China's Climate Policy: Mandate-Based vs. Market-Based Approaches

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Abstract: *Mandate-based and market-based mechanisms represent two primary approaches to achieving policy objectives, yet the debate over their relative effectiveness remains unresolved. The mandate-based approach is exemplified by pilot programs for low-carbon provinces and cities, referred to as "Low-Carbon Pilot Provinces/Cities", while the market-based mechanism is reflected in pilot programs for carbon emissions trading markets, or "Carbon Trading Pilot Programs". This paper employs event study analysis to compare the carbon emission reduction impacts of these two approaches. Our findings reveal that the Low-Carbon Pilot Provinces/Cities achieved emissions reduction primarily by curbing economic output, without significantly reducing carbon emissions intensity. In contrast, the Carbon Trading Pilot Programs led to an increase in total carbon emissions by driving economic growth, even as they reduced carbon emissions intensity. A heterogeneity analysis further indicates that the emissions reductions observed in the Low-Carbon Pilot Provinces/Cities were predominantly concentrated in economically less-developed regions, whereas the increase in carbon emissions associated with the Carbon Trading Pilot Programs was more significant in regions with lower initial carbon emissions intensity. Against the backdrop of China's efforts to achieve its carbon peak and neutrality goals, this paper offers valuable insights for the design of effective climate policies.*

Keywords: *Low-Carbon Pilot Provinces/Cities; Carbon Emissions Trading Pilot Programs; mandate-based policy; market-based policy*

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1. Introduction

The comparison of policy effects between mandate-based measures and market-based mechanisms has long been a central question in economics (Lange, 1942; Hayek, 1945; Arrow, 1951; Debreu, 1951; Weitzman, 1974; Acemoglu and Verdier, 2000; Acemoglu et al., 2008). In theory, perfectly functioning market-based mechanisms can enable socioeconomic systems to achieve an optimal state even without external government intervention. However, numerous frictions overlooked by theoretical models exist in practice.

In developing countries, for instance, command executors and market regulators often lack the capacity to effectively detect violations, and their regulatory and enforcement capabilities face significant limitations (Eskeland and Jimenez, 1992; Russell and Vaughan, 2003). As a result, the ideal outcomes envisioned by theoretically optimal policy designs may not be fully realized under real-world constraints, leading instead to suboptimal results. In the context of environmental and climate governance, empirical evidence from many developing countries suggests that mandate-based policies

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and market-based mechanisms often fail to produce the outcomes predicted by economic theories, complicating direct comparisons of their advantages and disadvantages (Blackman et al., 2018). This underscores the need for rigorous empirical analysis to evaluate the real-world effects and underlying mechanisms of climate policies. The existing research literature provides extensive theoretical insights into the carbon emissions-reducing impacts of mandate-based and market-based policies (Karp and Traeger, 2018; Mideksa and Weitzman, 2019). However, empirical studies directly comparing the effects of these two approaches remain scarce (He et al., 2022). This paper aims to address this gap by evaluating the effectiveness and mechanisms of administrative measures and market mechanisms in controlling greenhouse gas (GHG) emissions, using China's climate policies as a case study.

According to China's White Paper *Climate Change Response Policies and Actions*, we systematically identified the country's key pilot policies for climate change mitigation, focusing on two of the most significant initiatives: the pilot programs for low-carbon provinces and cities ("Low-Carbon Pilot Provinces/Cities") and the pilot programs for carbon emissions trading markets ("Carbon Trading Pilot Programs"). The Low-Carbon Pilot Provinces/Cities embody administrative measures, whereas the Carbon Trading Pilot Programs represent market mechanisms. Comparing the carbon emissions-reducing effects of these two types of pilot programs is crucial for understanding their impacts and informing future policy design. Using the event analysis method, we conducted a comprehensive and systematic evaluation of the effectiveness of these two approaches, shedding light on their respective contributions to climate change mitigation.

Our findings indicate that the Low-Carbon Pilot Provinces/Cities significantly reduced total carbon emissions, primarily by curbing economic output. In contrast, the Carbon Trading Pilot Programs led to a slight increase in total carbon emissions, as the growth in economic output offset reductions in carbon emissions intensity within the pilot counties and districts. This paper explores the underlying reasons for these outcomes. The Low-Carbon Pilot Provinces/Cities achieved reductions in total carbon emissions largely because local governments, under central government supervision and the competitive pressures among peer governments, adopted and often exceeded ambitious emissions reduction targets. On the other hand, the Carbon Trading Pilot Programs utilized a tradable performance standard (TPS) as the mechanism for carbon quota distribution. This approach focused on reducing carbon emissions intensity rather than total carbon emissions, which explains why these programs did not result in an absolute decline in emissions.

