Effects of Clean Energy Equipment Manufacturing Industry's Growth on Carbon Emissions in China: An Analysis Based on Emission-offsetting Effect

Abstract: We uncovered carbon emission-offsetting effect of clean energy equipment (CEE), namely emission-generating in CEE's production and emission-abating in CEE's consumption/application offset each other. We examined effects of CEE manufacturing industry's growth on carbon emissions in China by employing a reduced STIRPAT model and China's provincial level data from 2011 through 2021. Our results show that (1) CEE manufacturing industry's growth significantly inhibits carbon emissions, which exhibits heterogeneity among different product groups and regional groups, in particular, regional heterogeneity demonstrates that offsetting effect is conditional on co-location of CEE production and consumption/application and both types of heterogeneity confirm the existence of emission-offsetting effect. This result is still robust by using instrumental variables, (2) Effects of CEE manufacturing industry's growth on carbon emission are mediated by two variables: the industry's participation in global value chains and technological level, and (3) Other goods manufacturing industry's growth exhibits an inverted U-shaped relationship with carbon emissions, namely, it positively relates to carbon emissions at initial stages and then negatively relates to carbon emissions.

Keywords: clean energy equipment manufacturing industry, emission-offsetting effect, emission-reinforcing effect, carbon emission

I. Introduction

China put forward its dual-carbon goal, at the 75th session of the United Nations General Assembly in September 2020, toreach carbon peak by 2030 and carbon neutrality by 2060. In the face of a severe situation of large total carbon emissions and strong inertia in high-carbon development, China will have to achieve carbon peak in less than 10 years and carbon neutrality in about 30 more years, which is a very arduous task. The report of the 20th CPC National Congress proposes an overall goal of China's development in 2035, among which is a goal of beautiful China: the widespread formation of a green production and living style, a steady decline in carbon emissions after reaching the carbon peak, and a fundamental improvement in the ecological environment. In the realization of the dual-carbon goal and the beautiful China goal, China's clean energy equipment (CEE) manufacturing industry plays an important and key role. This paper aims to examine effects of CEE manufacturing industry's growth on carbon emissions in China. For the purpose of this paper, CEE refers to solar photovoltaics (PV), lithium-ion batteries, and wind turbines.

Examining effects of the growth of CEE manufacturing on China's carbon emissions is of two fold significance. *On the one hand*, the CCE manufacturing industry is China's dominant industry to realize its dual-carbon goal. Realizing the dual-carbon goal, in fact, is to realize a transformation from traditional energy-dominated energy structure to clean energy-dominated energy structure, and such a structural transformation relies on growth of CEE manufacturing industry, therefore, national governments around the world deem promoting CEE manufacturing industry as a right track of their economic development. Compared with the traditional manufacturing industry, CEE manufacturing industry has characteristics of more technology-intensive and resource-intensive, therefore, CEE manufacturing capacity represents a country's comprehensive strength of high-end equipment manufacturing. Since the beginning of this century, China’s central and local governments have been supporting the R&D and innovation of CEE manufacturing industry, and carrying out credit and taxation policies so as to provide CEE manufacturing industry with a favorable business environment. China's total output of wind turbines, lithium-ion batteries, and solar PV was 1,115 billions kilowatts in 2011 and 9,032 billions kilowatts in 2021, with an average annual growth rate of 20.5%. The proportion of China's clean energy power generation to total power generation was 0.188 in 2011 and 0.322 in 2021 respectively, with an average annual growth rate of 5.01%. China's clean energy is shifting from a compensatory energy source to an alternative energy source to traditional energy sources.

On the other hand, the CEE manufacturing industry has been the most booming growth pole of China's economy in the past years of more than one decade, and CEE exports are a new growth point for China's export trade. China's CEE manufacturing industry has been developing so rapidly that China has become a global leader in the manufacturing capacity of solar PV, lithium-ion batteries and wind turbines, and plays an important role in the global CEE supply chain. The statistics of General Administration of Customs of China shows that China's CEE exports have increased from US Dollars 3.597 billion in 2001 to US Dollars 98.446 billion in 2021, with an average annual growth rate of nearly 18%, which is higher than the growth rate of other equipment exports during the same period.

However, CEE has emission-offsetting effect: while production of CEE generates carbon emission, which is called emission-generating effect, application and/or consumption of CEE abates or eliminates carbon emission that would be generated by application and/or consumption of traditional equipment, which is called emission-abating effect. Other manufactured goods have emission-reinforcing effect: production of those goods has emission-generating effect, whereas application and/or consumption of those goods may have emission-generating effect, too. Such emission-offsetting effect of CEE results in that net effects of CEE manufacturing industry’s growth on a country’s carbon emission are not necessarily certain. CEE manufacturing industry’s growth may either positively or negatively relate to a country’s carbon emission, depending on which one, emission-generating effect or emission-abating effect, is greater. Therefore, it is quite worthwhile to uncover the mechanism of, as well as to conduct systematical econometric analysis of net effects of CEE manufacturing industry’s growth on China's carbon emissions.

There are two strands of literature directly relating to this paper. The *first strand* is the literature dealing with overall manufacturing industry and a country’s carbon emission. Obviously, overall manufacturing industry’s growth certainly intensifies a country’s carbon emissions, therefore, existing literature examine overall manufacturing industry’s effects on a country’s carbon emission from various perspectives other than the industry’s growth, for instance, but not limited to, *structural transformation of manufacturing* (Li et al., 2019), *technology-driven smart manufacturing* (Abudureheman et al., 2023), *manufacturing Servitization* (Zong and Gu, 2022), *digital economy and industrial structure* (Liang and Bian, 2024). There are at least two drawbacks that are found in this strand of literature. *First*, except Li et al. (2019), all the cited researches lack necessary classical models such as STIRPAT model to support their model specifications. *Secon*d, they obviously overlooked researches on effects of CEE manufacturing industry’s growth on a country's carbon emissions.

The *second strand* is the literature dealing with origin and extension of STIRPAT model necessary to specify regression model for analyzing effects of an explanatory variable on a country's air pollution. Methodologies for analyzing the driving forces behind air pollution fall into two categories (Li et al., 2020). *First*, Ehrlich and Holdren (1972) argued that the environmental impact is a product of population, affluence, and technology (IPAT). *Second*, Kaya (1990) proposed the Kaya equation, which focused on the relationship between energy and CO^2. Thesetwo frameworks can be applied to decompose changes in the aggregate environmental impact into socioeconomic driving forces but they are not suitable for econometric analysis (O'Mahony, 2013). A model of stochastic impacts by regression on population (P),affluence (A) and technology (T) (STIRPAT) developed by Dietz and Rosa (1994, 1997)as an extension of IPAT has gained more attention because it can be transformed easilyinto a logarithmic form for estimation and hypothesis testing. Considering the high tractability of the STIRPAT model in empirical analysis, we chose it to investigate the socioeconomic driving forces of carbon emission.

The STIRPAT model was further refined by York et al. (2003) in two ways (Li et al., 2020). The *first* refinement incorporated ecological elasticity so that the coefficient for population and affluence in the model can be interpreted as the percentage change in environmental impact in response to a 1 percent change in population and affluence. The *second* refinement is to disaggregate the technology term by incorporating other socioeconomic factors into the basic STIRPAT model.

