The Effect of the Multi-Target Energy and Climate Policy on Carbon Emissions: County-level Evidence from China

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Abstract: The use of command-and-control target policies for climate governance is crucial in achieving China's "dual carbon" goals. We investigate the impact of multi-target policy on county-level carbon emissions, using the generalized difference-in-differences model for the gradual implementation at different phases of multiple policies. We find that the Carbon Intensity Reduction Target (CIRT) and Total Energy Consumption Target (TECT) policies promote carbon reduction, while the Energy Intensity Reduction Target (EIRT) policy shows uncertainty. In the eastern and central regions, the initial phase of carbon reduction is primarily propelled by the EIRT policy, subsequently transitioning to the dominant influence of the CIRT policy. In the later phase, carbon reduction in the eastern region is predominantly attributed to the CIRT policy, whereas in the central region, it results from the combined effects of the EIRT, CIRT, and TECT policies. In the western region, early policies have an insignificant impact on carbon reduction, and the later-phase effects shift from being primarily influenced by the EIRT to being predominantly influenced by the CIRT. Additionally, neglecting the impact of other policies with similar targets during the same period may lead to overestimation of the effects of EIRT and TECT and underestimation of the effect of CIRT.

Keywords: Carbon emissions; Emission reduction targets; Multi-target policy; Generalized difference-in-differences model; China

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1. Introduction

China pledged to ensure that carbon emissions peak around 2030 and reach carbon neutrality before 2060. China has developed multiple target-constrained policies to reduce carbon emissions either directly or indirectly to achieve this “dual-carbon” goal. Chinese government first suggested the energy intensity reduction target (EIRT) during the 11th Five-Year Plan (FYP) period (2006–2010), explicitly stating that the energy consumption intensity should be decreased by 20% by 2010 over 2005. In addition to the 16% decrease in energy consumption intensity, a target of 17% reduction in carbon intensity was introduced for the 12th FYP period (2011–2015). In addition to EIRT and carbon intensity reduction target (CIRT), the total energy consumption target (TECT) must be regulated within 5 billion tons of standard coal during the “13th FYP” timeframe. The EIRT is set at 15% for the “13th FYP” (2016–2020) and 13.5% for the “14th FYP” (2021–2025) periods, with a CIRT of 18% for each. Setting mandatory constraint targets has become an indispensable policy tool for China to address carbon emissions reduction.

Existing research has extensively examined the effects of China’s environmental policies on carbon emissions [1-3]. The prevailing focus of these studies has revolved around evaluating the impact of individual energy or climate policies on carbon emissions [3]. Research has indicated that the implementation of low-carbon pilot policies has the potential to substantially enhance urban carbon efficiency [4], leading to a reduction in overall carbon emissions [5] as well as per capita carbon emissions [6]. Empirical investigations conducted at the micro-firm level have underscored that the adoption of low-carbon pilot policies (LCPPs) correlates with a decline in the carbon emission performance of enterprises [7]. The introduction of innovative city pilot policies has also been found to exert a substantial positive influence on carbon total factor productivity [8]. Additionally, the adoption of carbon emissions trading system (ETS) has demonstrated its effectiveness in curbing carbon emissions within pilot regions [9], with this mitigation effect persisting over the long term [10]. The implementation of energy-saving and emission reduction policies has notably led to a remarkable 15.26% reduction in carbon emissions [11]. These distinct policies, each targeting climate and energy concerns, have collectively played a pivotal role in the reduction of carbon emissions. They underscore the substantial contribution of China’s environmental policies toward addressing climate change. Nevertheless, it’s worth noting that these policies are often implemented concurrently with related policies that share similar objectives. In essence, the current decline in emissions can be attributed to the cumulative impact of multiple policies. However, limited studies have ventured into exploring the synergistic effects of various climate policies on carbon emissions [12]. Moreover, neither individual environmental policies nor numerous climate policies explicitly integrate target constraints for climate objectives. Consequently, there exists a relatively modest body of research on the influence of climate policies with specific target constraints on carbon emissions.

China’s carbon reduction policies mostly consist of command-and-control policies [9, 13, 14]. These policies encompass a range of mandatory target-driven command-and-control policies to achieve climate objectives [15, 16]. However, the research on the influence of target-constrained policies on carbon emissions remains relatively scarce. Existing research has demonstrated the effectiveness of the energy intensity constraint policy (EICP) and the carbon intensity constrain policies (CICP) in achieving their respective objectives of reducing energy intensity and carbon intensity [17, 18]. Additionally, investigations have revealed that EICP contributes to enhancing overall energy efficiency [19] and elevating the total factor carbon performance index (TCPI) [20]. However, the EICP can exert a notable adverse influence on total factor energy efficiency growth (TFEEG) in industries characterized by higher energy intensity levels [21]. Meanwhile, CICP has been found to have a positive impact on enhancing industrial green production performance [17]. Studies exploring the ramifications of implementing multiple target policies on green productivity have indicated that both energy-saving and emission reduction goals can lead to improvements in industrial green productivity [22]. This body of research underscores the pivotal role played by goal-constrained policies in shaping carbon intensity, TCPI, energy efficiency, and green productivity. It’s worth noting that only a number of study have evaluated the impact of EIRT policies on carbon emissions [23], often overlooking the influence of CIRT policies on carbon emissions and failing to discern the cumulative effects of these repeated policies. Although a substantial volume of research has affirmed the effectiveness of China’s goal-constrained policies, some studies have suggested that public policies in China may face challenges in effectively implementing EICP policy [24]. Hence, there is an urgent requirement for more extensive research to thoroughly evaluate the impact of energy and climate policies, such as EIRT, CIRT, and TECT, which have clearly defined objectives, on carbon emissions.

Current assessments of policy effects on carbon emissions primarily focus on the impact of non-binding energy and climate policies. Examples include the effects of a single LCPPs [5, 25], a carbon ETS [26, 27], and an energy conservation and emission reduction policy [4] on carbon emissions. A few studies have examined the concomitant effects of multiple climate policies on carbon emissions [12]. Whether it is a single environmental policy or the combined effects of multiple climate policies, these studies have dealt with environmental policies that lack specific mandatory targets. According to existing research, setting mandatory objective constraints can have a significant effect on energy intensity, carbon intensity [17], total factor productivity growth, and green productivity. Consequently, environmental policies with mandatory targets may also have a substantial effect on carbon emissions. A few studies have evaluated the effect of energy policies with explicit targets on carbon emissions [23], as well as the combined impact of multiple policies on carbon emissions [9]. Thus, a few studies have examined the impact on carbon emissions of multiple energy and climate policies with explicit goals that operate together. In addition, most existing studies concentrate on the provincial and municipal levels, the industry [17] or the enterprise level [28]. The county level is the most fundamental administrative unit in China, and its development priorities differ from those of the provincial and municipal levels [29]. The effectiveness of these multiple command-and-control environmental policies with specific targets at the county level also require further investigation.

This study investigates the impact of various energy and climate policies on county-level carbon emissions in China from 2000 to 2017. Three key policies EIRT, CIRT, and TECT were introduced sequentially, leading to overlapping effects in later phases. EIRT was enacted in 2006, CIRT in 2011, and TECT in 2016. The study used a chronological design to evaluate their individual impacts. It began with EIRT from 2000 to 2010, then assessed CIRT from 2006 to 2015 while considering EIRT, and finally examined TECT from 2011 to 2017, accounting for both EIRT and CIRT. All regions experienced different policy interventions simultaneously, but with varying intensity. The GDD method was employed to measure policy effects and regional disparities. The study draws several significant conclusions. First, when multiple policies were in effect simultaneously, not all of them contributed to carbon emissions reduction at the county level. While the CIRT and TECT policies were associated with reduced carbon emissions, the EIRT policy did not have a similar effect. Second, the effects of climate policies vary across regions and phases. The EIRT policy initially promotes emissions reduction in eastern and central regions [30], later observed in western and central regions. CIRT consistently reduces emissions, affecting various regions. TECT has a significant overall emission reduction effect, primarily in central and western regions. Third, analyzing a single target constraint policy in isolation can lead to overestimations for EIRT and TECT while underestimating CIRT's impact on county-level carbon emissions reduction.

The research contributes to the empirical studies on multiple target constraint policies. First, we extend the analysis of climate target policies, such as CIRT policy, by incorporating direct constraints on carbon emissions. This expansion moves beyond previous research that mainly focused on the impact of China's energy policies [31, 32], particularly the impacts of energy intensity targets on carbon emission [23, 32] and energy efficiency [23, 33]. Second, our study distinguishes the effects of multiple target constraint policies implemented in different phases on carbon emissions. Previous studies were limited in identifying clear phase characteristics, especially when these multiple policies are implemented simultaneously in China [12, 23, 34]. Multiple target constraint policies are implemented progressively in distinct phases, necessitating further exploration. We utilize the GDD method to evaluate both the combined effects of these policies and their individual contributions to carbon emissions reduction, considering the specific phase characteristics of each policy implemented in China. Third, we broaden the scope by examining the impact of multiple target-constrained policies at various levels. Previous studies have primarily focused on the effects of China's environmental policies at the provincial [35] and municipal levels [25], and limited studies have explored climate policies at the industry [36] or enterprise level [37, 38]. However, counties, as the fundamental administrative units in China, have unique development priorities distinct from provinces and municipalities. This leads to potentially diverse policy effects [39, 40].

The remainder of the paper is structured as follows. In Section 2, we introduce the China's climate policy background and data. Section 3 is our empirical strategy. In Section 4, we present our results. Then, in Section 5, we present an extension and conclusions in Section 6. The Appendices contain the nomenclature and all other information.