The TPS mechanism encouraged energy-intensive enterprises to adopt low-carbon technologies or purchase additional carbon quotas, thereby reducing overall carbon emissions intensity. However, the same rules incentivized cleaner enterprises to scale up production, which, in turn, could offset the emissions reductions achieved elsewhere. As a result, total carbon emissions within these regions did not necessarily decrease. In the long run, reducing carbon emissions through mandate-based measures by curbing output is inconsistent with the fundamental principles of sustainable development. Conversely, market-based mechanisms can drive reductions in carbon emissions intensity by stimulating both the market and economic growth. In this context, the effectiveness of the two approaches in mitigating climate change does not lie in their absolute advantages or disadvantages but in their alignment with policy goals. The key question is whether the policy aims to achieve short-term reductions in total carbon emissions or to tolerate a moderate increase in emissions while fostering economic growth and a clean energy transition. Notably, the design of a carbon market adopting a cap-and-trade (CAT) system could alter corporate incentives, potentially leading to conclusions that differ from those based on the effects observed in existing TPS carbon markets.

Furthermore, we have identified heterogeneous carbon emission reduction effects of climate policies across different regions. As a mandate-based climate policy, the emissions abatement effect of the Low-Carbon Pilot Provinces/Cities is not influenced by the initial carbon emissions levels of the pilot regions. However, the initial economic conditions at the county and district levels significantly impact the emissions abatement outcomes of these pilot programs at the provincial level. Specifically, regions with lower GDP exhibit greater emissions abatement effects compared to regions with higher GDP. This may be attributed to the lower opportunity costs for economically less-developed regions in reducing carbon emissions. On the other hand, as a market-based policy, the Carbon Trading Pilot Programs show an emissions-increasing effect, primarily in regions with lower initial carbon emissions intensity. This occurs because enterprises in these counties and districts often employ cleaner production practices and are more incentivized by the carbon market to expand production. As a result, the economies of scale effect offsets the technology effect, ultimately leading to an increase in carbon emissions.

The contributions of this paper are threefold:

First, it conducts a comprehensive and systematic ex-post evaluation of the carbon emission reduction effects of China's climate policies, spanning a long time frame (2008-2017) and offering fine-grained analysis at the county and district levels. In the existing literature on climate policies, the prevalent approach involves utilizing integrated evaluation models for ex-ante simulations of policy impacts, which often serve as a basis for policymaking. Most ex-ante research on China's climate policies has focused on the carbon trading market, concluding that carbon markets can achieve emissions reduction targets at relatively low costs (Wang et al., 2015; Li et al., 2018; Jin et al., 2020). However, assumptions underlying ex-ante models often deviate from real-world conditions, leading to discrepancies between forecasted results and those derived from ex-post analyses. As a result, ex-ante evaluations are often inadequate for accurately assessing the actual emissions reduction effects of climate policies (Qiu et al., 2020). Some studies have employed an ex-post analytical approach to evaluate the emissions-reduction effects of climate policies at the corporate or provincial level (Chen and Xu, 2018; Cui et al., 2021; Cao et al., 2021). However, the availability of high-quality and representative enterprise-level data nationwide remains limited, and challenges in conducting carbon market research at the corporate level persist. As a result, the regional impact of emissions abatement policies merits greater attention. Given the scarcity of detailed research at the provincial and prefectural city levels, our study addresses this gap by focusing on the county or district level, thereby contributing new insights to the existing body of literature.

Second, this paper contributes to the understanding of mandate-based and market-based environmental management policies in the context of climate change. Our findings reveal that under specific market system designs, significant differences exist in the emissions reduction effects and mechanisms of these two policy types. Mandate-based policies, while effective at reducing total carbon emissions by curbing overall economic output, showed minimal improvement in emissions intensity within the pilot counties and districts. In contrast, market-based policies significantly reduced emissions intensity and stimulated economic growth, though they led to a slight increase in total carbon emissions. Our conclusions regarding mandate-based policies align with real-world observations. For example, local governments often restrict power supply and industrial production to meet energy consumption and intensity targets set by higher-level authorities. Similarly, the potential emissions-increasing effects of market-based policies align with theoretical expectations and are consistent with the forecasted outcomes of Goulder et al.'s (2022) model for China's special carbon market. Overall, mandate-based policies exhibit stronger emissions abatement effects than market-based policies. However, market-based policies are better at balancing economic growth with clean development. Each policy type has distinct advantages and disadvantages, depending on the evaluation criteria used.

Third, our treatment of multiple gradualist implementation policy scenarios in our econometric analysis provides a benchmark for general research on policy evaluation. When evaluating a specific policy, the presence of a mixture of highly correlated policies, often stemming from the non-random selection of pilot policy programs, can complicate the analysis. This may introduce the problem of omitted variables, leading to endogeneity and compromising the unbiasedness and consistency of the estimated results. To address this, many studies in environmental economics have incorporated additional policy initiatives into their evaluations to mitigate bias from omitted variables (e.g., Greenstone, 2002; Auffhammer and Kellogg, 2011; Greenstone et al., 2012; Kahn and Mansur, 2013; Greenstone and Hanna, 2014; Li et al., 2020). Following this approach, our paper applies a similar methodology, integrating multiple climate policies within a unified analytical framework. This method not only avoids the bias associated with omitted variables but also facilitates a meaningful comparison and discussion of the effects of different types of climate policies.