Further improvements have been made to the basic STIRPAT model by otherresearchers in a way similar to those made by York et al. (2003). *Firstly*, the population term (P) was extended to include the number of households and average household size (Cramer, 1997), population in productive age categories (York et al., 2003),age structure (Fan et al., 2006), urbanization (York, 2007), and the size of families(Liddle, 2013). *Secondly*, the affluence term (A) was decomposed into GDP per capita(Ji et al., 2018; Luo et al., 2018; Zhou et al., 2018). *Thirdly*, the technology term (T) was extended in three ways: (i) T was included in the residual term (Dietz et al., 1997); (ii) T incorporated other factors that theoretically affect GDP level, such as the structure of industry (Ji et al., 2018;Liu et al., 2019), and energy efficiency (Luo et al., 2018); (iii) T also incorporated variables for an open economy, such as the degree of dependence on foreign trade (Wang et al., 2013; Shahbaz et al., 2015;Wang et al., 2017) and FDI (Dong et al., 2019;Liu et al., 2019).

Despite the improvements mentioned above, some shortcomings still exist. First, very little investigation has been done on effects of CEE manufacturing industry's growth on a country's carbon emission. Second, it is quite rare that existing researchers attempted to simplify IPAT equation in such a way that substituting the product of P and A with GDP and T may contain all other variables to be incorporated into IPAT equation. Such a substitution is because the affluence term A can be decomposed into GDP per capita.

To overcome these shortcomings, we propose extending the STIRPAT model by replacing lnP+lnA with lngdp as one of control variables. Following Li et al.(2020), we replace lnT by the following variables: explanatory variable lnce (clean energy equipment); other control variables: lnmio (other goods manufacturing industry's output), lnurb (urbanization), lnenrg (energy efficiency), lnserv (service industry's output). The coefficients of lnce and lnmio are emission-offsetting effect and emission-reinforcing effect respectively.

The rationality for drivers of generating carbon emission is as follows. Economic activity in a country, especially the production and consumption/application of goods, are direct drivers of carbon emission. Production includes the production of CEE and other goods, whereas consumption includes the consumption and/or application of CEE and consumption of other goods. Figure 1 shows the linkage mechanism of CEE with carbon emission.

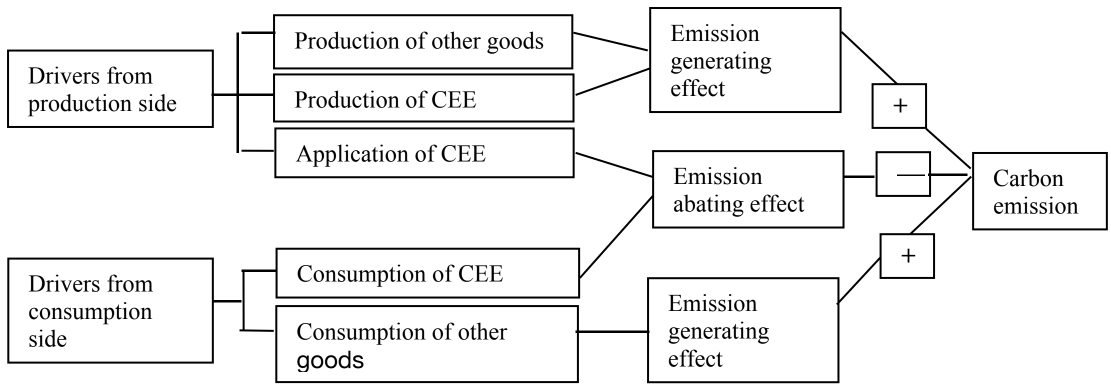

Figure 1. Linkage mechanism of CEE with carbon emission

The production of both CEE and other goods certainly intensifies the carbon emission because such production generates carbon emission. This is so called emission-generating effect. Both application of CEE in production side and consumption of CEE reduce the carbon emission because such application and consumption generate nearly zero carbon emission, in other words, application and/or consumption of CEE abates or eliminates carbon emission that would be generated by application and/or consumption of traditional equipment. This is so called emission-abating effect. Consumption of other goods intensifies the carbon emission because such consumption generates carbon emission, too.

This paper contributes to the existing literature in three important aspects. First, we uncovered an emission-offsetting effect of CEE, namely, while CEE's production has emission-generating effect, their application and/or consumption have emission-abating effect and emission-generating effect and emission-abating effect offset each other. *Second*, we filled in existing literature's gap by examining effects of CEE manufacturing industry's growth on carbon emissions in China. *Third*, we simplified IPAT equation by substituting the product of P and A with GDP and enabled T to contain all other variables to be incorporated into IPAT equation.

The remainder of this paper is arranged as follows: Section II specifies model for regression and states variable description data sources, Section III reports regression results of baseline model and improved model, Section IV firstly carries out heterogeneit analysis from product and regional perspective respectively, secondly makes robustness check, thirdly analyzes influence mechanism of GVC and technology respectively, Section V gives conclusion and policy recommendation.

II. Model Specification and Data Sources

First, we extended IPAT by substituting the product of P and A with GDP, this was because the affluence term A can equal to GDP per capita. Second, following Li et al.(2020), we extended STIRPAT model by replacing lnT with the following variables: explanatory variable lnce (clean energy equipment); other control variables: lnmio (other goods manufacturing industry's output), lnurb (urbanization), lnenrg (energy efficiency), lnserv (service industry's output). The coefficient of lnce is emission-offsetting effect, namely net effect of emission-generating effect in production and emission-abating effect in consumption/application, whereas, the coefficient of lnmio is emission-reinforcing effect, namely emission-generating effect in production plus emission-generating effect in consumption. Therefore, we specified our regression model as Equation (1):

$$lnCO_{2_{it}} = \alpha_0 + \alpha_1 lnCE_{it} + \alpha_2 lnMIO_{it-1} + \alpha_3 lnZ_{it} + \mu_{it}, \quad (1)$$

where CO_2 represents the carbon emissions of province i in year t, serving as the dependent variable in the model. CE is the output of the clean energy equipment manufacturing industry and is the explanatory variable of interest. MIO controls for the output of manufacturing industries of goods other than clean energy equipment, and is one period ahead to avoid potential covariance with GDP. The vector Z includes remaining control variables: gross domestic product (GDP), urbanization rate (URB), energy efficiency ($ENRG$), and industrial structure ($SERV$). Finally, μ denotes the random error term.

Variables and data sources are as follows.

(1) Dependent variable

The dependent variable in this study is the carbon emissions ($CO2$) of each province in China. There are two main sources of CO2 data commonly used in current research, namely two inventories provided by the China Carbon Accounting Databases (CEADs). The first is a carbon emission inventory based on the IPCC subsectoral accounting method, and the second is based on apparent energy consumption data. The apparent emission accounting method, in comparison to the IPCC subsectoral approach, provides a more accurate estimate of provincial carbon emissions by considering factors such as energy production, imports and exports, and inventory changes. Consequently, this paper adopts the Apparent Carbon Emission Inventory as the data source, utilizing provincial-level datasets to analyze CO2 across 30 provinces in China from 2011 to 2021 (excluding the Tibet Autonomous Region (TAR) due to significant data deficiencies).