2. Policy background and data

2.1. China's climate policy exploration and practice

China's climate policy focuses on addressing the global challenge of climate change, with a commitment to achieving ambitious, long-term objectives. These objectives include attaining carbon peaking by 2030 and ultimately realizing carbon neutrality by 2060. Central to this policy are command-and-control policies, and to achieve this objective, China has adopted a series of mandatory target-constrained policies at different phases. The policies include the "China National Plan to Address Climate Change", the "Work Plan for Controlling Greenhouse Gas Emission", and the "Comprehensive Work Plan for Energy Conservation and Emission Reduction". Different reduction targets are specified in different documents. The earliest proposal in China's National Climate Change Program, promulgated in 2007, aimed to achieve an actual 20% reduction in energy consumption intensity by 2010, compared to 2005 levels, as well as a corresponding reduction in CO_2 emissions [41]. During the 11th FYP period, carbon emissions were indirectly affected through EIRT. With the advent of the 12th FYP era, pivotal policy documents were introduced, namely the "Work Plan for Controlling Greenhouse Gas Emissions" and the "Comprehensive Work Plan for Energy Conservation and Emission Reduction." Both frameworks underscored the gravitas of mandatory targets, meticulously integrating CIRT and EIRT for each successive quinquennial interval. The CIRT and EIRT were set every five years. Figure 1 illustrates the evolution of China's EIRT and CIRT since the 11th FYP.

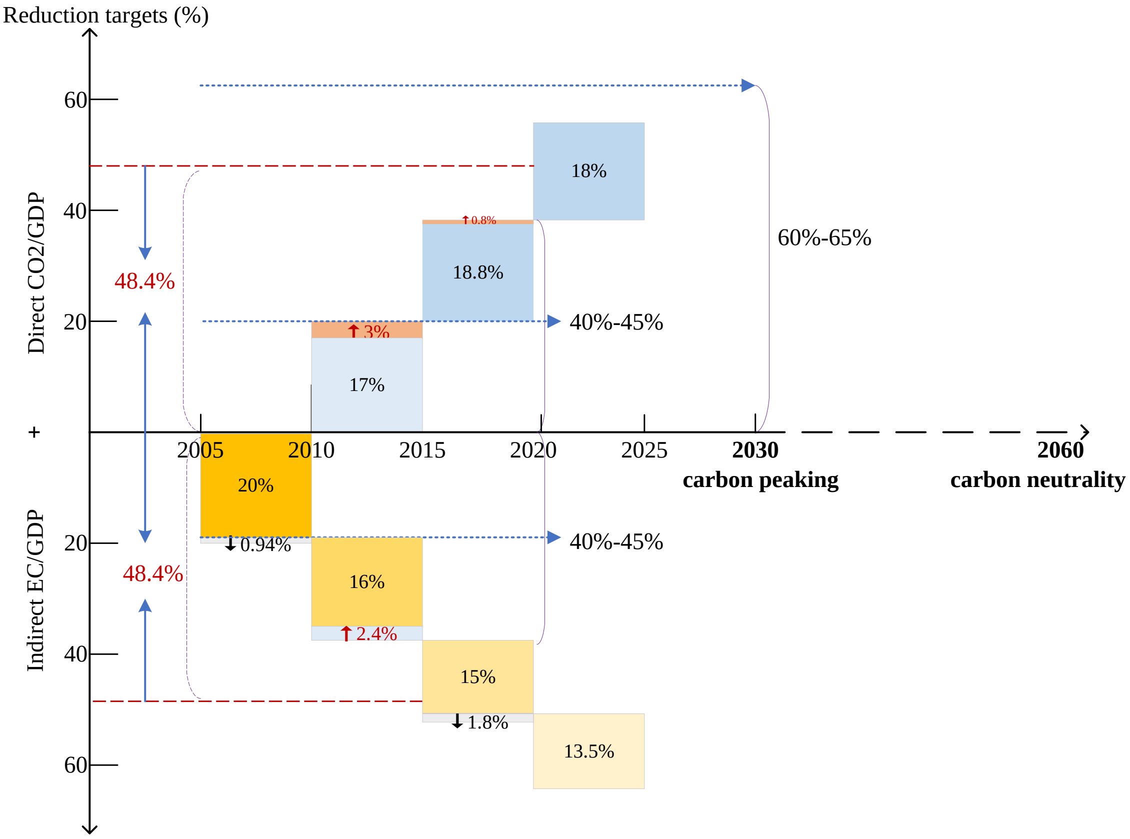

Figure 1 China's climate goals at various phases since the 11th FYP.

Notes: The timeline is depicted along the horizontal axis, while the vertical axis showcases the diminishing target values. Positioned above the axis are the designated targets for carbon intensity reduction, whereas below it lies the marked objectives for energy intensity reduction. The black text outside the box represents the final long-term goal, while the red text indicates the achieved value for the long term. Inside the box, the black text signifies the specific target for each phase. The red arrow denotes surpassing the target value, while the black arrow indicates falling short of the intended target.

The EIRT policy's long-term objective is to reduce energy intensity by 40%-45% compared to the 2005 level by the year 2020. During the 11th to the 14th FYP, the annual reduction targets for EIRT are 20%, 16%, 15%, and 13.5%, respectively. In reality, from the 11th to the 13th FYP, by the end of 2020 compared to 2005, EIRT decreased by 48.4%. More specifically, during the 11th FYP, China supported an annual 6.6% increase in energy consumption to achieve an 11.2% annual GDP growth [42], resulting in an actual 19.06% reduction in energy intensity, essentially fulfilling the planned objectives [43]. During the 12th FYP, China maintained a 3.6%annual energy consumption growth rate to support a7.9% actual annual GDP growth [44], achieving an 18.4% actual reduction in energy intensity, surpassing the planned objectives.

Initially announced in November 2009, this marked a significant milestone for China as it set a greenhouse gas reduction target. The CIRT has two long-term objectives: first, to reduce carbon intensity by 40-45% by 2020, compared to the base year of 2005. In 2011, these pivotal binding targets are seamlessly integrated into the 12th FYP [45]. Second, to reduce carbon intensity by 60%-65% by 2030 relative to 2005 [46], with an actual 2020 carbon intensity reduction of 48.4% relative to 2005

[47]. In terms of phasing, the CIRT began with the 12th FYP. The reduction targets set for the 12th, 13th, and 14th FYPs are 17%, 18% and 18%, respectively. The actual reduction targets for the 12th and 13th FYP are 20% and 18.8%, respectively [47], with each phase exceeding the set targets.

Starting with the 13th FYP, the country, building on the energy-saving efforts of the 11th and 12th FYPs, initiated a dual-control approach to manage both total energy consumption and energy intensity. In other words, the TECT policy is introduced, requiring that during the 13th FYP period, energy consumption remains within 5 billion metric tons of standard coal equivalent. In practice, during the 13th FYP period, China's total energy consumption was 4.98 billion metric tons of standard coal equivalent [48], staying within the 5 billion metric ton limit. As we move into the 14th FYP, the requirements for energy conservation and carbon reduction become even more stringent in the context of the dual carbon goals. The National Economic and Social Development Plan for the 14th FYP and the Outline of the 2035 Long-Range objectives propose energy intensity and carbon intensity reduction targets of 13.5% and 18%, respectively, by 2025 [49]. The EIRT, CIRT, and TECT policies not only specify the specific objectives at the national level for different phases (Table A3) but also break down the overall national targets into individual provinces (Table A3). To enhance readability, Table A1 provides the full names of abbreviations.

2.2. Data

(1) The data concerning EIRT, CIRT, and TECT are meticulously drawn from authoritative government documents. Specifically, EIRT_11[1] finds its source in the "11th FYP for Reducing Energy Consumption Targets per Unit of Gross Domestic Product in Each Region" [50]. EIRT_12 is anchored in the comprehensive blueprint titled "12th FYP Work Plan for Controlling Greenhouse Gas Emissions" [51]. The policy directions for EIRT_13 and TECT are detailed in the strategic framework encapsulated in the "13th FYP Work Plan for Controlling Greenhouse Gas Emissions" [52]. The CIRT is meticulously documented within the comprehensive "12th FYP Work Plan for Controlling Greenhouse Gas Emissions" [51]. The granular breakdown of EIRT, CIRT, and TECT data at the regional level during each phase is prominently featured in the 13th FYP [53], as succinctly encapsulated in Table A2.

(2) The county-level energy consumption data and CO_2 emissions data have been meticulously sourced from existing studies [54, 55]. These studies offer comprehensive insights into the estimated CO_2 emissions across 2735 counties in China, spanning the years 1997 to 2017. Notably, these studies, conducted by Chen et al. [54, 55], introduced a novel model utilizing the Particle Swarm Optimization Back Propagation (PSO-BP) algorithm for measuring carbon emissions and energy consumption at the county level. This model unified the scale of DMSP/OLS and NPP/VIIRS satellite images, presenting a comprehensive calculation for the specified counties. The results from both the original and econometric models demonstrated superior fitting performance compared to prior methods. Thorough validity tests on the data confirmed the

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[1] EIRT_11 represents EIRT during 11th FYP. EIRT_12 represents EIRT during 12th FYP. EIRT_13 represents EIRT during 13th FYP.

robustness and reliability of the estimation results.

(3) The county characteristic control variables are included [56, 57]. The rationale for the selection of control variables is predominantly discernible through two primary dimensions. First, a substantial body of research has consistently demonstrated that carbon emissions are significantly influenced by factors such as energy consumption [58], agricultural practices [59], the secondary industry [60], technological advancements [61], and population growth [62]. Second, these identified variables have consistently served as pivotal control parameters in prior investigations conducted by scholars at the county level in China [56, 57].Technical development is measured by a local telephone subscriber (TEL) [2]. The primary industry (PRI) and industrial structure ($STRU$) can be quantified by the added value of primary industry and the added value of secondary industry (SEC) to the GDP ratio. In addition, we also use regional GDP (GDP) and human capital ($POPU$) measured by registered permanent residents. All of these data are based on the China Statistical Yearbook (county-level)[3] [63]. The study does not include data prior to 2000 due to its unavailability. Some counties underwent changes in region names and region codes during the sample period, and for consistency, this paper uniformly employs the 2010 names and codes. By matching CO_2 emissions and energy consumption data at the county level, we compile a balanced panel dataset spanning 1963 counties from 2000 to 2017. To address data gaps, we identify and incorporate relevant information from provincial statistical yearbooks and the Wind database. Table 1 shows the descriptive statistical results.