The remaining structure of this paper is as follows: Section 2 explores the institutional background of China's climate policies. Section 3 introduces a basic theoretical model. Section 4 details the data utilized in this study. Section 5 conducts a regression analysis. Section 6 presents the quantitative results along with a cost-benefit analysis. Finally, Section 7 concludes with key insights and remarks.

2. Institutional Framework Underpinning China's Climate Policies

Climate change is widely recognized as one of the greatest challenges facing humanity in the 21st century. Global greenhouse gas (GHG) emissions between 2010 and 2019 reached record levels, surpassing those of any previous decade and highlighting the urgent need for effective climate change mitigation (IPCC, 2022). Since overtaking the United States as the world's largest GHG emitter in 2006, China's climate change mitigation efforts have garnered significant global attention. As a responsible stakeholder, China's approach to addressing climate change has shifted significantly, evolving from being seen as "a responsibility imposed upon us" to becoming "a mandatory initiative of our own choosing"[1]. On various international platforms, China has announced ambitious commitments to reduce carbon emissions[2]. To meet these commitments, China has implemented multidimensional climate policies.

Since the State Council Information Office first released *China's Climate Change Response Policies and Actions* ("White Paper") in 2008, China has published this document annually to elaborate on its climate change policies, actions, and achievements from the previous year. The "Low-Carbon Development Pilot and Demonstration Programs" section of the White Paper highlights the implementation of these policies and actions, as well as the outcomes achieved. Among the various initiatives, two long-term policies stand out: the Low-Carbon Pilot Provinces/Cities and the Carbon Trading Pilot Programs.

A review of the White Paper summaries on climate change mitigation pilot programs between 2008 and 2017 reveals that the Low-Carbon Pilot Provinces/Cities and the Carbon Trading Pilot Programs were the most consistently mentioned climate policies. These two initiatives appeared in nine out of the ten years, underscoring their centrality to China's climate strategy. In contrast, other pilot programs were not sustained as primary long-term policy instruments. For example, the Climate Adaptation City Pilot Programs were mentioned only once, while the Clean Development Mechanism (CDM) Pilot Programs, targeting corporate-level implementation, were cited in seven years but were absent from 2016 to 2021. Similarly, the Carbon Capture, Utilization, and Storage (CCUS) Pilot Programs, focusing on technical solutions, were mentioned in just one year.

The White Paper reflects the Chinese leadership's evolving understanding and evaluation of policy implementation. Following this framework, this paper focuses on the carbon emissions reduction

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[1] http://www.gov.cn/xinwen/2022-01/25/content_5670359.htm.

[2] For instance, in December 2009, then-Premier Wen Jiabao pledged at the Copenhagen Climate Conference to reduce China's carbon emissions per unit of GDP by 40% to 45% from 2005 levels by 2020. More recently, at the 75th United Nations General Assembly in December 2020, President Xi Jinping declared China's goals to peak CO2 emissions by 2030 and achieve carbon neutrality by 2060.

initiatives and mechanisms within the Low-Carbon Pilot Provinces/Cities and the Carbon Trading Pilot Programs. The subsequent sections will provide a detailed analysis of these two climate policies.

2.1 Low-Carbon Pilot Provinces/Cities

Amid China's rapid urbanization and industrialization, cities accounted for 60% of the nation's total energy consumption in 2009 (Song et al., 2019). To address the associated environmental challenges, the National Development and Reform Commission (NDRC) launched three waves of low-carbon pilot programs starting in 2010. These initiatives included ten provinces or municipalities, 68 prefectural cities or regions, and nine counties, districts, or county-level cities. The programs aimed to explore region-specific pathways for controlling greenhouse gas (GHG) emissions[3]. As the pilot programs unfolded, local governments refined and expanded their low-carbon initiatives. These included efforts to develop low-carbon cities, industrial parks, and communities[4]. These measures sought to establish sustainable modes of production and lifestyles.

The central government did not establish explicit carbon reduction targets or specific measures for the low-carbon pilot provinces and cities. However, it outlined several key requirements. These included incorporating climate change considerations into local development plans, setting local greenhouse gas (GHG) emission reduction targets, identifying priorities, and formulating action plans. Additionally, local governments were tasked with taking responsibility for reducing GHG emissions within their jurisdictions. To ensure the effective implementation of these initiatives, the National Development and Reform Commission (NDRC) introduced oversight mechanisms to regularly monitor and evaluate the progress of the pilot programs.