(2) Explanatory variables

The explanatory variable in this study is the output of clean energy equipment manufacturing industry (*CE*). In accordance withthe Green Industry Guidance Catalogue (2019 Edition)[①], we selected solar PV, lithium-ion batteries, and wind turbines as clean energy equipment. It should be noted that the statistical units of production for these different types of equipment vary. Production of wind turbines and solar PV is measured in units of 10,000 kilowatts, while production of lithium-ion batteries is measured in units of 10,000 units. To ensure consistency in the statistical representation of lithium-ion batteries, we employed the mean battery capacity of the top 20 models of China's new energy vehicle sales in 2023, multiplied by the quantity of

[①]According to the ‘Green Industry Guidance Catalogue (2019 Edition)’, new energy and clean energy equipment manufacturing includes wind turbines manufacturing, solar PV manufacturing, biomass energy utilization equipment manufacturing, hydroelectric power generation and pumped storage energy equipment manufacturing, smart grid products and equipment manufacturing, gas turbine equipment manufacturing, fuel cell equipment manufacturing, geothermal energy development and utilization equipment manufacturing, ocean energy development and utilization Equipment Manufacturing. According to the division of energy industry chain ecosystem, clean energy equipment includes four aspects of ‘source, network, load and storage’ ‘source’ includes hydroelectric equipment, wind power equipment, nuclear power equipment, gas turbines, solar power equipment, etc.; ‘network’ includes ultra-high voltage power generation and pumped storage equipment. Grid includes ultra-high voltage transmission, substation and distribution equipment, smart grid equipment, energy Internet equipment, etc.; “Load” includes industrial energy-saving equipment, electric energy substitution equipment, switching equipment, new energy transport, smart home appliances, etc.; “Storage” includes electrochemical energy storage equipment, mechanical energy storage equipment, and mechanical energy storage equipment. including electrochemical energy storage equipment, mechanical energy storage equipment, hydrogen energy storage equipment, thermal energy storage equipment, etc.

lithium-ion batteries produced, and converted to kilowatt-hours (kWh). Subsequently, the output of solar PV, lithium-ion batteries, and wind turbines is aggregated to obtain the total output of CEE manufacturing industry (CE). The data are derived from the China Industrial Economy Database of the National Bureau of Statistics (NBS) and are weighed according to the proportion of the output value of the electrical industry in each province, ensuring the accuracy of the data.

(3) Control variables

We employed five control variables, detailed as follows. The data are sourced from the China Statistical Yearbook (NBS, 2011-2021), except for the MIO data for the period 2011-2016, which was obtained from the China Industrial Statistical Yearbook (NBS, 2011-2016).

Other Goods Manufacturing Industry Output (*MIO*): *MIO* serves as a crucial indicator of industrial activity, directly impacting carbon emissions. We used the overall manufacturing industry output value as an approximate indicator for other goods manufacturing industry output, excluding clean energy equipment manufacturing industry output. We did so due to the unavailability of data to separate CEE manufacturing industry output from the overall manufacturing industry output. A possible covariance between GDP and *MIO* is avoided by using one period ahead samples of *MIO*. Another possible covariance between *MIO and CE* is avoided by measuring clean energy equipment industry output based on quantity of electricity generation rather than on monetary value. Missing data for certain years were supplemented using the three-year moving average method. MIO is expected to have a positive effect on carbon emissions.

Gross Domestic Product (*GDP*):GDP reflects the population size and per capita economic output of a country or region. In the STIRPAT model, population (P) and affluence (A) are key factors influencing the environment, with both population growth and increased wealth driving carbon emissions (He et al., 2019). To simplify the STIRPAT equation, we used GDP as a substitute for the product of population and affluence, and it is expected to have a positive effect on carbon emissions.

Urbanization Rate (*URB*):Urbanization has a dual impact on the environment; it can increase energy consumption and exacerbate environmental degradation (Parikh et al., 1995; Cole et al., 2004), but it can also reduce energy consumption and improve the environment by enhancing the efficiency of public facilities and transportation (Fan et al., 2006; Liddle et al., 2010). In this study, the urbanization rate, i.e. the proportion of the urban population to the total population, measures the scale and extent of urbanization.

Energy Efficiency (*ENRG*):Improvements in energy efficiency generally reflect advancements in environmental technology, such as the promotion of green buildings and electric vehicles (Zhang et al., 2019), which definitely affect emission intensity. We used the ratio of GDP to local electricity consumption as a measure of energy efficiency, with an expected negative effect on carbon emissions.

Industrial Structure (*SERV*):The secondary sector, especially manufacturing, significantly raises carbon emissions; while a higher share of the tertiary sector, which is less energy-dependent, reflects a shift towards a low-carbon economy (Gong & Liu, 2020). The industrial structure, measured by the tertiary sector's contribution to GDP, is expected to negatively impact emissions as economic activities become less polluting with industrial upgrading.

Table 1 presents the descriptive statistics of samples for all of the variables contained in the regression model.

Table 1. Descriptive Statistics

Variable	Definition	Unit	Sample number	Mean	Standard Deviation	Min	Max
CO2	Provincial annual average carbon emissions	million tons	330	385.977	325.297	41.32	2099.79
CE	Output of clean energy equipment	Ten thousand kilowatts	330	1336188	1376252.9	44884.104	8539394.5
MIO	Output value of other manufacturing	Hundred million yuan	330	31332.181	33648.285	1191.35	165103.8
GDP	Gross domestic product constant RMB (2011)	Hundred million yuan	330	26676.285	21734.434	1670.44	124369.7
URB	Share of urban population		330	59.983	12.098	36	90.6
ENRG	GDP per unit of electricity consumption	yuan/ kw.h	330	15.929	12.225	3.083	86.214
SERV	Ratio of added value from the tertiary sectors to GDP		330	48.66	9.729	30.7	84.9

Source: CEADs and NBS(2011-2021).

III. Regression Results of Baseline Model and Improved Model

Column 2 of Table 2 presents the regression results of equation (1). All coefficients in Column 2 of Table 2 align with our expectations, except for the coefficient of MIO. The relationship between CEE manufacturing and carbon emissions is largely a linear, monotonically decreasing one. This suggests that the negative impact of CEE on carbon emissions outweighs the positive one. In other words, the emission-abating effect of CEE completely offsets the **emission-generating effect**, resulting in a negative net effect of CEE manufacturing industry's growth on carbon emissions.