Table 1

Descriptive statistics.

Variables	unit	obs	mean	sd	min	max
CO_2	million tons	35334	2.25	2.34	0.04	12.50
EC	million tons of coal equivalents	35334	107.8	112.2	2.450	619.2
TEL	ten thousand households	35334	6.849	7.531	0.104	44.06
POPU	one hundred thousand people	35334	4.939	3.451	0.313	16.09
GDP	billion yuan	35334	7.878	10.69	0.0970	85.55
PRI	billion yuan	35334	1.233	1.082	0.030	6.689
SEC	billion yuan	35334	3.907	6.001	0.0171	46.33
STRU	/	35334	0.416	0.167	0. 0759	0.931

3. Empirical strategy

In this work, we analyze the impacts of multiple energy and climate policies on county-level carbon emissions, with specified goal restrictions. Our analysis is based on information gathered from 1,963 Chinese counties between 2000 and 2017. This

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[2] TEL is the reverse index of the technical development measured by fixed telephone subscribers, which is referred to as a local telephone subscriber before 2010.

[3] Note: Names of the China Statistical Yearbook (county-level) in different periods are different, China Statistical Yearbook (county-level 2014-2018), China County Statistical Yearbook (2013), China Socioeconomic Statistical Abstract Summary of socioeconomic statistics of Chinese counties (cities) (2000)

study involves three policies: EIRT, CIRT, and TECT, which were implemented in 2006, 2011, and 2016, respectively. This makes it possible to assess the effects of individual policies when multiple policies are implemented concurrently. From 2000 to2010, the EIRT policy was implemented exclusively starting in 2006, with no interventions from other policies. During this phase, we evaluate the effectiveness of the EIRT policy. From 2006 to 2015, the CIRT policy is implemented in 2011, while the EIRT policy continue. During this phase, we control for the effects of the EIRT policy to assess the impact of the CIRT policy. From 2011 to 2017, the TECT policy is implemented in 2016, and during this phase, we control for the effects of the already-implemented EIRT and CIRT policies to assess the impact of the TECT policy. All regions are simultaneously affected by different policy shocks, but the intensity of these policies varied across regions. After conducting a thorough analysis of pertinent literature, we decide to use the GDD method for this study [40, 64]. To address potential multicollinearity among the multiple policies considered, we conduct a multicollinearity test (Table A4-A5), revealing no significant multicollinearity among the variables under investigation. Subsequently, the following section outlines the research design employed at each distinct phase of the study.

3.1. The impact of EIRT policy in the first phase (2000-2010)

3.1.1. Estimating the effects of EIRT (2000-2010)

$$lnCO_{2,it} = \beta_0 + \beta_1 EIRT_{it} * D_{t1} + \sum C_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1\text{-}1)$$

The sample time for Equation (1-1) is the first phase from the years 2000 to 2010, during which only EIRT policies are implemented and there are no other target constraint policies. The purpose of this assessment is to evaluate the influence of the EIRT policy on carbon emissions at the county level. One of the variables under consideration is $lnCO_{2,it}$, which represents the logarithmic value of carbon emissions. The subscripts i and t denote the specific county and year, respectively. The core explanatory variable is $EIRT_{it} * D_{t1}$,where D_{t1} represents a dummy variable denoting the policy implementation timeframe. Specifically, it takes the value of 1 when year > 2005 and 0 otherwise. $EIRT_{it}$ represents the desired reduction in the target variable for the specific period for each county within the province. C_{it}represents a set of control variables that influence carbon emissions at the county level, as previously discussed. μ_i represents the county fixed effect, which serves to account for elements that remain constant at the county level and do not vary over time. λ_t represents the time fixed effect, controlling for common annual variations shared across all counties. ε_{it} represents the random error component.

3.1.2. EIRT regional heterogeneity

Location is a significant factor influencing policy effectiveness. China’s vast territory and disparities in the regional development contribute to substantial differences in resource endowments across the counties [65]. Regions with geographical advantages may experience more favorable policy outcomes. This study examines the regional heterogeneity in the impact of EIRT on county-level carbon emissions. The 1963 counties are categorized into eastern, central, and western regions

(Table A6)[4], and the baseline model is extended by introducing location indicators. In general, researchers tend to use triple-difference for heterogeneity analysis [29]. The benchmark model in this study employs GDD. To ensure comparability between the heterogeneity results and the benchmark model, we continued to use GDD in all subsequent heterogeneity analyses. The specific model is defined as follows:

$$lnCO_{2,it} = \beta_0 + \beta_1 EIRT * D_{t1} * region + \sum C_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1\text{-}2)$$

In Equation (1-2), $region$ is the location variable that represents the eastern, central, and western regions, and β_1 represents the effect of EIRT on county-level carbon emissions in different regions. The dummy variables east, central, and west describe the location of counties ($region$), which designate the eastern, central, and western regions, respectively. When assessing the effect of EIRT on county-level carbon emissions in the eastern region, we set east = 1, central = 0, and west = 0. Similarly, when evaluating the effect of EIRT on county-level carbon emissions in the central region, we set east = 0, central = 1, and west = 0. Finally, when evaluating the effect of EIRT on county-level carbon emissions in the western region, we set east = 0, central = 0, and west = 1. The other variables conform to the description provided in Equation (1-1).

3.1.3. EIRT_11 Standard heterogeneity

Countries with varying EIRT standards exhibit significant variations in emission reduction potential, as well as the pressure to cut emissions. Differences in EIRT standards may lead to heterogeneity in the impact of EIRT on county-level carbon emissions. Therefore, this study categorizes the 1963 counties into low, medium, and high standards groups (Table A7). The EIRT standard indicator is introduced to extend the baseline model (1-1) and examine the influence of EIRT standard differences on carbon emissions. The following is the specific model:

$$lnCO_{2,it} = \beta_0 + \beta_1 EIRT_{it} * D_{t1} * standard + \sum C_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1\text{-}3)$$

In equation (1-3), a $standard$ dummy variable is categorized into three groups, based on the relative size of PEIRT and NEIRT during the 11th FYP period: low standard (PEIRT_11 < NEIRT_11)[5], medium standard (PEIRT_11 = NEIRT_11), and high standard (PEIRT_11 > NEIRT_11). β_1 is the effect of different standards on carbon emissions. These dummy variables denote low, medium, and high EIRT standards. When assessing the impact of low standard EIRT on county-level carbon emissions, we assign values as follows: low = 1, medium = 0, and high = 0. Similarly, when calculating the impact of medium standard EIRT, we set low = 0, medium = 1, and high = 0. Finally, when evaluating the impact of high standard EIRT, we set low=0, medium = 0, and high = 1. The other variables conform to the description provided in Equation (1-1).

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[4] The categorization of the three regions—east, central, and west—is based on the Seventh FYP (1986-1990).

[5] PEIRT_11 represents provincial EIRT during 11th FYP.
NEIRT_11 represents national EIRT during 11th FYP.

3.2. The impact of CIRT policy in the second phase (2006-2015)

3.2.1. Estimating the effects of CIRT (2006-2015)

$$lnCO_{2,it} = \beta_0 + \beta_1 EIRT_{it} * D_{t1} + \beta_2 CIRT_{it} * D_{t2} + \sum C_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad \text{(2-1)}$$

Equation (2-1) covers the sample period from 2006 to 2015, which corresponds to the second phase. During this period, the EIRT policy remained in effect, and the CIRT policy began in 2011, without interference from other policies aimed at targets reduction. It is used to assess the impact of the CIRT policy on county-level carbon emissions, controlling for concurrent EIRT policy effects. The core explanatory variable is represented as $CIRT_{it} * D_{t2}$. Here, D_{t2} is a time dummy variable, taking the value of 1 when year > 2010 and 0 otherwise. $CIRT_{it}$ represents the continuous variable of intensity reduction targets for each region, specifically the reduction targets for each province, where each county is located during that period. The other variables conform to the description provided in Equation (1-1).

3.2.2. CIRT regional heterogeneity

$$lnCO_{2,it} = \beta_0 + \beta_1 EIRT_{it} * D_{t1} * region + \beta_2 CIRT_i * D_{t2} * region + \sum C_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad \text{(2-2)}$$

The variables conform to the description provided in Equation (2-1) and Equation (1-1).

3.2.3. Heterogeneity criteria of CIRT_12

$$lnCO_{2,it} = \beta_0 + \beta_1 EIRT_{it} * D_{t1} + \beta_2 CIRT_{it} * D_{t2} * standard + \sum C_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad \text{(2-3)}$$

In Equation (2-3), $standard$ is categorized into low standards (PCIRT_12 < NCIRT_12)[6], medium standards (PCIRT_12 = NCIRT_12), and high standards (PCIRT_12 > NCIRT_12) based on the relative size of PCIRT and NCIRT during the 12th FYP period (Table A8). Its specific dummy variable settings are similar to those in Equation (1-3). β_2 measures the impact of CIRT policies at different standards on county-level carbon emissions. Other variables conform to the description provided in Equation (2-1).

3.2.4. EIRT_12 standard heterogeneity

$$lnCO_{2,it} = \beta_0 + \beta_1 EIRT_{it} * D_{t1} * standard + \beta_2 CIRT_{it} * D_{t2} + \sum C_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad \text{(2-4)}$$

In Equation (2-4), $standard$ is categorized into low standards (PEIRT_12 < NEIRT_12)[7], medium standards (PEIRT_12 = NEIRT_12), and high standards (PEIRT_12 > NEIRT_12) based on the relative sizes of PEIRT and NEIRT during the 12th FYP period (Table A9). Its specific dummy variable settings are similar to those

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[6] PCIRT_12 represents provincial CIRT during 12th FYP.
NCIRT_12 represents national CIRT during 12th FYP.

[7] PEIRT_12 represents provincial EIRT during 12th FYP.
NEIRT_12 represents national EIRT during 12th FYP.

in Equation (1-3). β_1 measures the impact of EIRT policies at different standards on county-level carbon emissions. Other variables remain consistent with Equation (2-1).

