0.224, -0.317, 0.046, 0.479, -0.376, 0.075, -0.368, 0.172, -0.411, 0.127, -0.436, and -0.160, respectively. According to this, the canonical variable 1 equation of set 1 can be written as follows:

$$CY_1 = 0.434 \times BFLP - 0.224 \times IGCP - 0.317 \times FLCP + 0.046 \times PGBP + 0.479 \times HEMP \\ - 0.376 \times HDEP + 0.075 \times OTCP - 0.368 \times WDEP + 0.172 \times SLEP - 0.411 \times GTEP \\ + 0.127 \times OPHP - 0.436 \times UWHP - 0.160 \times DPMP, (6)$$

Equation (6) shows that HEMP, UWHP, BFLP, GTEP, HDEP, WDEP, FLCP, IGCP, SLEP, DPMP, and OPHP have relatively large effects on alternative energy technology patents, with HEMP, BFLP, SLEP, and OPHP having positive effects and UWHP, GTEP, HDEP, WDEP, FLCP, IGCP, and DPMP having negative effects. For information on the remaining groups in set 2, see Table 16.

4.3.5. Correlation Coefficients Between CO₂ Emissions from Primary Energy Consumption and Alternative Energy Patents

Table 14 shows that there is a significant positive correlation between the first group of data between CO₂ emissions from primary energy consumption and alternative energy patents, and the correlation coefficient is 0.948. Information on the other 6 groups of CCA will not be repeated here, for brevity.

From Tables 15 and 16, we have

$$\begin{cases} CX_1 = -0.158 \times CECL + 0.111 \times CECK - 0.302 \times CECO - 0.524 \times CEG L + 0.005 \times CEKS \\ \quad + 0.519 \times CEDS + 0.195 \times CEFO - 0.774 \times CELG - 0.111 \times CENG \\ CY_1 = 0.434 \times BFLP - 0.224 \times IGCP - 0.317 \times FLCP + 0.046 \times PGBP + 0.479 \times HEMP \\ \quad - 0.376 \times HDEP + 0.075 \times OTCP - 0.368 \times WDEP + 0.172 \times SLEP - 0.411 \times GTEP \\ \quad + 0.127 \times OPHP - 0.436 \times UWHP - 0.160 \times DPMP \end{cases} . (7)$$

Table 14 and Equation (7) show that UWHP, GTEP, HDEP, WDEP, and FLCP are significantly negatively correlated with CY_1 ; therefore, the higher the patents of these five alternative energy technological fields, the smaller the CY_1 . HEMP and BFLP are significantly positively correlated with CY_1 . CY_1 is significantly positively correlated with CX_1 , meaning the smaller the CY_1 , the smaller the CX_1 . Because CX_1 is significantly negatively correlated with CELG, CEG L, and CECO, and significantly positively correlated with CEDS, CX_1 is small. Namely, patents for using waste heat, geothermal energy, hydro energy, wind energy, and fuel cell should be encouraged, as should be the consumption of liquefied petroleum gas, gasoline, and crude oil, while the consumption of diesel should be strictly controlled. In conclusion, China's total CO₂ emissions are inversely proportional to patents in technological fields for using waste heat, geothermal energy, hydro energy, and wind energy, respectively, and are inversely proportional to CO₂ emissions from the consumption of liquefied petroleum gas, gasoline, and crude oil. They are also proportional to patents for harnessing energy from manmade waste and inversely proportional to CO₂ emissions from diesel consumption.

4.3.6. Proportion of Variance Explained

Table 17 shows the proportion of explained independent variables in sets 1 and 2, and the proportion of cross variables explained between sets 1 and 2, which are important components in CCA. Table 17 also shows that the proportion of the variables reflecting the CO₂ emissions of primary energy consumption explained by the first group of canonical related variables is 35.0%, the proportion of the variables reflecting alternative energy patents explained by the first group of canonical related variables is 52.6%, the proportion of the variable of CO₂ emissions of primary energy consumption explained by the first group of canonical related variables of alternative energy patents is 31.5%, and the proportion of the alternative energy patents explained by the first group of canonical related CO₂ emissions of primary energy consumption is 47.3%. In summary, the explanatory power of the independent variables is relatively good.

5. Conclusion and Policy Implications

5.1. Conclusions

In 2021, the Chinese government pledged to reduce China's carbon intensity by 65%, with non-fossil energy accounting for more than 25% of its energy structure by 2030 [33]. To effectively control CO₂ emissions by limiting primary energy consumption and developing alternative energy technology, this study analyzes the effects of CO₂ emissions from primary energy consumption and alternative energy technology patents on CO₂ emission intensity, CO₂ emissions per capita, and total emissions per capita in China using MLR. It also analyzes the relationship between CO₂ emissions from primary energy consumption and alternative energy technology patents using CCA. This study draws the following three conclusions. First, CO₂ emissions from natural gas and liquefied petroleum gas have positive effects, while CO₂ emissions from gasoline, fuel oil, diesel, and kerosene have negative effects on CO₂ emission intensity; furthermore, CO₂ emissions from liquefied petroleum gas and kerosene have positive effects, while CO₂ emissions from gasoline, diesel, and fuel oil have negative effects on CO₂ emissions per capita. Second, patents for devices for producing mechanical power from muscle energy, pyrolysis or gasification of biomass, hydro energy, and harnessing energy from manmade waste technologies have positive effects, while patents for ocean thermal energy conversion technology have negative effects on total CO₂ emissions; patents for devices for producing mechanical power from muscle energy technology have a positive effect, while patents for ocean thermal energy conversion technology have negative effects on CO₂ emissions per capita. Third, China's total CO₂ emissions are inversely proportional to patents for technologies using waste heat, geothermal energy, hydro energy, and wind energy, and to CO₂ emissions from the combustion of liquefied petroleum gas, gasoline, and crude oil. They are also proportional to patents for technology harnessing energy from manmade waste and inversely proportional to CO₂ emissions from diesel combustion.