Table 2 Regression Results of Baseline model and Improved Model

	(1)	(2)

VARIABLES	Baseline model	Improved model
lnCE	-0.244***	-0.215***
	(0.0755)	(0.0750)
lnMAN_lag_sq		-0.0511***
		(0.0165)
lnMAN_lag	-0.239***	0.801**
	(0.0815)	(0.345)
lnGDP	1.388***	1.287***
	(0.139)	(0.141)
lnURB	1.172***	1.166***
	(0.235)	(0.231)
lnENRG	-1.125***	-1.138***
	(0.0966)	(0.0952)
lnSERV	-0.966***	-0.891***
	(0.278)	(0.275)
Constant	-0.537	-5.381***
	(0.782)	(1.741)
Observations	300	300
R-squared	0.698	0.708

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

It should be noted that the relationship between MIO and carbon emissions is linearly monotonically decreasing, too, which seems to be contrary to our perception that the production of other manufactured goods has a carbon generating effect, while their application and/or consumption may have a carbon generating effect, too, and that these two result in an emission-reinforcing effect of MIO growth on carbon emissions. The reason for such an unreasonableregression results may be that a non-linear relationship that probably exists between CO2 and MIO has not been taken into account. Therefore, we introduce a quadratic term for MIO as shown in equation (2).

$$lnCO_{2_{it}} = \beta_0 + \beta_1 lnCE_{it} + \beta_2 (lnMIO_{it-1})^2 + \beta_3 lnMIO_{it-1} + \beta_4 lnZ_{it} + \mu_{ijt} \quad (2)$$

Column 3 of Table 2 presents regression results of improved model in equation (2). Model (1), which only includes MIO primary term, represents the baseline model's regression results, while Model (2), which incorporates a quadratic MIO term, represents the improved model. In both models, the coefficients for CEE are negative and statistically significant, indicating that the net effect of growth in the CEE manufacturing industry on carbon emissions is negative. In the improved model, the coefficient for the MIO primary term turns positive (0.801), while the coefficient for the quadratic MIO term becomes negative (-0.0511). This result suggests an inverted U-shaped relationship between MIO and carbon emissions. This result aligns with China's reality: in the early stages of manufacturing industry development, the growth of other manufactured goods may lead to an increase in carbon emissions. However, as technological advancement and efficiency improve, carbon emissions may gradually decrease as the manufacturing industry continues to develop. Additionally, the higher R^2 value in the improved model compared to the baseline model indicates that accounting for this nonlinear relationship enhances the model's fitting accuracy and explanatory power. The significance of lnCE is slightly weakened (-0.215), and the complex relationship between MIO and carbon emissions may partially explain the effect of lnCE on carbon emissions, thus making the direct effect of lnCE somewhat weaker.

IV. Analysis and Checks

(1) Heterogeneit Analysis

Considering the heterogeneity among different products, we conducted grouping regressions for wind turbines, solar PV, and lithium-ion batteries to assess whether the emission-offsetting effect varies across equipment. Equation (3) represents the model for the impact of three types of product manufacturing output growth on carbon emissions in province i at time t for equipment j:

$$\ln CO_{2_{ijt}} = \gamma_0 + \gamma_1 \ln CE_{ijt} + \gamma_2 (\ln MIO_{ijt-1})^2 + \gamma_3 \ln MIO_{ijt-1} + \gamma_4 \ln Z_{ijt} + u_{ijt} \quad (3)$$

The results of product heterogeneity regression are shown in Table 3. Increases in PV and LIB significantly reduce carbon emissions, aligning with the overall effect of the CEE manufacturing industry output growth on carbon emissions. However, the reduction in carbon emissions from WIND is insignificant, likely due to two key factors: *first*, the small share of wind power in the total energy mix, and *second*, existing infrastructure and technological constraints. **On the one hand,** as of 2023, the installed grid-connected capacity of wind power accounts for less than 15% of the country's total installed power supply, with its power generation comprising less than 8% of total electricity consumption. Consequently, wind power's ability to replace traditional fossil fuel power generation is limited, restricting its overall emission-abating effect. **On the other hand,** consumption and absorption challenges stem from several factors: (1) mismatches between the power system and infrastructure construction, (2) the intermittency of wind power relative to demand, and (3) imperfections in the power market mechanism and scheduling methods. These issues further prevent wind power generation from fully realizing its potential, thereby weakening its emission-abating effect. There remains significant room for improvement in the emission-abating effect of wind power generation.

Table 3 Results of Product Heterogeneity

	WIND	PV	LIB
VARIABLES	lnCO2	lnCO2	lnCO2

lnWIND	-0.0870		
	(0.0694)		
lnPV		-0.182***	
		(0.0604)	
lnLIB			-0.215***
			(0.0750)
lnMAN_lag_sq	-0.0540***	-0.0529***	-0.0511***
	(0.0167)	(0.0164)	(0.0165)
lnMAN_lag	0.872**	0.846**	0.801**
	(0.350)	(0.342)	(0.345)
lnGDP	1.117***	1.249***	1.287***
	(0.133)	(0.129)	(0.141)
lnURB	1.127***	1.131***	1.166***
	(0.238)	(0.229)	(0.231)
lnENRG	-0.991***	-1.121***	-1.138***
	(0.0814)	(0.0881)	(0.0952)
lnSERV	-1.205***	-0.827***	-0.891***
	(0.254)	(0.282)	(0.275)
Constant	-5.706***	-7.415***	-5.381***
	(1.786)	(1.871)	(1.741)
Observations	300	300	300
R-squared	0.701	0.709	0.708

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Additionally, to account for the varying levels of development across different regions in China, we categorize the country's 30 provinces into four regions based on the classification prescribed by the National Bureau of Statistics of China. These four regions are: Eastern Region (ER), Central Region (CR), Western Region (WR), and Northeastern Region (NR)[①]. We then conducted a regional grouping regression to uncover the differences in emission-abating effects across these regions. The basic model for the CO2 level at time t for province i in region r is established in equation (4):

[①] China's geographical regions are divided into four major parts: the Northeastern Region includes the three provinces of Liaoning, Jilin, and Heilongjiang; the Eastern Region covers coastal provinces and municipalities such as Beijing, Tianjin, Hebei, Shanxi, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; the Central Region comprises six provinces (autonomous regions) of Inner Mongolia, Anhui, Jiangxi, Henan, Hubei, and Hunan; and the Western Region includes ten provinces (autonomous regions and municipalities) of Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. This regional classification is used to analyze the distribution of wind energy, photovoltaic equipment, and *lithium-ion batteries* production and consumption across different regions.

$$lnCO_{2_{irt}} = \delta_0 + \delta_1 lnCE_{irt} + \delta_2 (lnMIO_{irt-1})^2 + \delta_3 lnMIO_{irt-1} + \delta_4 lnZ_{irt} + u_{irt} \quad (4)$$

The results from Table 4 highlight the geographical mismatch between the production and consumption/application of CEE. The production of CEE is predominantly concentrated in the eastern and certain central regions, such as Hebei, Anhui, Hunan, Jiangsu, and Guangdong; while the application of wind turbines and solar PV is concentrated in resource-rich western and central regions, such as Inner Mongolia, Xinjiang, Gansu, Qinghai. In the central region, the concentration of CEE production results in higher energy consumption and carbon emissions during production, which offsets the potential emission-abating effects of CEE and leads to a positive correlation between CE growth and carbon emissions. In other regions, the uneven distribution of CEE production and consumption/application results in less significant emission-offsetting effects. These findings reveal a fact that when production and consumption/application are geographically separated, the anticipated offsetting effects do not happen.