3.2.5. Implications of the 11th to 12th FYP EIRT criteria conversion

Previous research has shown that the strengthening or easing of policies can affect policy outcomes [66, 67]. The EIRT policy is implemented in two phases, from the 11th FYP to the 12th FYP. The EIRT standards may differ between these phases. In other words, there could be changes in EIRT standards from the 11th FYP to the 12th FYP, with three possible states: strengthening, no change, or relaxation of EIRT standards. Therefore, this study considers the impact of changes in EIRT standards between the 11th and 12th FYPs on county-level carbon emissions. Other variables conform to the description provided in Equation (2-1).

$$lnCO_{2,it} = \beta_0 + \beta_1 EIRT_{it} * D_{t1} * change + \beta_2 CIRT_{it} * D_{t2} + \sum C_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2\text{-}5)$$

In Equation (2-5), the coefficient $\beta_1$quantifies the impact of a change in the EIRT status on carbon emissions at the county level. $change$ represents the rate of change of EIRT from the 11th to the 12th FYP. “Strengthen,” “no_change”, and “loosen” serve as dummy variables to describe different types of $change$. Specifically, “strengthen” denotes the category of enhancing EIRT from the 11th to the 12th FYP. This study examines two scenarios, denoted as PEIRT_11 < NEIRT_11, PEIRT_12 >= NEIRT_12 and PEIRT_11 = NEIRT_11, PEIRT_12 > NEIRT_12 to analyze their respective outcomes. The term “no_change” represents the scenario where there is no change in EIRT standards from the 11th FYP to the 12th FYP. Specifically, it means PEIRT_11 < NEIRT_11 and PEIRT_12 < NEIRT_12, PEIRT_11 = NEIRT_11 and PEIRT_12 = NEIRT_12, or PEIRT_11 > NEIRT_11 and PEIRT_12 > NEIRT_12. “loosen” indicates that the EIRT standards are relaxed from the 11th FYP to the 12th FYP, including two cases: first, PEIRT_11 > NEIRT_11 and PEIRT_12 <= NEIRT_12, and second, PEIRT_11 = NEIRT_11 and PEIRT_12 < NEIRT_12 (Table A20). When assessing the impact of strengthened EIRT standards, we set “strengthen” to 1, “no_change” to 0, and “loosen” to 0. When assessing the effect of unchanged EIRT policy intensity, we set “strengthen” to 0, “no_change” to 1, and “loosen” to 0. When evaluating the impact of relaxed EIRT standards, we set “strengthen” to 0, “no_change” to 0, and “loosen” to 1. Other variables conform to the description provided in Equation (2-1).

3.3. The impact of TECT policy in the third phase *(2011-2017)*

3.3.1. Estimating the effects of total energy consumption targets (TECT) (2011-2017)

$$lnCO_{2,it} = \beta_0 + \beta_1 EIRT_{it} * D_{t1} + \beta_2 CIRT_{it} * D_{t2} + \beta_3 TECT_{it} * D_{t3} + \sum C_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3\text{-}1)$$

Equation (3-1) covers the sample period from 2011 to 2017, which represents the third phase. Within this duration, both the EIRT and CIRT policies have been effectively implemented. The TECT policy came into effect starting from 2016. Equation (3-1) evaluates the impact of the TECT policy on carbon emissions, controlling for concurrent EIRT and CIRT policies. The core explanatory variable in this study is denoted as $TECT_{it} * D_{t3}$. D_{t3} is a time dummy variable that takes a value of 1 when year > 2015, and 0 otherwise. $TECT_{it}$ represents the continuous variable of TECT in each region, which specifically refers to the TECT of the province where each county is located during the specified period. Other variables conform to the description provided in Equation (2-1).

3.3.2. TECT regional heterogeneity

$$lnCO_{2,it} = \beta_0 + \beta_1 EIRT_{it} * D_{t1} * region + \beta_2 CIRT_{it} * D_{t2} * region + \beta_3 TECT_{it} * D_{t3} * region + \sum C_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3\text{-}2)$$

Variables conform to the description provided in Equation (3-1) and Equation (1-1).

3.3.3. CIRT_13 standard heterogeneity

$$lnCO_{2,it} = \beta_0 + \beta_1 EIRT_{it} * D_{t1} + \beta_2 CIRT_{it} * D_{t2} * standard + \beta_3 TECT_{it} * D_{t3} + \sum C_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3\text{-}3)$$

In Equation (3-3), $standard$ is categorized into low standards (PCIRT_13 < NCIRT_13)[8], medium standards (PCIRT_13 = NCIRT_13), and high standards (PCIRT_13 > NCIRT_13) based on the relative size of PCIRT and NCIRT during the 13th FYP period (Table A21). Its specific dummy variables setting are similar to Equation (1-3). β_2 measures the impact of CIRT policies at multiple standards on county-level carbon emissions. Other variables conform to the description provided in Equation (3-1).

3.3.4. EIRT_13 standard heterogeneity

$$lnCO_{2,it} = \beta_0 + \beta_1 EIRT_{it} * D_{t1} * standard + \beta_2 CIRT_{it} * D_{t2} + \beta_3 TECT_{it} * D_{t3} + \sum C_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3\text{-}4)$$

In Equation (3-4), $standard$ is categorized into low standards (PEIRT_13 < NEIRT_13)[9], medium standards (PEIRT_13 = NEIRT_13), and high standards (PEIRT_13 > NEIRT_13) based on the relative size of PEIRT and NEIRT during the 13th FYP period (Table A22). Its specific dummy variable settings are similar to those in Equation (1-3). $\beta_1$assesses the impact of EIRT policies at multiple standards on county-level carbon emissions. Other variables conform to the description provided in Equation (3-1).

4. Results

Tables (3) to (11) show the main regression results. Table 11 shows the endogeneity test results. Tables (3) to (4) show the effectiveness and heterogeneity results of the initial phase of the EIRT policy. Tables (5) to (7) show the policy effectiveness and heterogeneity results after the introduction of CIRT in the second

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[8] PCIRT_13 represents provincial CIRT during 13th FYP.
NCIRT_13 represents national CIRT during 13th FYP.

[9] PEIRT_13 represents provincial EIRT during 13th FYP.
NEIRT_13 represents national EIRT during 13th FYP.

phase. Table (8) provides the policy effects from changes in EIRT policies between the first and second phases. Tables (9) to (11) show the policy effectiveness and heterogeneity results following the incorporation of TECT in the third phase.

4.1. Impact of EIRT policy on CO_2 emissions in the first phase (2000-2010)

Table 2

EIRT impact effects on carbon emissions at the county level.

	nation		east	central	west
	(1)	(2)	(3)	(4)	(5)
Variables	$\ln CO_2$	$\ln CO_2$	$\ln CO_2$	$\ln CO_2$	$\ln CO_2$
EIRT	0.0175	0.0147*			
	(0.016)	(0.008)			
EIRT_east			-0.0028		
			(0.002)		
EIRT_central				-0.0010	
				(0.001)	
EIRT_west					0.0046**
					(0.002)
lnEC		0.6320***	0.6369***	0.6280***	0.6170***
		(0.078)	(0.080)	(0.080)	(0.074)
STRU		0.2019***	0.1856***	0.1980***	0.1738***
		(0.060)	(0.058)	(0.059)	(0.050)
lnGDP		0.0310**	0.0395**	0.0414**	0.0394**
		(0.012)	(0.017)	(0.017)	(0.015)
lnPRI		0.0447***	0.0398***	0.0472***	0.0340**
		(0.016)	(0.013)	(0.015)	(0.013)
lnTEL		-0.0026	-0.0055	-0.0025	-0.0073
		(0.011)	(0.011)	(0.011)	(0.011)
lnPOPU		-0.0232	-0.0691	-0.0600	-0.0859*
		(0.039)	(0.046)	(0.047)	(0.050)
Constant	-0.1639	-2.8739***	-2.6699***	-2.6928***	-2.5622***
	(0.142)	(0.331)	(0.314)	(0.321)	(0.294)
Observations	21,593	21,593	21,593	21,593	21,593
R-squared	0.985	0.994	0.994	0.994	0.994

Notes: Robust standard errors are in parentheses.

*, ** and *** refer to 1%, 5% and 10% significant levels, respectively.

Table 2 presents the impact of the EIRT policy on carbon emissions. Columns (1) and (2) represent the national-level effects, with column (1) lacking control variables, while column (2) includes all control variables. Columns (3) to (5) provide regional regression results, specifically for the eastern, central, and western regions, showing the influence of EIRT on county-level carbon emissions. First, at the national level, whether control variables are added or not, the impact of the first-phase EIRT policy on county-level carbon emissions is significantly positive, indicating that during the 11th FYP, the EIRT policy did not result in a reduction in county-level carbon emissions. This could be attributed to the fact that during the 11th FYP, China witnessed an annual 6.7% increase in energy consumption, and achieved an annual 11.3% GDP growth, resulting in a 19.06% decrease in energy intensity. The substantial reduction in EIRT is primarily due to rapid GDP growth, which doesn't imply an overall decrease in carbon emissions [68]. Second, the significantly negative coefficients of EIRT policy impact on county-level carbon emissions in columns 3 and 4 (respectively -0.0028 and -0.0010), are indicating that the EIRT policy in the eastern and central regions promoted a reduction in county-level carbon emissions. Moreover, the effect of the EIRT policy on carbon emissions reduction in the eastern region is greater than that in the central region. In contrast, the EIRT policy had no significant effect on carbon emissions reduction in the western region.