Reductions in both total CO_2 emissions and emissions intensity are crucial for mitigating climate change. However, in the implementation efforts of pilot provinces and cities, locally designed emissions reduction targets tend to prioritize reductions in total emissions over emissions intensity. For instance, between 2013 and 2014, Shenzhen emerged as a frontrunner among the first wave of Low-Carbon Pilot Cities, committing to peak its carbon emissions between 2017 and 2020. Similarly, all 29 pilot regions in the second wave set carbon emissions peak targets or total emissions control targets. By 2015, all pilot provinces and cities had either established or were in the process of developing carbon peak targets, with most aiming to achieve these peaks by 2025. By 2017, the majority of pilot cities had already adopted their carbon peak targets.

Reduction of carbon emissions intensity requires industrial transformation and technological upgrades, which pose significant challenges for local governments compared to the relatively straightforward goal of reducing total carbon emissions. To meet their commitments to emissions reduction, local governments may resort to less costly, "one-size-fits-all" measures, such as closures, suspensions, mergers, production shifts, and power rationing. However, these measures often come at the expense of short-term economic growth to achieve the goal of reducing total carbon emissions. Traditional research on government performance evaluation has largely focused on the relationship between economic performance and the promotion prospects of local officials. In recent years, however, environmental and energy management have emerged as critical dimensions in the evaluation of local government performance. Studies have shown that local officials in regions with better outcomes in air pollution control and energy efficiency are more likely to receive promotions (Zheng et al., 2014; Chen

[3] See NDRC *Circular on Carrying Out Pilot Work for Low-Carbon Provinces and Cities* (NDRC Climate No. 1587 [2010]), *Circular on Carrying Out the Second Wave of Pilot Programs for Low-Carbon Provinces/Cities* (NDRC Climate No. 3760 [2012]), and *Circular on Carrying Out the Third Wave of Pilot Programs for National Low-Carbon Cities* (NDRC Climate No. 66 [2017]).

[4] For instance, Ankang City in Shaanxi Province announced plans to promote low-carbon commerce, towns, and communities following the implementation of pilot programs at the levels of cities, counties or districts, industrial parks, and key enterprises (https://www.ccchina.org.cn/Detail.aspx?newsId=73194&TId=282).

et al., 2016; Wang and Lei, 2020; Wu and Cao, 2021). This shift highlights the growing importance of environmental protection as a key criterion in assessing government officials' performance. The proactive efforts of some government officials to achieve environmental objectives further support the hypothesis that "local governments will strive to meet emissions reduction targets even at the expense of economic growth."

The concept of environmental management through mandate-based policies is not new. For example, in the power sector, China shut down 4,144 units of 538 power plants, primarily those with an installed capacity below 25,000 kW (Zhang, 2022). Similarly, mandate-based policies in Low-Carbon Pilot Provinces/Cities emphasize controlling emissions through direct regulations rather than market-based tools. Local governments regulate emission quantities via command-and-control mechanisms, consistent with academic perspectives on mandate-based interventions (Sterner & Robinson, 2018).

Hence, we hypothesize that Low-Carbon Pilot Provinces/Cities can reduce total carbon emissions, but not necessarily carbon emissions intensity.

2.2 Carbon Trading Market

In alignment with the 12th Five-Year Plan's goal to "gradually establish a carbon emissions trading market", the General Office of the NDRC issued the *Circular on the Implementation of Pilot Programs for Carbon Emissions Rights Trading* on October 29, 2011 (NDRC Climate [2011] No. 2601). The Circular called for the launch of pilot programs for carbon emissions trading in Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong, and Shenzhen, aiming to achieve greenhouse gas (GHG) emissions reduction targets at relatively low costs through market-based mechanisms. Among them, Shenzhen was the first to establish a carbon market, launching operations in June 2013. By the end of 2013, carbon markets in Shanghai, Beijing, Guangdong, and Tianjin also became operational. Hubei and Chongqing followed, opening their carbon markets in April and June 2014, respectively. Additionally, Sichuan and Fujian provinces established nationally registered carbon trading institutions, commencing operations in December 2016.

Unlike the command-and-control approach employed in the Low-Carbon Pilot Provinces and Cities, carbon trading is widely recognized as a quintessential market-based instrument. It incentivizes enterprises to achieve carbon emission reduction targets through economic mechanisms by establishing a carbon trading market designed around the allocation of carbon emission rights (Blackman et al., 2018; Sterner and Robison, 2018).

A key distinction among the various carbon trading markets worldwide lies in the allocation of carbon emission quotas. Common types of carbon markets include cap-and-trade (CAT) systems and tradable performance standard (TPS) markets. In most CAT systems, corporate carbon emission quotas are allocated externally and must not exceed the sum of the assigned quota and any additional quota purchased from other enterprises.