Table 4 Results of Regional Heterogeneity by Traditional Regional Classification

VARIABLES	(1) Northeast	(2) East	(3) Central	(4) West
lnCE	-0.173	-0.00772	0.408***	-0.131
	(0.118)	(0.0794)	(0.0889)	(0.126)
lnMAN_lag_sq	-0.0323	-0.0242*	0.149	-0.330***
	(0.0955)	(0.0141)	(0.0914)	(0.0431)
lnMAN_lag	0.149	1.006***	-3.526*	6.240***
	(1.820)	(0.275)	(1.859)	(0.840)
lnGDP	2.538***	0.222	0.530***	0.623***
	(0.270)	(0.176)	(0.188)	(0.218)
lnURB	-2.085	-2.492***	-3.478***	1.549***
	(1.416)	(0.321)	(0.571)	(0.311)
lnENRG	-1.240***	-0.561***	-1.147***	-1.126***
	(0.384)	(0.155)	(0.121)	(0.129)
lnSERV	-0.452	1.293***	0.841*	-1.547***
	(0.274)	(0.359)	(0.459)	(0.383)
Constant	-1.163	2.706	29.09***	-25.65***
	(12.01)	(1.669)	(8.919)	(3.588)
Observations	30	100	60	110
R-squared	0.944	0.956	0.940	0.792

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

In the Northeast and Central regions, the relationship between MIO and CO2 does not exhibit a significant inverted U-shape, as seen in the regression results of Model (2). This is due to these regions absorbing high-carbon industries from the eastern coastal areas and having lower energy efficiency, where improvements in energy efficiency are insufficient to offset the increase in carbon emissions. Additionally, environmental policies in these regions may be more focused on attracting industries rather than strictly limiting carbon emissions, further hindering the development of an inverted U-shaped relationship.

To further validate the requirement that the offsetting effect relies on the geographical co-location of CEE production and consumption/application, we further divided the regions into consumption/application clusters[①] and non-clusters[②] to more directly reveal the emission-offsetting effect of CEE. The new regression results are presented in Table 5.

Table 5 Results of Regional Heterogeneity by CEE Application Clustering

	(1)	(2)
VARIABLES	Clusters	Non-clusters
lnCE	-0.457***	0.0537
	(0.116)	(0.0771)
lnMAN_lag_sq	-0.0240	-0.0135
	(0.0249)	(0.0267)
lnMAN_lag	-0.0757	0.101
	(0.601)	(0.524)
lnGDP	2.614***	0.741***
	(0.294)	(0.151)
lnURB	-1.548***	1.391***
	(0.374)	(0.265)
lnENRG	-1.956***	-0.643***
	(0.181)	(0.101)
lnSERV	-0.116	-1.938***
	(0.388)	(0.289)
Constant	0.708	1.337
	(2.904)	(2.315)
Observations	110	190
R-squared	0.859	0.683

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

By redefining the regions, the results indicate that within the consumption/application clusters, the widespread use of CEE has indeed led to significant emission-offsetting effect. This aligns with expectations that CEE can effectively replace traditional energy sources, thereby abating carbon emissions. In contrast, non-cluster regions, where the density of CEE consumption/application is lower, do not exhibit a significant reduction in carbon emissions. And these findings validate the earlier conclusion.

(2) Robustness Check

[①] Inner Mongolia, Xinjiang, Hebei, Shanxi, Shandong, Gansu, Qinghai, Fujian, Jiangsu, Guangdong, Zhejiang.

[②] Beijing, Tianjin, Shanghai, Chongqing, Liaoning, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, Sichuan, Guizhou, Yunnan, Shaanxi, Ningxia, Tibet, Hainan, Guangxi.

We then replaced the dependent variable CO2 with its one-period lagged value in Model (2) to conduct a robustness check. This is a further consideration for the potential issue of dynamic autocorrelation in the baseline regression. Additionally, to eliminate potential endogeneity in the model, we employed a lagged instrumental variable strategy, using the one-period lagged CEE (CE-lag) as an instrumental variable.

Table 6 presents the results after substituting the dependent variable and conducting the instrumental variable regression. The results show that the direction and significance of most variable coefficients are consistent with the baseline regression results, particularly for the core explanatory variable—CE—thereby confirming the robustness of the baseline model.

Table 6 Regression Results with Instrumental Variables

	(1)	(2)	(3)
VARIABLES	lnCO2_lag	lnCO2	lnCO2
lnCE	-0.227***		
	(0.0728)		
lnCE_lag		0.933***	
		(0.0192)	
lnCE_hat			-0.236***
			(0.0794)
lnMAN_lag_sq	-0.0537***	0.00513	-0.0506***
	(0.0160)	(0.00425)	(0.0165)
lnMAN_lag	0.876***	-0.120	0.788**
	(0.335)	(0.0889)	(0.345)
lnGDP	1.264***	0.0979***	1.313***
	(0.136)	(0.0360)	(0.144)
lnURB	1.074***	0.00838	1.177***
	(0.225)	(0.0599)	(0.232)
lnENRG	-1.119***	-0.0661***	-1.158***
	(0.0925)	(0.0245)	(0.0988)
lnSERV	-0.783***	0.0700	-0.860***
	(0.267)	(0.0713)	(0.278)
Constant	-5.573***	0.677	-5.386***
	(1.690)	(0.450)	(1.739)
Observations	300	300	300
R-squared	0.714	0.984	0.708

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

(3) Influence Mechanism of GVC and Technology

The above research indicates that the emission-abating effect of CEE manufacturing growth outweighs its emission-generating effectand to analyze the mechanisms behind the net negative impacton carbon emissions, two main pathways are identified: technological progress and changes in GVC participation and position. Therefore, based on the basic regression of Model (2), we selected patent counts ($Patent$), GVC participation (GVC_{pt}), and GVC position (GVC_{p}) as mediating variables to more comprehensively reveal the emission-abating effect of CEE manufacturing growth on carbon emissions. A detailed discussion of these variables is as follows.

GVC participation (GVC_{pt}): GVC_{pt} measures the depth of participation in GVC by a country's or a region's industry. It is a key indicator of the industry's integration into the global production network. Following the method proposed by Koopman et al. (2014), we calculated this index by summing forward[①](GVC_{pt_f}) and backward[②] GVC participation (GVC_{pt_b}), as shown in equation (5). The larger the GVC_{pt}, the greater the extent to which a country's industry participates in the division of labor within GVC. We used GVC_{pt} as a mediating variable to reveal the effect of deep participation in GVC on carbon emissions within this industry.

$$GVC_{participation} = GVC_{pt\_f} + GVC_{pt\_b} \tag{5}$$

GVC Position (GVC_p): GVC_p measures the relative position of an industry in a country or region within GVC, reflecting its technical and value-added status within the global production network. Following Koopman et al. (2014), we calculated GVC_p by weighting upstream and downstream activities in GVC, as shown in equation (6). A higher GVC_p indicates that the

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[①]The calculation formula for GVC_{pt_f} is as follows: $GVC_{pt\_f} = \frac{V\_GVC}{Va'} = \frac{V\_GVC\_S}{Va'} + \frac{V\_GVC\_C}{Va'}$. GVC forward participation $\frac{\text{V\_GVC}}{\text{Va'}}$ is the sum of simple GVC forward participation $\frac{\text{V\_GVC\_S}}{\text{Va'}}$ and complex GVC forward participation $\frac{\text{V\_GVC\_C}}{\text{Va'}}$. Here, Va' represents the value-added of various countries and industries, and V_GVC represents the domestic value-added contained in exported intermediate goods. V_GVC_S is the portion of the value-added in exported intermediate goods that is absorbed by the direct importing country for the production of domestically consumed goods, i.e., simple GVC. V_GVC_C represents the portion of the value-added in exported intermediate goods that is absorbed by the direct importing country for the production of export goods, i.e., complex GVC (Wang et al., 2017).