Second, the four factors of $lnEC$, measured by energy consumption, $STRU$, measured by industrial structure, $lnGDP,$ measured by economic development, and $lnPRI$,measured by primary industry development showing a significant positive impact on carbon emissions at the county level, indicating that four factors contribute to carbon emissions. Energy consumption is the primary cause of a rise in carbon emissions because its influence coefficient is much bigger than those of the other variables. In column (2), the influence coefficients of $lnTEL$ and $lnPOPU$ on national carbon emissions are negative but not statistically significant. There is clear regional variability in the impact of communication technology on carbon emissions as indicated by the number of fixed-line telephone users. The coefficients of fixed-line telephone use on carbon emissions at the national and western levels are negative. The impact of information and communication technology development, represented by fixed-line telephone users, on carbon emissions displays distinct regional heterogeneity. In the western region, the development of information and communication technology significantly promotes carbon emissions reduction, while in the eastern and central regions, the effect of information and communication technology on carbon emissions reduction is not statistically significant. This could be attributed to inconsistencies in indicator selection; prior research often utilized indicators like internet penetration rates and broadband internet access users to measure information and communication technology development, but these indicators were not available at the county level. However, there are no statistical indicators of internet penetration rate or internet broadband at the county level. Additionally, as China's information and communication technology developed over time, the number of fixed-line telephone users, particularly in developed areas, sharply declined from 2005 onwards. Thus, fixed-line telephone users no longer fully represent information and communication technology development. Human capital, measured by registered population ($lnPOPU$), has negative and statistically insignificant effects on county-level carbon emissions at both the national and regional levels. This might be due to different measurement choices in previous studies, which uses average years of education or year-end population as proxies for human capital. Due to data limitations, this study chooses to measure human capital using registered population, which is more stable and less mobile, and as a result, the impact of $lnPOPU$ on carbon emissions is negative and insignificant.

Table 3

Impact of different standard EIRTs on county carbon emissions.

	(1)	(2)	(3)
	PEIRT_11<NEIRT_11	PEIRT_11=NEIRT_11	PEIRT_11>NEIRT_11
Variables	lnCO_2	lnCO_2	lnCO_2
EIRT_low	-0.0038		
	(0.004)		
EIRT_medium		-0.0005	
		(0.002)	
EIRT_high			0.0038
			(0.002)
lnEC	0.6285***	0.6328***	0.6283***
	(0.081)	(0.081)	(0.078)
STRU	0.2102***	0.1962***	0.1898***
	(0.062)	(0.056)	(0.056)
lnGDP	0.0378**	0.0402**	0.0320**
	(0.016)	(0.017)	(0.012)
lnPRI	0.0445**	0.0479***	0.0488***
	(0.017)	(0.015)	(0.015)
lnTEL	-0.0048	-0.0019	-0.0003
	(0.011)	(0.010)	(0.010)
lnPOPU	-0.0422	-0.0561	-0.0346
	(0.036)	(0.047)	(0.046)
Constant	-2.7023***	-2.7183***	-2.7340***
	(0.322)	(0.330)	(0.318)
Observations	21,593	21,593	21,593
R-squared	0.994	0.994	0.994

Notes: Robust standard errors are in parentheses.

*, ** and *** refer to 1%, 5% and 10% significant levels, respectively.

Table 3 examines the influence of different standard EIRTs on carbon emissions throughout the 11th FYP period. Columns (1) to (3) exhibit the outcomes of PEIRT < NEIRT, PEIRT = NEIRT, and PEIRT >NEIRT, respectively, throughout the 11th FYP. Specifically, in column (1), the regression coefficient for the PEIRT < NEIRT group is -0.0038, suggesting that for each unit increase in PEIRT, there is a corresponding decrease of 0.38% in county carbon emissions. In column (2), the regression coefficient for the PEIRT = NEIRT group is -0.0005, indicating that for each unit increase in PEIRT < NEIRT, there is a decrease of 0.05% in county-level carbon emissions. The PEIRT <= NEIRT group is associated with a reduction in carbon emissions, while the PEIRT > NEIRT group does not exhibit a significant impact on carbon emissions. This phenomenon can be attributed to the initial implementation of the EIRT policy during the 11th FYP period, wherein it is determined that setting an excessively high EITR would not be conducive to achieving carbon reduction objectives. Based on the current state of energy intensity reduction during the 11th FYP period, it is observed that only one region, Xinjiang, failed to meet the target for reducing energy intensity in both the PEIRT < NEIRT and PEIRT = NEIRT groups. Conversely, all other regions exceeded their targets. This suggests that establishing an appropriate EIRT is conducive to carbon emissions reduction. There are four regions where PEIRT > NEIRT, namely Shanxi, Inner Mongolia, Jilin, and Shandong. The planned EIRT values for these regions are 25%, 25%, 30%, and 22%, respectively, while the actual EIRT values are 22.66%, 22.62%, 22.40%, and 22.09%. Only Shandong barely achieved its target, with the other regions significantly falling short of their planned EIRTs [51]. This indicates that during the initial phases of the implementation of the 11th FYP EIRT policy, the excessively high EIRT poses challenges for the host counties in fulfilling the requirements. Therefore, it does not result in a reduction of carbon emissions.

4.2. Impact of CIRT policy on CO_2 emissions in the second phase (2006-2015)

Table 4

Impact of CIRT on county carbon emissions.

	nation		east	central	west
	(1)	(2)	(3)	(4)	(5)
Variables	$lnCO_2$	$lnCO_2$	$lnCO_2$	$lnCO_2$	$lnCO_2$
CIRT	-0.0657***	-0.0551***			
	(0.013)	(0.006)			
EIRT	0.0065	0.0083**			
	(0.005)	(0.003)			
CIRT_east			-0.0053**		
			(0.002)		
EIRT_east			0.0036		
			(0.011)		
CIRT_central				-0.0010	
				(0.003)	
EIRT_central				0.0028	
				(0.005)	
CIRT_west					0.0013
					(0.004)
EIRT_west					-0.0157
					(0.012)
lnEC		0.6777***	0.7001***	0.7116***	0.6575***
		(0.076)	(0.113)	(0.119)	(0.104)
STRU		0.1292***	0.1256**	0.1914***	0.1524**
		(0.039)	(0.055)	(0.067)	(0.058)
lnGDP		0.0131*	0.0086	0.0153	0.0118
		(0.007)	(0.008)	(0.009)	(0.008)
lnPRI		0.0026	0.0091	0.0263	0.0174
		(0.019)	(0.022)	(0.024)	(0.022)
lnTEL		-0.0034	-0.0031	-0.0066	-0.0066
		(0.004)	(0.005)	(0.006)	(0.005)
lnPOPU		0.0031	0.0089	0.0101	0.0100
		(0.017)	(0.015)	(0.015)	(0.013)

Constant	0.9554***	-2.2333***	-2.6799***	-2.8539***	-2.4339***
	(0.101)	(0.322)	(0.434)	(0.455)	(0.434)
Observations	19,630	19,630	19,630	19,630	19,630
R-squared	0.990	0.996	0.995	0.994	0.995

Notes: Robust standard errors are in parentheses.

*, ** and *** refer to 1%, 5% and 10% significant levels, respectively.

Table 4 shows the impact of CIRT policy on county-level carbon emissions. Column (1) and (2) show the national impact, with column (1) lacking control variables, while column (2) includes all control variables. Columns (3) to (5) show the results by region, specifically for the eastern, central, and western regions, showing the influence of the CIRT policy on carbon emissions.

At the national level, column (2) shows that the CIRT policy reduces county-level carbon emissions, with a regression coefficient of -0.0558 significant at the 1% significant level. The coefficient of EIRT on carbon emissions, which represents that each unit decrease in CIRT can reduce county-level carbon emissions by 5.58%, demonstrating that it is statistically significant and that, between 2006 and 2015, the EIRT policy have no effect on carbon emissions.

When CIRT and EIRT are applied concurrently, the coefficients for the impact of CIRT on carbon emissions in the eastern, central, and western regions are -0.0054, -0.0008, and 0.0015, respectively, all statistically significant. This indicates that during the 12th FYP, the implementation of the CIRT policy promotes carbon emissions reduction in the eastern and central regions, while in the western region, the CIRT policy does not lead to a reduction in carbon emissions. However, EIRT does not result in a reduction in carbon emissions in the eastern and central regions, but it did result in a reduction in carbon emissions in the western region between 2006 and 2015. This might be due to the fact that, while the eastern and central regions experienced a significant decrease in energy intensity, this reduction was largely driven by their GDP growth. In contrast, the western region, with its lower GDP, does not experience a significant decrease in energy intensity, despite a noticeable slowdown in energy consumption growth [68].

Table 5

Impact of different standard CIRTs on carbon emissions.

	(1)	(2)	(3)
	PCIRT_12<NCIRT_12	PCIRT_12=NCIRT_12	PCIRT_12>NCIRT_12
Variables	$\ln CO_2$	$\ln CO_2$	$\ln CO_2$
CIRT	0.0073**		
	(0.003)		
CIRT		-0.0020	
		(0.002)	
CIRT			-0.0063***
			(0.002)
EIRT	-0.0053	-0.0085	0.0003
	(0.005)	(0.007)	(0.007)

lnEC	0.7002***	0.7086***	0.7056***
	(0.105)	(0.108)	(0.109)
STRU	0.1819***	0.1915***	0.1476**
	(0.059)	(0.064)	(0.056)
lnGDP	0.0117	0.0154*	0.0098
	(0.008)	(0.009)	(0.008)
lnPRI	0.0029	0.0253	0.0012
	(0.021)	(0.025)	(0.021)
lnTEL	-0.0028	-0.0059	-0.0008
	(0.005)	(0.006)	(0.004)
lnPOPU	0.0182	0.0141	0.0108
	(0.018)	(0.016)	(0.015)
Constant	-2.6126***	-2.6713***	-2.6668***
	(0.404)	(0.422)	(0.407)
Observations	19,630	19,630	19,630
R-squared	0.995	0.994	0.995

Notes: Robust standard errors are in parentheses.

*, ** and *** refer to 1%, 5% and 10% significant levels, respectively.