Each pilot program has implemented a distinct quota allocation scheme tailored to a specific sector. Notably, the TPS mechanism was adopted for both the electric power and heating supply sectors, which accounted for the largest share of carbon emissions across various pilot programs (Zhang et al., 2017; Cui et al., 2023). Under the TPS system, the carbon quota allocated to each enterprise during a given period is determined by a combination of its output and the sectoral emissions intensity criterion (i.e., carbon quota per unit of output). In other words, the carbon quota an enterprise receives is endogenous to its production process during each period, rather than being predetermined. Enterprises can influence their quotas by adjusting their production output. While the sectoral emissions intensity is exogenously determined, the total carbon emissions for the entire carbon market are endogenous, as enterprise quotas depend on their current production output. Thus, even though market regulators can set the sectoral emissions intensity criteria, they cannot finalize the total carbon quota allocation until the production processes conclude at the end of the period.

Under the CAT system, the carbon market ensures that the marginal cost of emissions reduction for all enterprises aligns with the price of carbon quotas, thereby minimizing the overall cost of carbon emissions reduction. In contrast, the TPS system effectively imposes an implicit carbon tax while simultaneously subsidizing production output (Fischer, 2001). This characteristic results in heterogeneous effects of China's carbon market on different enterprises. Under the TPS system, each enterprise engages in continuous carbon trading until its marginal cost of emissions reduction equals the net price of carbon quotas, adjusted for production subsidies. The carbon emissions per unit of output vary across enterprises due to differences in technological levels and carbon intensity. Consequently, the net price of carbon quotas, after accounting for output subsidies, differs among enterprises. As a result, the marginal cost of emissions reduction also varies between enterprises at equilibrium.

Enterprises must either reduce production output or carbon intensity to comply with carbon emissions standards. Under the CAT system, enterprises have primarily adopted the strategy of reducing output (Goulder et al., 2022). However, under the TPS system, corporate responses differ significantly. Enterprises can be categorized as energy-intensive or non-energy-intensive based on whether they exceed their sectoral emissions intensity criteria. This distinction helps to analyze heterogeneous corporate responses under the TPS framework. According to TPS rules, non-energy-intensive enterprises, being below their sectoral emissions intensity criteria, generate a net surplus of carbon quota for each unit of increased production. This surplus arises because the carbon quota they receive exceeds their actual carbon emissions, allowing them to sell the excess in the carbon market for profit. In contrast, energy-intensive enterprises face a net deficit in carbon quota for each additional unit of production, requiring them to purchase extra quotas in the carbon trading market. Consequently, non-energy-intensive enterprises are incentivized to increase production to benefit from the surplus, while energy-intensive enterprises must either reduce output or lower carbon intensity to comply with emissions regulations.

The above logical deduction illustrates that, within the framework of the TPS mechanism, energy-intensive enterprises are incentivized to reduce their carbon intensity, whereas non-energy-intensive enterprises show no motivation to increase theirs. In other words, the reduction in carbon emissions intensity observed in pilot regions is an inherent outcome of the carbon trading market under the TPS mechanism. While the TPS mechanism drives energy-intensive enterprises to cut back on production, it simultaneously encourages non-energy-intensive enterprises to expand their output. As a result, Chen (2021) found that clean enterprises tend to increase their production in response to the carbon market, thereby offsetting the reductions in carbon emissions intensity and potentially leading to an overall increase in total carbon emissions.

Therefore, we hypothesize that the Carbon Trading Pilot Programs are likely to reduce carbon emissions intensity in the pilot regions. However, since the carbon trading market could potentially boost the production output of clean enterprises, the exact impact on total carbon emissions remains uncertain. This ambiguity necessitates empirical analysis to determine the actual direction of change.

2.3 Spatial Overlap between the Low-Carbon Pilot Provinces/Cities and the Carbon Trading Pilot Programs

It needs to be noted that there exists a significant overlap in the spatial distribution of the Low-Carbon Pilot Provinces/Cities and the Carbon Trading Pilot Programs. Take the samples of 2017 for instance, 36.93% of the counties and districts were covered by only one pilot policy, and as much as 13.36% of the counties and districts were selected as Low-Carbon Pilot Promises/Cities and Carbon Trading Pilot Programs at the same time. Such overlap stems from the non-representativeness of selected pilot programs, which can be ascribed to the following reasons: First, a province or city is selected by the central government for the implementation of more than one pilot program because it possesses better conditions to experiment with and demonstrate the effects of new policies. Second, another reason is that some government officials are incentivized to participate in multiple central government pilot programs under career promotion considerations, leading to the non-representativeness in the selection of pilot programs (Wang and Yang, 2021). As such, the evaluation of the emissions reduction effect of a single climate policy is likely to lead to the bias of omitted variables, leading to a misjudgment of the claimant policy's emissions reduction effect.