[②]The calculation formula for GVC_{pt_b} is as follows: $GVC_{pt\_b} = \frac{Y\_GVC}{Y'} = \frac{Y\_GVC\_S}{Y'} + \frac{Y\_GVC\_C}{Y'}$. GVC backward participation $\frac{Y\_GVC}{Y'}$ is the sum of simple GVC backward participation $\frac{Y\_GVC\_S}{Y'}$ and complex GVC backward participation $\frac{Y\_GVC\_C}{Y'}$. Here, Y' represents the value-added of the final output of various countries and industries, and Y_GVC represents the value-added contained in imported intermediate goods. Y_GVC_S is the portion of the value-added in imported intermediate goods used for the production of domestically produced consumer goods, i.e., simple GVC. Y_GVC_C represents the portion of the value-added in imported intermediate goods used for the production of export goods or returned to the home country, i.e., complex GVC (Wang et al., 2017).

industry is positioned upstream in the value chain, engaging in production activities with higher technical content and value-added; conversely, a lower GVC_p suggests that the industry is downstream, likely involved in low-tech assembly process. We used GVC_p as a mediating variable to analyze how the relative position of this industry within GVC affects carbon emission levels.

$$GVC_{position} = \ln(1 + GVC_{pt\_f}) - \ln(1 + GVC_{pt\_b}) \tag{6}$$

*CEE*analyzed in this paper primarily includes solar PV, wind turbines and lithium-ion batteriesasenergy storage devices. According to National Economic Industry Classification (GB/T 4754-2017), the manufacturing of solar PV and energy storage devices like lithium-ion batteries falls under category C38, "Manufacture of Electrical Machinery and Equipment," while wind turbine manufacturing is classified under C34, "Manufacture of General-Purpose Machinery." Given the relatively small data volume and limited time span for wind turbines, its calculations are omitted from this paper. As a result, the CEE manufacturing industry is mainly associated with C38, "Manufacture of Electrical Machinery and Equipment." Based on the sector classification standards of the *ADB MRIO* database and *National Economic Industry Classification*, we used the raw data under the C14 "Electrical and Optical Equipment" category from *ADB MRIO 2022* to calculate GVC_{pt} and GVC_p for CEE manufacturing industry (i.e., C38, "Manufacture of Electrical Machinery and Equipment").

Patent Count ($Patent$): Patent represents the level of technological innovation in CEE manufacturing industry. An increase in $Patent$ usually indicates technological progress, which can reduce carbon emission intensity by improving production efficiency and energy utilization. In this study, $Patent$ refers to the number of patents granted between 2011 and 2021 in China for solar PV, wind turbines, and lithium-ion batteries, with data sourced from*China National Intellectual Property Administration (CNIPA)*. As a mediating variable, $Patent$ reflects the contribution of technological innovation to the carbon emission-abating effect of the CEE manufacturing industry and is expected to have a negative impact on carbon emissions.

Theoretical analysis suggests that the degree to which a country's industry is embedded in GVC affects the carbon emissions of that industry. GVC_{pt_b} has a positive correlation with carbon emissions. This is because backward participation in GVC reflects that an industry primarily undertakes high-energy-consuming and low value-added processing and assembly activities within GVC. *On the one hand*, this exacerbates carbon emissions in the home country, and *on the other hand*, it creates dependency on the import of high-tech components from developed countries, leading to a "low-end lock-in," which further increases carbon emissions.

The relationship between GVC_{pt_f} and carbon emissions exhibits an inverted "U" shape, meaning that before approaching a "threshold," GVC_{pt_f} is positively correlated with carbon emissions; however, once the threshold is reached, this relationship turns negative. At the initial stages of forward embedding in GVC, an industry in a country may provide energy-intensive or low-tech intermediate goods to other countries, leading to significant energy consumption and environmental pollution. In this stage, as GVC_{pt_f} increases, carbon emissions rise, too. As GVC_{pt_f} continues to increase, developed countries—often the leading firms in the GVC—implement high environmental standards, forcing GVC-participating companies in developing countries to adopt low-carbon, cleaner technologies to reduce carbon emissions. Additionally, through the "learning-by-doing" effect, GVC participants in developing countries gradually acquire advanced production technologies and management experience from developed countries, improving production efficiency and energy utilization, which in turn reduces carbon emissions. In other words, with the increase in GVC_{pt_f}, carbon emissions gradually decrease (Wang et al. 2019; Li &Song 2023).

Thus, whether GVC_{pt} increases or decreases carbon emissions depends on the combined effects of GVC_{pt_f} and GVC_{pt_b}. Before reaching the threshold of, the combined emission-generating effects of forward and backward participation result in an overall increase in carbon emissions.Once the threshold is reached, the impact of GVC_{pt} on carbon emissions depends on the net effect of the emission-abating effect of forward participation and the emission-generating effect of backward participation. Current researches (Liu et al., 2023; Gao& Yue, 2022) show that most industries in China have not yet reached the threshold for GVC_{pt_f} and are still in the emission-generating stage of GVC_{pt_f}. Thus, at this stage, GVC_{pt_f}, GVC_{pt_b}, and overall GVC_{pt} exacerbate carbon emissions.

GVC_{p} measures the status of a country's industry within GVC. The larger the index, the higher the industry's position in GVC, indicating a stronger ability to lead GVC and optimize resource allocation globally for maximum benefit. This allows for the selection of high-value-added, low-carbon production activities in the home country. Therefore, an increase in GVC_{p} effectively reduces carbon emissions (Liu et al. 2020; Zhang& Sun 2024; Zhaoet al. 2021), suggesting a negative correlation between GVC_{p} and carbon emissions.