Table 5 shows the impact of CIRT policy on carbon emissions based on CIRT during the 12th FYP period, distinguishing between different carbon intensity reduction standards of CIRT policy on carbon emissions. Columns (1) to (3) correspond to groups where PCIRT is less than, equal to, and greater than NCIRT, respectively. The coefficients representing the impact of CIRT policies on carbon emissions are 0.0073, -0.0020, and -0.0063 for these respective groups. The CIRT policy leads to a reduction in carbon emissions only in the group where PCIRT >= NCIRT does. If the PCIRT standard is too low, it is not conducive to carbon emissions reduction. In this scenario, the impact coefficients of EIRT on carbon emissions for each group are -0.0053, -0.0085, and 0.0003, respectively. In the group with PCIRT <= NCIRT, the impact coefficient of EIRT on carbon emissions is negative. Only when PCIRT = NCIRT do both CIRT and EIRT policies drive down county-level carbon emissions.

Table 6

Impact of different standard EIRTs on carbon emissions at the county level.

	(1)	(2)	(3)
	PEIRT_12<NEIRT_12	PEIRT_12=NEIRT_12	PEIRT_12>NEIRT_12
Variables	$\ln CO_2$	$\ln CO_2$	$\ln CO_2$
EIRT	0.0001		
	(0.005)		
EIRT		0.0046	
		(0.003)	
EIRT			0.0103
			(0.009)
CIRT	-0.0486***	-0.0478***	-0.0465***
	(0.009)	(0.005)	(0.004)

lnEC	0.6744***	0.6695***	0.6707***
	(0.077)	(0.076)	(0.077)
STRU	0.1319***	0.1422***	0.1159***
	(0.041)	(0.037)	(0.032)
lnGDP	0.0132*	0.0141**	0.0114*
	(0.007)	(0.007)	(0.007)
lnPRI	0.0045	0.0062	0.0009
	(0.019)	(0.019)	(0.018)
lnTEL	-0.0030	-0.0032	-0.0035
	(0.004)	(0.004)	(0.004)
lnPOPU	0.0059	0.0051	0.0047
	(0.017)	(0.017)	(0.017)
Constant	-2.1398***	-2.1767***	-2.1594***
	(0.327)	(0.325)	(0.327)
Observations	19,630	19,630	19,630
R-squared	0.996	0.996	0.996

Notes: Robust standard errors are in parentheses.

*, ** and *** refer to 1%, 5% and 10% significant levels, respectively.

Table 6, based on the 12th FYP EIRT, divides the sample into three groups: Columns (1) to (3) represent PEIRT_12 < NEIRT_12, PEIRT_12 = NEIRT_12, and PEIRT_12 > NEIRT_12, respectively. The impact coefficients of EIRT_12 policies on county-level carbon emissions are 0.0001, 0.0046, and 0.0103, and the coefficient is not significant in all groups. During the 11th and 12th FYPs, EIRT policies did not lead to a reduction in county-level carbon emissions. In columns (1) to (3), the impact of CIRT on county-level carbon emissions is significantly negative, indicating that starting from the 11th FYP, when EIRT and CIRT simultaneously affect carbon emissions, only the CIRT policy can reduce county-level carbon emissions. EIRT policies during 2006-2015 did not lead to a reduction in county-level carbon emissions, consistent with the baseline findings in Table 4.

Table 7

Impact of EIRT standard shift on carbon emissions.

	(1)	(2)	(3)
	EIRT_Tighter_11to12	EIRT_no_change_11to12	EIRT_looser_11to12
Variables	lnCO$_2$	lnCO$_2$	lnCO$_2$
EIRT_11to12	-0.0025		
	(0.011)		
EIRT_11to12		0.0083	
		(0.006)	
EIRT_11to12			0.0024
			(0.003)
CIRT	-0.0488***	-0.0494***	-0.0504***
	(0.005)	(0.006)	(0.006)
lnEC	0.6746***	0.6694***	0.6770***

	(0.076)	(0.077)	(0.076)
STRU	0.1338***	0.1496***	0.1279***
	(0.038)	(0.037)	(0.041)
lnGDP	0.0133*	0.0143**	0.0130*
	(0.007)	(0.007)	(0.007)
lnPRI	0.0047	0.0034	0.0044
	(0.019)	(0.019)	(0.020)
lnTEL	-0.0031	-0.0041	-0.0029
	(0.004)	(0.003)	(0.004)
lnPOPU	0.0060	0.0065	0.0050
	(0.017)	(0.017)	(0.017)
Constant	-2.1307***	-2.1921***	-2.1428***
	(0.328)	(0.334)	(0.321)
Observations	19,630	19,630	19,630
R-squared	0.996	0.996	0.996

Notes: Robust standard errors are in parentheses.

*, ** and *** refer to 1%, 5% and 10% significant levels, respectively.

Table 7 presents the impact of EIRT changes from the 11th FYP to the 12th FYP on county-level carbon emissions. Columns (1) to (3) represent the transition from the 11th FYP to the 12th FYP, with EIRT standards strengthening (PEIRT_11 < NEIRT_11 and PEIRT_12 >= NEIRT_12, or PEIRT_11 = NEIRT_11 and PEIRT_12 > NEIRT_12), EIRT standards remaining unchanged (PEIRT_11 < NEIRT_11, PEIRT_11 = NEIRT_11, PEIRT_11 > NEIRT_11, corresponding to PEIRT_12 < NEIRT_12, PEIRT_12 = NEIRT_12, PEIRT_12 > NEIRT_12), and EIRT standards loosening (PEIRT_11 > NEIRT_11 and PEIRT_12 <= NEIRT_12, or PEIRT_11 = NEIRT_11 and PEIRT_12 < NEIRT_12) on county-level carbon emissions. Column (1), the regression coefficient of the enhanced group of EIRT on county-level carbon emissions is -0.0025, which indicates that the enhancement of EIRT can bring about a reduction in county-level carbon emissions [30]. The impact coefficients of the groups with unchanged EIRT and relaxed EIRT are 0.0083 and 0.0024, respectively, which are both significant at the 1% level, demonstrating that neither a constant EIRT nor a loosened EIRT encourages a decrease in county-level carbon emissions. The coefficients for the CIRT policies in columns (1) to (3) are all markedly negative and have about equivalent effects, indicating that changes in EIRT have no impact on the effectiveness of CIRT in reducing county-level carbon emissions.

4.3. Impact of TECT policy on CO_2 emissions in the third phase (2011-2017)

Table 8

Effect of TECT on county-level carbon emissions.

	(1)	(2)	(3)	(4)	(5)
Variables	lnCO$_2$	lnCO$_2$	lnCO$_2$	lnCO$_2$	lnCO$_2$
lnTECT	-0.0213	-0.0112			
	(0.019)	(0.011)			
CIRT	-0.0075	-0.0216			

	(0.024)	(0.014)			
EIRT	0.0204	0.0171			
	(0.030)	(0.016)			
lnEC		0.3593***	0.3583***	0.3589***	0.3518***
		(0.049)	(0.049)	(0.049)	(0.050)
STRU		0.1128**	0.1118**	0.1139**	0.1124**
		(0.046)	(0.046)	(0.047)	(0.045)
lnGDP		0.0010	-0.0004	0.0015	0.0013
		(0.012)	(0.013)	(0.011)	(0.013)
lnPRI		0.0264*	0.0188	0.0264	0.0241
		(0.015)	(0.015)	(0.016)	(0.016)
lnTEL		-0.0011	-0.0007	-0.0004	-0.0023
		(0.002)	(0.003)	(0.002)	(0.002)
lnPOPU		-0.0331	-0.0311	-0.0351	-0.0337
		(0.038)	(0.038)	(0.032)	(0.042)
lnTECT_east			0.0222		
			(0.014)		
CIRT_east			-0.0603**		
			(0.028)		
EIRT_east			0.0708*		
			(0.041)		
lnTECT _central				-0.0010	
				(0.003)	
CIRT_central				-0.0047	
				(0.008)	
EIRT_central				-0.0219	
				(0.026)	
lnTECT _west					0.0138*
					(0.008)
CIRT_west					-0.0230
					(0.019)
EIRT_west					0.0234
					(0.021)
Constant	0.5489**	-0.9427***	-1.0532***	-0.9279***	-1.0111***
	(0.207)	(0.276)	(0.221)	(0.243)	(0.248)
Observations	13,741	13,741	13,741	13,741	13,741
R-squared	0.996	0.998	0.998	0.998	0.998

Notes: Robust standard errors are in parentheses.

*, ** and *** refer to 1%, 5% and 10% significant levels, respectively.

Table 8 shows the impact of TECT policy on county-level carbon emissions, while accounting for EIRT and CIRT policies. Looking at the overall sample, during the 13th FYP period, the TECT policy led to a reduction in county-level carbon emissions. In column (2), the coefficient for TECT is -0.0112. This indicates that for every one-unit increase in TECT, county-level carbon emissions decrease by 0.0112 units. At this point, the impact of CIRT (-0. 0216) remains significantly negative, while the impact of EIRT is significantly positive (0.0171). This suggests that when these three policy types simultaneously affect carbon emissions, both CIRT and TECT significantly promote a reduction in county-level carbon emissions. The main reason that TECT can reduce carbon emissions is that, on the one hand, the growth rate of energy consumption decreases significantly, and the growth rates of energy consumption in the 11th, 12th, and 13th FYP are 37.98%, 20.37%, and 14.79%, respectively; on the other hand, the proportion of fossil energy decreases significantly in the years 2000, 2005, 2010, 2015, 2020, and is 92.6%, 90.6%, 88%, 84.1%, respectively. As a result, TECT can help to reduce carbon emissions at the county level.

Looking at different regions, the coefficients of TECT on carbon emissions in the eastern, central, and western regions are 0.0222, -0.0010, and 0.0138, respectively. TECT only leads to a reduction in county-level carbon emissions in the central region, without driving down carbon emissions in the eastern and western regions. Specifically, when all three policies are implemented simultaneously, as shown in column (3) for the eastern region, the coefficients for TECT, CIRT, and EIRT on county-level carbon emissions are 0.0222, -0.0603, and 0.0708, respectively. This indicates that the carbon reduction effect in the eastern region during the 13th FYP primarily comes from CIRT. In column (4) for the central region, all three policies significantly promote a reduction in county-level carbon emissions, with the EIRT policy having the most significant effect. In column (5) for the western region, only the CIRT policy drives a reduction in county-level carbon emissions.