It is important to note that there is a significant overlap in the spatial distribution of Low-Carbon Pilot Provinces/Cities and Carbon Trading Pilot Programs. For instance, in 2017, 36.93% of counties and districts were covered by only one pilot policy, while 13.36% were simultaneously designated as Low-Carbon Pilot Provinces/Cities and included in Carbon Trading Pilot Programs. This overlap arises from the non-representativeness of the selected pilot programs, which can be attributed to several factors: First, provinces or cities are often chosen by the central government for multiple pilot programs because they possess favorable conditions for experimenting with and demonstrating the impact of new policies. Second, some government officials may be motivated to participate in multiple central government pilot programs as a means to advance their careers, further contributing to the non-representativeness of the selection process (Wang and Yang, 2021). As a result, overlooking other climate policies when evaluating the emission reduction effect of a single climate policy may lead to omitted variable bias, resulting in a misjudgment of the effectiveness of that climate policy in reducing emissions.

3. Theoretical Model

Based on the characteristics of the Low-Carbon Pilot Provinces/Cities and the Carbon Trading Pilot Programs, we have developed a simplified static model to illustrate the responses of energy-intensive and clean enterprises to both mandate-based measures and market-based mechanisms. This model allows us to analyze changes in carbon emissions, total output, and carbon emissions intensity at the regional level. We will examine four distinct scenarios: No Climate Policy, the Low-Carbon Pilot Provinces/Cities, the Carbon Trading Pilot Programs, and the Overlap between the Two Policies.

3.1 Basic Model Specifications and the No-Climate-Policy Scenario

In reference to the classical model specification for environmental economics, it is assumed that enterprises $i \in [0,1]$ are continuously uniformly distributed across a region and accept the external product price p. The production cost function is $C_0 + C(q_i)$ for all enterprises, where q_i is the production output, C_0 is the fixed cost of production, and $C(q_i)$ is the variable cost of production. It is assumed that the production cost function increases with output, i.e., $MC(q_i)=C'(q_i)>0$. Furthermore, the production cost function is a concave function of output, i.e., $MC'(q_i)=C''(q_i)>0$. As a result, the marginal cost function has an inverse relationship with production output.

Differences between enterprises lies in the carbon emissions intensity μ_i. It is assumed that μ_i does not change with time. This assumption is supported by reality because technological progress is a long process and free from "low-hanging fruit", making it difficult for enterprises to reduce carbon emissions intensity on their own initiative (Cao et al., 2021; Chen et al., 2021). Carbon emissions from enterprises are $e_i=\mu_i q_i$. The decision-making variable for enterprises is corporate output q_i, and the decision-making objective is to maximize profit π_i. As far as this region is concerned, the total output is $q=\int_0^1 q_i di$, carbon emissions are $e^*=\int_0^1 \mu_i q_i di$, and carbon emissions intensity is $\mu=e/q$.

The differences between enterprises lie in their carbon emissions intensity μ_i. It is assumed that μ_i does not change over time. This assumption reflects reality, as technological progress is a slow process and devoid of 'low-hanging fruit,' making it difficult for enterprises to independently reduce their carbon emissions intensity (Cao et al., 2021; Chen et al., 2021). The carbon emissions from enterprises are denoted as $e_i=\mu_i q_i$. The decision-making variable for enterprises is their output q_i, with the objective of maximizing profit π_i. For this region, the total output is $q=\int_0^1 q_i di$, total carbon emissions are $e^*=\int_0^1 \mu_i q_i di$, and the carbon emissions intensity is $\mu=e/q$.

Under the No Climate Change Policy scenario, an enterprise i makes the following decision:

$$\max_{q_i} \pi_i = pq_i - C_0 - C(q_i) \tag{1}$$

Taking the partial derivative of production output with respect to the profit function allows us to determine the enterprise's optimal output based on the first-order condition $q_i^*=MC^{-1}(p)$. Under the No Climate Policy scenario, the regional total output is specified as $q^*=\int_0^1 q_i^* di=MC^{-1}(p)$, carbon emissions are $e=\int_0^1 \mu_i q_i^* di=q^*\int_0^1 \mu_i di$, and carbon emissions intensity is $\mu^*=e^*/q^*=\int_0^1 \mu_i di$. This analysis helps to assess the economic and environmental trade-offs in the absence of climate policies.

3.2 Low-Carbon Pilot Province/City Scenario

Mandate-based measures are designed for aggregate control, as it is challenging for the government to obtain precise information about enterprises' carbon emissions intensity. In our model, these measures are represented as a proportional restriction on corporate production output, ensuring it does not exceed λ, $\lambda \in (0,1)$ of the production level under the No Climate Policy scenario. Enterprise i make decisions based on the following approach:

$$\max_{q_i} \pi_i = pq_i - C_0 - C(q_i) \tag{2}$$

$$\text{s.t.}\, q_i \leq \lambda q_i^* \tag{3}$$

Compared to the No Climate Policy scenario, it is evident that the restrictive condition is a tight constraint $q_i^G=\lambda q_i^*$ (as shown in Figure 1a). Under the Low-Carbon Pilot Province/City scenario, total regional output is $q^G=\int_0^1 q_i^G di=\lambda q^*$, carbon emissions are $e^G=\int_0^1 \mu_i q_i^G di=\lambda e^*$, and carbon emissions intensity is $\mu^G=e^G/q^G=\mu^*$. This indicates that while mandate-based measures have successfully reduced regional carbon emissions, their effect on carbon emissions intensity remains neutral.