So how does the participation and position of CEE manufacturing industry in GVC affect China's carbon emissions? To reveal this influence mechanism, we introduced GVC-related indices for CEE manufacturing industry and constructed models (7) and (8).

$$lnGVC_{pt_{it}} = \theta_0 + \theta_1 lnCE_{it} + \theta_2 (lnMIO_{it-1})^2 + \theta_3 lnMIO_{it-1} + \theta_4 lnZ_{it} + u_{1it} \quad (7)$$

$$lnGVC_{p_{it}} = \rho_0 + \rho_1 lnCE_{it} + \rho_2 (lnMIO_{it-1})^2 + \rho_3 lnMIO_{it-1} + \rho_4 lnZ_{it} + u_{2it} \quad (8)$$

Furthermore, a significant factor influencing the position in GVC is technological change. Thus, we use $Patent$ toreflect the role of technological innovation(measured by the number of patents) in reducing carbon emissions. We constructed Model (9) including *Patent* as follow.

$$lnPatent_{it} = \sigma_0 + \sigma_1 lnCE_{it} + \sigma_2 (lnMIO_{it-1})^2 + \sigma_3 lnMIO_{it-1} + \sigma_4 lnZ_{it} + u_{3it} \quad (9)$$

Table 7 presents the estimated effects of the growth of CEE manufacturing industry on GVC_{pt_f}, GVC_{pt_b}, GVC_{pt}, GVC_p and *Patent*.

Columns (1) to (3) show that the growth of theCEE manufacturing industry negatively affects GVC_{pt_f}, GVC_{pt_b} and GVC_{pt} respectively. Referring to Table 8, from 2011 to 2021, GVC_{pt} of the CEE manufacturing industry has shown a declining trend.This can be understood by dividing the period into two distinct phases, with 2018 as the turning point.

Before 2018, the decline was primarily due to a significant reduction in GVC_{pt_b}, which can be attributed to the following three reasons:(1) The impact of the financial crisis and the European debt crisis led to slower growth in Western developed economies and a "slowdown" in global trade, combined with rising trade protectionism, which restricted the expansion space of GVC. (2) The rapid increase in labor costs in China due to an aging population has led to the relocation of labor-intensive and low-end manufacturing industries to Southeast Asia, South Asia, and Mexico, resulting in a decline in GVC_{pt_b}. (3) With policy support, Chinese CEE manufacturing enterprises actively engaged in technological research and development, achieving the substitution of imported intermediate goods, which led to a reduction in GVC_{pt_b} due to the industry's upward movement in GVC, thus causing a decrease in GVC_p.

After the outbreak of the China-US trade friction in 2018, intensified technology blockades further led to a sharp decline in GVC_{pt_f}. Although there was a recovery in the following years, it has not yet returned to the pre-trade friction levels. Based on theoretical analysis, before GVC_{pt_f} reaches a "threshold," the growth of the CEE manufacturing industry, which leads to a reduction in GVC_{pt_f}, GVC_{pt_b}, and GVC_{pt}, is generally associated with a decrease in carbon emissions.This is mainly because as the industry progress upstreams in GVC, the reliance on low-end processing and manufacturing decreases, leading to a reduction in carbon intensity.

Table 7 Regression Results of Mediation Effect

	(1)	(2)	(3)	(4)	(5)
VARIABLES	GVC_{pt_f}	GVC_{pt_b}	GVC_{pt}	GVC_{p}	$lnPatent$
lnCE	-0.00460***	-0.00399***	-0.00859***	-0.00052	0.626***
	-0.000918	-0.00117	-0.00206	-0.000366	-0.0266
lnMAN_lag_sq	0.00356***	0.00435***	0.00791***	-0.000638***	-0.0223***
	-0.000202	-0.000257	-0.000452	-8.05E-05	-0.00586
lnMAN_lag	-0.0648***	-0.0802***	-0.145***	0.0126***	0.352***
	-0.00422	-0.00539	-0.00945	-0.00168	-0.123
lnGDP	0.00870***	0.0105***	0.0192***	-0.00142**	-0.458***
	-0.00172	-0.0022	-0.00386	-0.000687	-0.05
lnURB	0.00916***	0.0122***	0.0214***	-0.00248**	-0.125
	-0.00283	-0.00361	-0.00634	-0.00113	-0.0822
lnENRG	-0.00552***	-0.00514***	-0.0107***	-0.000336	0.412***
	-0.00117	-0.00149	-0.00261	-0.000465	-0.0338
lnSERV	0.00105	-0.00259	-0.00154	0.00295**	0.00653
	-0.00337	-0.0043	-0.00755	-0.00135	-0.0978
Constant	0.244***	0.295***	0.539***	-0.0413***	2.654***
	-0.0213	-0.0272	-0.0477	-0.00851	-0.619
Observations	300	300	300	300	300
R-squared	0.754	0.736	0.75	0.404	0.796

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Column (4) indicates that CEE manufacturing growth has no significant impact on GVC_p. This indicates that, at this stage, the CEE manufacturing industry has not yet significantly influenced carbon emissions through its GVC advancement. However, the negative correlation between GVC_p and carbon emissions implies that China's carbon reduction goals place greater demands on CEE technology development. As shown in Table 8, since 2011, China's GVC_{pt_f} has risen, while GVC_{pt_b} has declined, reflecting early successes in CEE technological innovation and its positive effect on GVC_p. Notably, GVC_p shifted from negative to positive in 2015. However, the China-US trade friction in 2018 reversed this trend, leading to a sharp decline in GVC_p, which has remained at a lower level since.

Looking ahead, with continued breakthroughs in technological innovation in China's CEE manufacturing industry and the easing of China-US trade tensions, GVC_p is expected to rise steadily. At that point, the carbon-abating effect of CEE manufacturing industry is likely to exceed its carbon-generating effect, thereby further driving reductions in overall carbon emissions. For example, in the product heterogeneity analysis, photovoltaic equipment and lithium-ion batteries have shown significant emission-offsetting effects.

Table 8 GVC-Related Indices of China's CEE Manufacturing Industry

	GVC_{pt_f}	GVC_{pt_b}	GVC_{pt_f} Proportion	GVC_{pt_b} Proportion	GVC_{pt}	GVC_p
2011	0.219589068	0.2978449	0.424380851	0.575619149	0.517433968	-0.062191147
2012	0.211632506	0.281475187	0.429181108	0.570818892	0.493107692	-0.056043275
2013	0.225024676	0.278610085	0.44680132	0.55319868	0.50363476	-0.042812629
2014	0.22945412	0.25534982	0.473292607	0.526707393	0.48480394	-0.020844008
2015	0.215338814	0.206367164	0.510637329	0.489362671	0.421705978	0.007409398
2016	0.205889051	0.203564623	0.502838451	0.497161549	0.409453673	0.001929424
2017	0.214947165	0.212379082	0.503004827	0.496995173	0.427326247	0.002115977
2018	0.165724101	0.258002292	0.391111113	0.608888887	0.423726393	-0.07618254
2019	0.177179346	0.260746748	0.404587323	0.595412677	0.437926094	-0.06858301
2020	0.186236632	0.250615277	0.426315253	0.573684747	0.436851909	-0.05284985
2021	0.192905634	0.275201446	0.412097236	0.587902764	0.46810708	-0.066712123

Column (5) shows that CEE manufacturing growth has significantly boosted technological innovation, resulting in an increase in $Patent$. From 2011 to 2021, the number of CEE patents steadily rose. Supported by domestic policies and the "12th Five-Year Plan," China's CEE industry increased R&D investment, promoted independent innovation, and enhanced technological capabilities. This has led to the rise of leading GVC companies like CIMC Enric and Shanghai Electric. Ongoing innovation in CEE technology has advanced the industry's development, improved production efficiency and energy utilization, and reduced carbon emission intensity.