Table 9

Impact of CIRT standards on county carbon emissions during the 13th FYP.

Variables	(1) PCIRT_13<NCIRT_13 lnCO$_2$	(2) PCIRT_13=NCIRT_13 lnCO$_2$	(3) PCIRT_13>NCIRT_13 lnCO$_2$
CIRT	0.0467***		
	(0.016)		
CIRT		-0.0133	
		(0.008)	
CIRT			-0.0164*
			(0.009)
TECT	0.0044	-0.0188*	-0.0009
	(0.013)	(0.011)	(0.014)
EIRT	0.0022	-0.0043	0.0187
	(0.008)	(0.010)	(0.015)
lnEC	0.3487***	0.3554***	0.3567***
	(0.048)	(0.049)	(0.048)
STRU	0.1148**	0.1131**	0.1107**
	(0.043)	(0.046)	(0.045)
lnGDP	0.0052	0.0006	0.0006
	(0.011)	(0.012)	(0.012)
lnPRI	0.0260*	0.0293*	0.0202

	(0.014)	(0.016)	(0.016)
lnTEL	-0.0019	-0.0018	-0.0004
	(0.002)	(0.002)	(0.002)
lnPOPU	-0.0288	-0.0379	-0.0313
	(0.032)	(0.037)	(0.038)
Constant	-1.2255***	-0.8879***	-1.1719***
	(0.246)	(0.293)	(0.301)
Observations	13,741	13,741	13,741
R-squared	0.998	0.998	0.998

Notes: Robust standard errors are in parentheses.

*, ** and *** refer to 1%, 5% and 10% significant levels, respectively.

Table 9 presents the outcomes of grouping with CIRT during the 13th FYP period. The columns (1) to (3) represent the categories PCIRT_13 < NCIRT_13, PCIRT_13 = NCIRT_13, and PCIRT_13 > NCIRT_13, respectively. In column (1), when PCIRT < NCIRT, the regression coefficients for CIRT, TECT, and EIRT are 0.0467, 0.0044, and 0.0022, respectively, all being positive. None of the three policies contribute to carbon emission reduction in this scenario. When PCIRT is too low, not only does the CIRT policy fail to reduce carbon emissions, but it also hinders the synergy among policies. In column (2), when PCIRT = NCIRT, the regression coefficients for CIRT, TECT, and EIRT are -0.0133, -0.0188, and -0.0043, respectively, all negative. All three policies lead to a reduction in carbon emissions in this case. In column (3), when PCIRT > NCIRT, the regression coefficients for CIRT, TECT, and EIRT are -0.0164, -0.0009, and 0.0187, respectively. TECT and CIRT policies contribute to a reduction in carbon emissions, while the EIRT policy has no effect on carbon reduction. Compared to column (2) with a CIRT coefficient of -0.0133, the absolute value of the CIRT coefficient in column (3), at-0.0164, is larger, indicating that higher CIRT standards have a greater impact on carbon emissions.

Table 10

Impact of EIRT standards on county carbon emissions during the 13th FYP.

	(1)	(2)	(3)
	PEIRT_13<NEIRT_13	PEIRT_13=NEIRT_13	PEIRT_13>NEIRT_13
Variables	lnCO$_2$	lnCO$_2$	lnCO$_2$
EIRT	-0.0073		
	(0.014)		
EIRT		0.0171	
		(0.015)	
EIRT			0.0163
			(0.018)
TECT	-0.0094	-0.0104	-0.0078
	(0.012)	(0.011)	(0.013)
CIRT	-0.0115	-0.0179	-0.0140
	(0.009)	(0.011)	(0.010)
lnEC	0.3599***	0.3588***	0.3611***

	(0.050)	(0.049)	(0.050)
STRU	0.1204**	0.1153**	0.1204**
	(0.047)	(0.049)	(0.049)
lnGDP	0.0019	-0.0003	0.0030
	(0.012)	(0.011)	(0.012)
lnPRI	0.0230	0.0231	0.0243
	(0.016)	(0.016)	(0.016)
lnTEL	-0.0005	-0.0008	-0.0006
	(0.002)	(0.002)	(0.002)
lnPOPU	-0.0335	-0.0372	-0.0303
	(0.037)	(0.037)	(0.037)
Constant	-0.8158***	-0.7612***	-0.9673***
	(0.238)	(0.236)	(0.291)
Observations	13,741	13,741	13,741
R-squared	0.998	0.998	0.998

Notes: Robust standard errors are in parentheses.

*, ** and *** refer to 1%, 5% and 10% significant levels, respectively.

Table 10 presents the findings of a grouping analysis based on EIRT during the 13th FYP period. It also illustrates the effects of different EIRTs on carbon emissions at the county level during the same period. Columns (1) to (3) represent the groups of PEIRT_13 < NEIRT_13, PEIRT_13 = NEIRT_13, and PEIRT_13 > NEIRT_13, respectively. The coefficients of EIRT, TECT, and CIRT on carbon emissions are presented in column (1) of the table. These coefficients, -0.0073, -0.0094, and -0.0115, respectively, are all significantly negative. This indicates that all three policies contribute to a reduction in carbon emissions. In column (2), the coefficients representing the impacts of EIRT, TECT, and CIRT on carbon emissions are 0.0171, -0.0104, and -0.0179 respectively. At present, only the TECT and CIRT policies, are found to be in favor of reducing carbon emissions. In column (3), the impact coefficients of EIRT, TECT, and CIRT on carbon emissions are 0.0163, -0.0078, and -0.0140 respectively. These coefficients are similar to the results obtained in column (2). Notably, the study underscores that exclusively the TECT and CIRT policies emerge as effective catalysts for curbing carbon emissions.

4.4. Endogeneity assessment

In the model design of the third section, each stage exclusively addresses the efficacy of newly implemented policies. Control measures are implemented to mitigate multicollinearity and endogeneity issues arising from pre-existing policy effects. The instrumental variable method is employed in this study. We draw on established research [69] and utilize the lagged period of new policies in each stage as the respective instrumental variable to assess the primary models of the three stages—Equation (1-1), Equation (2-1), and Equation (3-1). The results of instrumental variable regression are presented in Table 11.

Table 11

Instrumental variable method for benchmark model regression.

Variables	(1) iv-l.EIRT $\ln CO_2$	(2) iv-l.CIRT $\ln CO_2$	(3) iv-l.TECT $\ln CO_2$
EIRT	0.0123	0.0081**	0.0171
	(0.008)	(0.004)	(0.016)
CIRT		-0.0545***	-0.0214
		(0.007)	(0.015)
TECT			-0.0122
			(0.023)
lnEC	0.5989***	0.6781***	0.3592***
	(0.081)	(0.075)	(0.049)
STRU	0.1998***	0.1298***	0.1125**
	(0.058)	(0.040)	(0.047)
lnGDP	0.0326***	0.0132*	0.0009
	(0.012)	(0.007)	(0.012)
lnPRI	0.0449***	0.0029	0.0261*
	(0.015)	(0.020)	(0.015)
lnTEL	-0.0036	-0.0034	-0.0011
	(0.011)	(0.004)	(0.003)
lnPOPU	-0.0189	0.0033	-0.0330
	(0.037)	(0.017)	(0.038)
Observations	19,630	19,630	13,741
R-squared	0.5808	0.6742	0.3371
county FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
First-stage F-statistic	141851	146.1	285.0

Notes: Robust standard errors are in parentheses.

*, ** and *** refer to 1%, 5% and 10% significant levels, respectively.

Table 11 presents our baseline IV estimates. Model (1) entails the estimated outcome of the first stage, employing the lagged period of EIRT as an instrumental variable; Model (2) reflects the estimation outcome of the second stage, utilizing the lagged CIRT as the instrumental variable; Model (3) captures the estimation outcome of the third stage, employing the lagged TECT as the instrumental variable. All models exhibit a First Stage F-statistic exceeding 10, successfully passing the weak instrumental variable test. The regression result of EIRT in Model (1) reveals a coefficient not significantly different from the benchmark model's regression coefficient of 0.0147 in Table 2. Similarly, the CIRT coefficient of 0.0545 in Model (2) aligns closely with the benchmark model coefficient of -0.0551 in Table 4. Furthermore, the regression result of TECT in Model (3) closely mirrors the benchmark model TECT regression coefficient of 0.0112 in Table 8. This robust consistency fortifies the credibility and reliability of the research findings.

5. Extension

The effect of a single EIRT policy on provincial carbon emissions has been studied at the provincial level [23]. This study uses the previous evaluation of the impact of a singular policy on carbon emissions at the county level and juxtaposes it with the findings of this study, which examines the simultaneous consideration of many overlapping policies. The specific model is set up as follows:

$$lnCO_{2,it} = \beta_0 + \beta_1 EIRT_{it} * D_{t1} + \sum C_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (5\text{-}1)$$

$$lnCO_{2,it} = \beta_0 + \beta_2 CIRT_{it} * D_{t2} + \sum C_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (5\text{-}2)$$

$$lnCO_{2,it} = \beta_0 + \beta_3 TECT_{it} * D_{t3} + \sum C_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (5\text{-}3)$$

The variable interpretations of Equations (5-1), (5-2), and (5-3) are, respectively, Equations (1-2), (2-1), and (3-1). Table 12 displays the regression findings for Equation (5-1), whereas Table 13 displays the regression results for Equations (5-2) and (5-3).

Table 12

Effects of individual EIRT policies.