3.3 Carbon Trading Pilot Programs Scenario

Under the TPS system, it is assumed that the sectoral emissions intensity criterion $\bar{\mu}$ and the unit price of carbon $\tau>0$ in the carbon trading market are externally determined for the enterprise. If the enterprise's actual emissions intensity is below the criterion $\mu_i<\bar{\mu}$, it can sell its surplus carbon quota in the market. Conversely, if the emissions intensity exceeds the criterion, the enterprise must purchase additional carbon quotas from the market. Accordingly, Enterprise i makes the following decision:

$$\max_{q_i} \pi_i = pq_i - C_0 - C(q_i) - \tau(\mu_i - \bar{\mu})q_i \tag{4}$$

Taking the partial derivative of production output with respect to the profit function, we arrive at the first-order condition $q_i^M=MC^{-1}(p+\tau\bar{\mu}-\tau\mu_i)$. For clean enterprises, $\mu_i<\bar{\mu}$, and $q_i^M>q_i^*$ leads to an increase in corporate production output. Conversely, for energy-intensive enterprises, $\mu_i>\bar{\mu}$, and $q_i^M<q_i^*$ leads to a reduction in corporate production output. The carbon trading market effectively acts as an implicit subsidy provided by energy-intensive enterprises to clean enterprises. This mechanism causes the marginal yield curve of clean enterprises to shift upward, while that of energy-intensive enterprises shifts downward, as illustrated in Figure 1a.

Under the Carbon Trading Pilot Program policy scenario, total regional output is $q^M=\int_0^1 q_i^M di= \int_0^1 MC^{-1}(p+\tau\bar{\mu}-\tau\mu_i)di$, carbon emissions are $e^M=\int_0^1 \mu_i q_i^M di= \int_0^1 \mu_i MC^{-1}(p+\tau\bar{\mu}-\tau\mu_i)di$, and carbon emissions intensity is $\mu^M=e^M/q^M=\int_0^1 \mu_i q_i^M d_i/\int_0^1 q_i^M di$. However, we cannot directly determine the signs of q^M relative to q^* and e^M to e^*, as these depend on the specific form of the marginal cost function and the distribution of corporate carbon emissions intensity. As a result, the theoretical model alone cannot provide definitive predictions and must instead be validated through empirical testing.

However, we can demonstrate that regional carbon emissions intensity has decreased. This can be explained as follows: $\mu^*=\int_0^1\mu_i\,di$ represents the mean value of corporate emissions intensity, while $\mu^M=\int_0^1\mu_i\,(q_i^M/\int_0^1 q_j^M dj)di$ denotes the weighted average of corporate emissions intensity based on corporate production output. Due to the increased weight of clean enterprises and the decreased weight of energy-intensive enterprises, we have: $\mu^M<\mu^*$.

In essence, the carbon trading market reduces overall carbon emissions intensity by promoting the growth of clean enterprises and curbing the output of energy-intensive ones.

3.4 Overlap between the Two Policy Scenarios

When a region simultaneously implements Low-Carbon Province/City Pilot Programs and Carbon Trading Pilot Programs, certain enterprises will participate in the carbon market, while those outside it will be governed by mandate-based regulations. We assume enterprises outside the carbon market are $i\in[0,\alpha]$, and those within the carbon market are $j\in(\alpha,1]$, $\alpha\in(0,1)$.

When the two policies overlap, regional total output becomes $q^{G+M}=\int_0^{\alpha} q_i^G di+\int_{\alpha}^1 q_j^G dj=\alpha q^G+(1-\alpha)q^M$, carbon emissions are $e^{G+M}=\alpha e^G+(1-\alpha)e^M$, and carbon emissions intensity is $\mu^G=e^{G+M}/q^{G+M}$. Under such overlap, it is not possible to theoretically predict changes in these variables, necessitating empirical testing. More importantly, evaluating one policy without considering the influence of the other may result in biased conclusions. Therefore, it is essential to integrate both policies simultaneously into the regression analysis framework.