However, GVC_p is still at a relatively low level, and core technologies remain partially restricted. To address this challenge, companies need to continue increasing R&D investments and cultivating highly skilled research talent, especially focusing on advanced materials, smart manufacturing, and energy storage technologies. These efforts will help reduce reliance on foreign technologies and achieve independent breakthroughs in critical technologies.

In summary, the growth of CEE manufacturing has had multiple impacts on its GVC participation and position, which in turn has produced emission-abating effects. Specifically, the growth of CEE manufacturing industry has weakened GVC_{pt_f}, GVC_{pt_b}, and GVC_{pt}, and this process is closely linked to the abatingin carbon emissions. Meanwhile, the industry's capacity for technological innovation has significantly improved, and the growth in patent development has effectively contributed to reducing carbon emission intensity.

From a policy perspective, further promoting international technological cooperation and optimizing industrial policy support is crucial for accelerating the industry's upgrading. The government should encourage breakthroughs in core technologies by introducing more tax incentives, providing research subsidies, and improving access to financing. Additionally, promoting the digital transformation of CEE manufacturing industry will enhance production efficiency, reduce production costs, and further improve energy utilization efficiency, thereby reducing carbon emission intensity.

Although China's position in GVC of CEE manufacturing has improved, GVC_p has remained relatively low since the onset of China-US trade friction in 2018. Developed countries may adopt trade protection measures to limit China's ascent in the high end of CEE manufacturing value chain. Should such measures come into effect, China could face the risk of "low-end lock-in," which could exacerbate domestic carbon emissions issues. Therefore, China must strengthen its awareness of external risks, continue advancing independent technological innovation, and enhance cooperation with countries along the "Belt and Road" initiative. Optimizing the trade structure of CEE manufacturing industry will improve its position in GVC, ensuring sustainable development and further advancing carbon reduction goals.

V. Conclusions and Policy Recommendation

We examined the interplay between growth of CEE manufacturing industry and carbon emissions bytaking a provincial-level dataset of China from 2011 to 2021. This research is motivated by China's dual-carbon goal of reaching carbon peak by 2030 and carbon neutrality by 2060, and a rapid growth of CEE manufacturing industry in China. Our research focuses on three primary CEE products: solar PV, lithium-ion batteries, and wind turbines. We used a STIRPAT modelwhich is a commonly used tool for examining environmental impact caused by socioeconomic factors. This model is simplified by using GDP as a substitute for the product of population and affluence.

Amid the challenging "dual carbon" goal facing China, the growth of CEE manufacturing industry not only supports the achievement of these goals but also helps enhance China's leadership in the global CEE supply chain. Based on this, we focus on China's CEE manufacturing industry, exploring effects of its growth on carbon emissions and analyzing the mediating role of technological progress and the industry's integration into GVC in the relationship between industry growth and carbon emissions.

We obtained the following findings: *First*, the growth of the CEE manufacturing industry has, overall, reduced China's carbon emissions, showing that the industry's emission-abating effect exceeds emission-generating effect during its production process. This conclusion remains robust even after replacing the dependent variable and controlling for endogeneity issues, demonstrating that the emission-offset effect of the CEE manufacturing industry plays a critical role in China's emission reduction efforts. *Second*, the expansion of other goods manufacturing industry follows an inverted U-shaped pattern, initially driving emissions higher before technological advancements lead to eventual reductions, confirming the non-linear relationship between industry growth and emissions. *Third,* the negative relationship between the growth of the CEE manufacturing industry and carbon emissions exhibits heterogeneity among different product groups and regional groups. Among product groups, the solar PV and lithium-ion battery sectors have made significant contributions to reducing carbon emissions, while wind turbines still require infrastructure and technological improvements. Among regional groups, the production and consumption/application of CEE are imbalanced across economically stratified traditional regions. In contrast, clean energy clusters show stronger carbon-abating effects, underscoring the effectiveness of CEE in replacing traditional energy sources in these areas. Regional heterogeneity indicates that the emission-offsetting effect is contingent upon the geographical alignment between CEE production and its consumption/application. *Fourth,* the analysis of GVC integration and technological development mechanisms further reveals the emission-abating pathways for CEE manufacturing growth. The research indicates that the growth of the CEE manufacturing industry has decreased its GVC participation level, especially in terms of backward participation, which may be related to international industrial shifts, thus reducing carbon emissions. Meanwhile, there is an inverted-U relationship between forward participation and carbon emissions. Before reaching the threshold, a partial decline in GVC forward participation has also contributed to carbon emission reductions. Although the improvement in GVC position generally leads to emission reductions, U.S.-China trade frictions and high-tech blockades have kept China's current GVC position in the CEE manufacturing industry relatively low, limiting its mitigating effects. Moreover, technological innovation has boosted production efficiency and energy utilization, further promoting carbon emission reductions. This suggests that trade policies and technological innovation will play crucial roles in future emission reduction efforts.

Based on the research conclusions and the evolving dynamics between the growth of China's CEE manufacturing industry and carbon emissions, we propose the following policy recommendations.

First, actively expand the installed capacity of solar PV, wind turbines, and other clean energy sources to accelerate the transition of domestic energy consumption. This will meet growing energy demands and support the development of China’s CEE manufacturing industry, helping achieve the 2030 carbon peak and 2060 carbon neutrality goals. The government should support provinces based on their resource advantages to specialize in specific CEE, such as solar in Gansu and wind in Inner Mongolia, optimizing resource allocation and accelerating the energy transition. *Second*, regional heterogeneity in CEE reflects disparities in economic development, industrial structures, energy efficiency, and policies, leading to uneven emission reductions. To achieve national carbon balance, regional policy coordination should be strengthened, aligning CEE production with local resources and economic conditions. At the same time, industries should establish sustainable supply chains to reduce transportation-related carbon emissions and ensure a stable supply of raw materials, leading to more balanced emission reductions. *Third*, GVC analysis shows that China's CEE manufacturing industry improved its GVC position after 2015, but the 2018 U.S.-China trade friction hindered this progress, weakening the moderating effect on the growth-carbon emissions relationship. To fully harness the carbon-reduction potential of CEE manufacturing, it is crucial to enhance independent R&D and innovation, expand international trade, and elevate the industry’s GVC position. The government should increase funding for R&D in key provinces' universities and research institutions, promote energy-efficient manufacturing practices and circular economy models to reduce the carbon footprint in production. *Fourth*, adopt a development strategy combining policy support and market guidance. Leverage platforms such as the Regional Comprehensive Economic Partnership (RCEP) and the Belt and Road Initiative to deepen cooperation with Southeast Asia and Belt and Road countries, optimize CEE trade partnerships, and encourage Chinese manufacturers to expand globally. Foster collaboration between leading global companies and local manufacturers to transfer clean technologies and best practices, building a complete and sustainable supply chain to mitigate the impact of trade protection from developed countries. In the current complex and volatile international landscape, where economic development and environmental governance are global priorities, China should seize the opportunity to drive the high-quality development of its CEE manufacturing industry, creating a new engine for economic growth.

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