5.2. Policy Implications

Based on the above conclusions, we make the following policy recommendations. First, to successfully achieve carbon peaking and carbon neutrality, policymakers should further increase the investment in alternative energy technologies, strengthen patent protection, improve technology transformation efficiency, and effectively use these technologies to control CO₂ emissions from primary energy consumption. Second, they should comprehensively analyze the differences in the CO₂ "emission" levels of different primary energy components and the difference in the "substitution" degrees of CO₂ emissions by different types of alternative energy technologies, and formulate precise policies to effectively control CO₂ emissions. Third, policymakers should reduce CO₂ emission intensity by moderately encouraging the combustion of gasoline, fuel oil, diesel, and kerosene; they can reduce CO₂ emissions per capita by moderately encouraging the combustion of gasoline, diesel, and fuel oil. Fourth, policymakers should focus on increasing investment in ocean thermal energy conversion technologies to promote technological innovation, improve the quality and quantity of patents, and reduce total CO₂ emissions and CO₂ emissions per capita. Finally, policymakers need to focus on increasing R&D in technology fields using waste heat, geothermal

energy, hydro energy, and wind energy; strengthen intellectual property protection; and create more patents. Simultaneously, they should encourage the combustion of liquefied petroleum gas, gasoline, and crude oil and strictly control the combustion of diesel.

5.3. Limitations and Future Research Prospects

Given the space considerations, this study has the following limitations. First, the analysis of the influence mechanism between the amount of CO₂ emitted by different types of primary energy sources and between different types of alternative energy technology patents is insufficient. Second, the relationship between the “emissions” of CO₂ from primary energy consumption and the “control” of CO₂ emissions from patents for alternative energy technologies requires further research. Therefore, considering these shortcomings of this study, we will conduct in-depth and systematic research on the above problems to provide a decision-making reference for optimizing energy policy.

Appendix A

Table A1. International Patent Classifications (IPC) of the technological fields included in alternative energy.

No.	Technology fields patent	IPC
1	BFLP	C10L 5/00, 5/40-5/48; C10L 1/00, 1/02, 1/14; C02F 3/28, 11/04; C10L 3/00; C12M 1/107; C12P 5/02; C12N 1/13, 1/15, 1/21, 5/10, 15/00; A01H
2	IGCP	C10L 3/00; F02C 3/28
3	FLCP	H01M 4/86-4/98, 8/00-8/24, 12/00-12/08; H01M 4/86-4/98; H01M 8/00-8/24, 50/00-50/171; H01M 12/00-12/08
4	PGBP	C10B 53/00; C10J
5	HEMP	C10L 5/00;C10J 3/02, 3/46; F23B 90/00; F23G 5/027; B09B 3/00; F23G 7/00; C10L 5/48; F23G 5/00, 7/00; B09B 3/00; F23G 5/00; B09B; C10L 5/46; F23G 5/00
6	HDEP	E02B 9/00-9/06; F03B; F03C; F03B 15/00-15/22; B63H 19/02, 19/04
7	OTCP	F03G 7/05
8	WDEP	F03D; H02K 7/18; B63B 35/00, E04H 12/00; F03D 13/00; B60K 16/00; B63H 13/00
9	SLEP	F24S; H02S; F24S; H01L 31/0525, H02S 40/44; B60K 16/00; F03G 6/00-6/06; E04D 13/00, 13/18; F22B 1/00, F24V 30/00; F25B 27/00; F26B 3/00, 3/28; F24S 23/00, G02B 7/183; F24S 10/10
10	GTEP	F24T; F01K, F24F 5/00, F24T 10/00-50/00, H02N 10/00, F25B 30/06; F03G 4/00-4/06, 7/04
11	OPHP	F24T 10/00-50/00; F24V 30/00-50/00; F24D 11/02; F24D 15/04; F24D 17/02, 18/00; F24H 4/00; F25B 30/00
12	UWHP	F01K 27/00; F01K 23/06-23/10; F01N 5/00; F02G 5/00-5/04; F25B 27/02; F01K 17/00, 23/04; F02C 6/18; F25B 27/02; C02F 1/16; D21F 5/20; F22B 1/02; F23G 5/46; F24F 12/00; F27D 17/00; F28D 17/00-20/00; C10J 3/86
13	DPMP	F03G 5/00-5/08

Source: The Green Inventory, the International Patent Classification (IPC).

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