	2000-2010		2000-2015		2000-2017	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	$lnCO_2$	$lnCO_2$	$lnCO_2$	$lnCO_2$	$lnCO_2$	$lnCO_2$
EIRT	0.0175	0.0147*	-0.0124	-0.0062	-0.0170	-0.0096
	(0.016)	(0.008)	(0.014)	(0.008)	(0.016)	(0.008)
lnEC		0.6320***		0.7413***		0.7429***
		(0.078)		(0.080)		(0.078)
STRU		0.2019***		0.2353***		0.2234***
		(0.060)		(0.060)		(0.052)
lnGDP		0.0310**		0.0310**		0.0289**
		(0.012)		(0.014)		(0.013)
lnPRI		0.0447***		0.0645***		0.0628**
		(0.016)		(0.022)		(0.023)
lnTEL		-0.0026		-0.0051		-0.0037
		(0.011)		(0.010)		(0.009)
lnPOPU		-0.0232		-0.0032		-0.0092
		(0.039)		(0.018)		(0.018)
Constant	-0.1639	-2.8739***	0.3541**	-3.1670***	0.4686**	-3.1013***
	(0.142)	(0.331)	(0.159)	(0.281)	(0.181)	(0.268)
Observations	21,593	21,593	31,408	31,408	35,334	35,334
R-squared	0.985	0.994	0.976	0.992	0.975	0.991

Notes: Robust standard errors are in parentheses.

*, ** and *** refer to 1%, 5% and 10% significant levels, respectively.

Table 12 displays the emission reduction effects of the EIRT policy alone. Columns (1) and (2) represent the initial implementation effects of the EIRT policy, while columns (3) and (4), as well as columns (5) and (6), show the medium-term and long-term effects, respectively. Columns (1), (3), and (5) present the results of regression without control variables. Columns (2), (4), and (6) are the results of the addition of the control variables, column (4), the average treatment effect of EIRT policy from the beginning of the 11th FYP to the 12th FYP is -0.0062, which indicates that, EIRT policy has a significant carbon reduction effect from the beginning of the 12th FYP, which is in line with the findings of the previous study [23], column (6) is the long term average treatment effect since the implementation of the EIRT policy, and the regression coefficient is -0.0101 is also significant at 1% level, the absolute value of -0.0096 is greater than -0.0062, indicating that the long-run average treatment effect of the EIRT policy increases progressively with increasing implementation time. The EIRT regression coefficients in column (2) of Table 2, column (2) of Table 4, and column (2) of Table 8 are all positive, indicating that EIRT does not promote the reduction of county carbon emissions when considering the effects of CIRT and TECT policies on county carbon emissions over the same period of time, suggesting that considering the effect of a single EIRT policy will overestimate the emission reduction effect of EIRT policy.

Table 13

	2000-2015		2000-2017		2000-2017	
	(1)	(2)	(3)	(4)	(5)	(6)
	CIRT_2	CIRT_12	CIRT_3	CIRT_13	TECT_3	TECT_13
Variables	lnCO$_2$	lnCO$_2$	lnCO$_2$	lnCO$_2$	lnCO$_2$	lnCO$_2$
CIRT	-0.0692***	-0.0493***	-0.0704***	-0.0506***		
	(0.023)	(0.009)	(0.021)	(0.009)		
TECT					-0.0731**	-0.0726**
					(0.033)	(0.028)
lnEC		0.7211***		0.7205***		0.7507***
		(0.065)		(0.061)		(0.084)
STRU		0.2060***		0.1948***		0.2191***
		(0.049)		(0.043)		(0.052)
lnGDP		0.0321**		0.0314**		0.0239
		(0.014)		(0.013)		(0.015)
lnPRI		0.0432**		0.0366*		0.0627**
		(0.020)		(0.020)		(0.025)
lnTEL		-0.0070		-0.0079		-0.0052
		(0.009)		(0.008)		(0.009)
lnPOPU		-0.0108		-0.0127		-0.0052
		(0.023)		(0.023)		(0.019)
Constant	0.5789***	-2.7789***	0.7431***	-2.6469***	0.3134***	-3.1979***
	(0.119)	(0.240)	(0.141)	(0.233)	(0.019)	(0.345)
Observations	31,408	31,408	35,334	35,334	35,334	35,334
R-squared	0.978	0.993	0.978	0.993	0.974	0.991

Effectiveness of the respective individual policies of CIRT and TECT.

Notes: Robust standard errors are in parentheses.

*, ** and *** refer to 1%, 5% and 10% significant levels, respectively.

Table 13 presents the regression results of CIRT policy's impact on county-level carbon emissions in columns (1) to (4), while columns (5) and (6) show the regression results for TECT policy's impact. Columns (1), (3), and (5) provide the regression results without controlling for additional variables. Columns (2), (4), and (6) include the control variables. In column (2), the initial effect of the CIRT policy is shown, with a significant coefficient of -0.0493 indicating a significant reduction in carbon emissions due to CIRT policy implementation. Column (4) represents the long-term average treatment effect of CIRT policy on carbon emissions, with a significant coefficient of -0.0506, indicating a sustained and significant reduction in carbon emissions over time due to CIRT policy. The comparison between columns (2) and (4) suggests that the carbon reduction effect of CIRT policy strengthens with increased implementation time. In Table 4, column (2) indicates a significant coefficient of -0.0551 for CIRT policy's impact on carbon emissions at the 1% level. However, the absolute values of the coefficients in columns (2) and (4) of Table 13 are smaller than the absolute value of the coefficient in Table 4, column (2). This suggests that not considering the concurrent implementation of the EIRT policy would underestimate the carbon reduction effect of the CIRT policy. Column (6) displays the regression results for the impact of the TECT policy on carbon emissions. The coefficient for TECT policy is significantly negative at -0.0726, indicating that the TECT policy leads to a reduction in county-level carbon emissions. In Table 8, column (2), the coefficient for TECT policy on county-level carbon emissions is -0.0112 and significant. However, the absolute value of the coefficient in Table 13, column (2), for the TECT policy is greater than the absolute value of the coefficient in Table 8, column (2). This suggests that not considering the concurrent implementation of the EIRT and CIRT policies would overestimate the promoting effect of the TECT policy on reducing county-level carbon emissions.

In general, while evaluating the impact of a single policy on emissions reduction, it is important to include the potential influence of similar duplicate policies implemented concurrently. Failure to do so may result in an overestimation or underestimation of the true effect of multiple policies on emissions reduction. The evaluation results pertaining to a specific policy demonstrate a propensity to overstate the impacts of the energy-related EIRT and TECT policies on carbon emissions, while concurrently underestimating the impacts of the CIRT policy on carbon emissions at the county level.

6. Discussion

6.1. Ranking policy impact on carbon emissions

In this section, we rank all influencing factors to identify the most impactful ones. Overall, the impact of the three policies, EIRT, CIRT, and TECT, on carbon emission reduction is ranked in descending order as follows: CIRT, TECT, EIRT. CIRT demonstrates a pronounced promotional effect on reducing carbon emissions, maintaining a consistent reduction trend since its inception. Within the domain of energy consumption-related TECT and EIRT policies, TECT encourages carbon emission reduction, albeit without achieving statistical significance. EIRT, in its entirety, does not significantly contribute to a decrease in carbon emissions.

6.2 Policy implications

Based on our findings, we offer the following policy implications. The first is about climate target policies, which directly control carbon emissions, have consistently demonstrated effective carbon reduction results compared to energy target policies. Therefore, it is crucial to continue steadily advancing the implementation of climate target policy CIRT. While the primary goal of EIRT policy is not carbon reduction, adjustments the implement of the energy target policy EIRT to maximize its carbon reduction effects. The second policy recommendation concerns the implementation of regional policy differentiation, where the carbon reduction effects of multiple target-constrained policies are most pronounced in central regions. Therefore, when formulating standards, more focus should be placed on adjusting targets in the eastern and western regions. Third, we recommend recognizing the fact that current emissions reduction results do not solely arise from single policies. Hence, assessing the combined effects of multiple policies is a crucial aspect of rationally evaluating relevant climate policies. This is especially important when multiple policies with the same objectives are executed in distinct phases. To better differentiate the effects of multiple policies, the evaluation of earlier-executed policies does not include sample time periods for subsequent policies, and efforts to control for the effects of earlier-executed policies when evaluating the impacts of later policies.

In terms of the applicability at the international level, first, this study reveals different impacts of energy and climate target policies on carbon reduction. We find that, in China, climate target policies which directly control carbon emissions have performed more effective to reduce carbon emissions compared to energy target policies. Given that other countries and economies have implemented or aim to pilot energy and climate target policies, China can be taken as an example, when considering multi-target policies. Second, the multi-target policies may be gradually implemented in several stages. The phase-based empirical strategy designed for China in this study can be applied to other nations and regions.

7. Conclusions

In this study, we use balanced panel data of 1963 counties from mainland China from 2000 to 2017 to evaluate the effects of multiple energy and climate targeted policies on county-level carbon emissions. There are three main findings. First, at the national level, the EIRT policy did not reduce carbon emissions during the 11th FYP; only the CIRT policy was effective in emission reduction in the 12th FYP; both CIRT and TECT policies contributed to reductions in the 13th FYP. Second, the impact of these policies varied regionally and by intensity. Initially, the effects of EIRT were localized in eastern and central regions, then shifted to western regions. The effects of CIRT expanded from eastern to central regions, and TECT initially promoted reductions in central regions. Regarding intensity, early lower to moderate EIRT standards aided emissions reduction, with stronger later phases being more effective. Higher CIRT standards led to greater reductions. Third, individual policy assessments tend to overestimate the indirect effects of EIRT and TECT and underestimate CIRT's direct impact on carbon emissions. Based on these findings, the possible applicability includes: First, the study suggests prioritizing the impact of CIRT on carbon emissions. In addition, our research proposes a consideration of region-specific adaptations in environmental policies, particularly for the eastern and western regions. Furthermore, the study recommends the evaluation of combined policy effects, particularly for policies with overlapping objectives and timelines.

Limited to the city-level data availability, the energy and climate target values used in this study are derived from provincial data. The city-level data is associated with more missing values, which may introduce unpredictable errors. Future studies may explore two aspects. First, energy and climate target constraints may impact pollutants; therefore, future research could investigate the co-benefits of pollution reduction and carbon reduction resulting from energy and climate target policies. Second, our study assessed the impact of target-constrained quantity tools on carbon emissions. There is a need for empirical research to investigate the influence of both target-constrained quantity tools and subsidy-based price tools on carbon emissions.

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