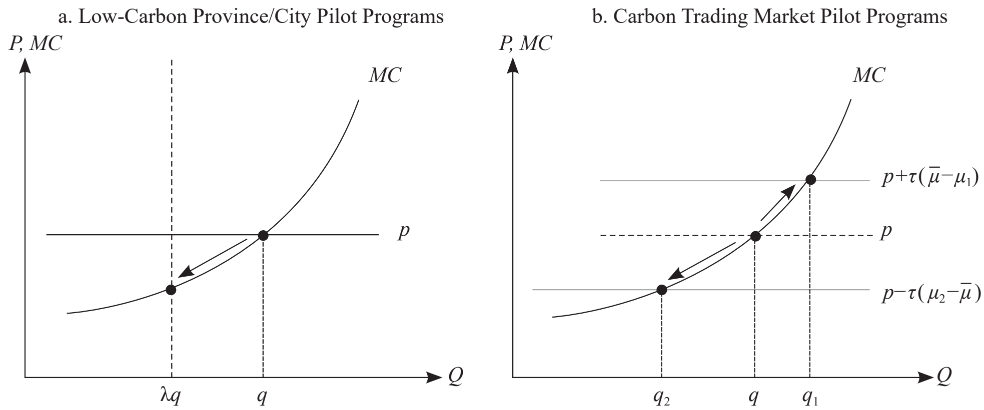

Figure 1: Theoretical Model Illustration

Notes: Subscript 1 in Figure 1b denotes clean enterprises, and Subscript 2 denotes energy-intensive enterprises, i.e. $\mu_1<\bar{\mu}<\mu_2$.
Source: Drawn by the authors based on the model.

4. Data Source

We compiled the list of names and initiation dates of the three waves of low-carbon provinces and cities based on public announcements from the National Development and Reform Commission (NDRC). Additionally, we gathered the market launch dates for various carbon trading pilot programs using publicly available online resources. Using carbon emissions data from the Carbon Emissions Accounts and Datasets (CEADs) and socioeconomic data from the China Stock Market & Accounting Research Database (CSMAR), we conducted a regression analysis to evaluate the effects of China's major climate policies on CO_2 emissions reduction at the county level between 2008 and 2017. This section provides a detailed description of the data employed in the analysis.

4.1 CO_2 Emissions Data

Carbon dioxide (CO_2) is the greenhouse gas with the most significant impact on climate change. Reducing CO_2 emissions is, therefore, a central objective of climate governance (Solomon et al., 2009; Montzka et al., 2011). This study employs China's county-scale carbon emissions dataset, developed by Chen et al. (2020) through the CEADs. This dataset provides CO_2 emissions data for 2,735 counties and districts in China, covering the period from 1997 to 2017. Given that China did not publish a white paper systematically outlining its climate policy until 2007, and that the county-scale carbon emissions data extend only through 2017, our analysis focuses on evaluating the emissions reduction effects of China's climate policy during the decade from 2008 to 2017.

Our climate change research is primarily limited by the availability of carbon emissions accounting and monitoring data from China. By integrating various previous accounting methods, CEADs have enabled the calculation of carbon emissions on both long-term and highly granular scales.

First, we multiplied the consumption of different types of energy by their respective carbon emissions coefficients to estimate the emissions from each energy source, based on officially published provincial-level energy emissions data. These energy-specific emissions were then aggregated to calculate total carbon emissions at the provincial level.

Next, we downscaled the provincial-level energy-related carbon emissions using nighttime light data as a weight, to derive carbon emissions estimates at the county level. County-level emissions data are disaggregated from the provincial totals based on the intensity of economic activities, while provincial-level emissions are calculated based on energy consumption. Economic activity is quantified using nighttime light data, which, along with the energy consumption data, avoids the "spatial spillover" problem. As a result, the county-level carbon emissions data are not subject to the spatial spillover issues often present in satellite-retrieved emissions data.

CEAD carbon emissions data cover 87% of China's land area, 90% of its population, and 90% of its GDP, providing the most detailed and comprehensive database of county-level emissions in the country.

4.2 Climate Policy Data

In its circular on the implementation of Low-Carbon Pilot Provinces/Cities[5], the NDRC has outlined the scope for each phase of the Low-Carbon Pilot Provinces/Cities program. Based on this, we have compiled a list of the names and initiation dates for the three waves of pilot provinces/cities. The second wave of pilot programs was announced in December 2012, with 2013 designated as the initiation year for this phase. The initiation dates for the first and third waves of pilot programs are based on the release dates of the official documents.

Utilizing publicly available information from the Internet, we identified the market opening dates of various carbon trading pilot programs as the initiation dates for these programs. We did not use the NDRC's notification dates for the Carbon Trading Pilot Programs, as there was often a significant delay between the official designation and the actual launch of the programs. For instance, while the NDRC issued a notice in October 2011 (NDRC Climate [2011] No. 2601) regarding the implementation of the first wave of pilot programs in "two provinces and five cities", it wasn't until June 2013 that Shenzhen's carbon market was initiated, and Chongqing's market only opened in June 2014, taking the longest time to start. Therefore, using the carbon market opening dates as the starting point for policy implementation is more consistent with the actual timeline. Additionally, although Sichuan and Fujian provinces were not part of the initial wave of pilot programs, they also established nationally registered carbon trading institutions and are included in the carbon trading policy treatment group.

[5] NDRC Climate [2010] No.1587, NDRC Climate [2012] No.3760, and NDRC Climate [2017] No.66.

4.3 Socioeconomic Data

The socioeconomic data used in this paper are sourced from the CSMAR database, covering the total population, regional GDP, and per capita regional GDP for counties and districts in China from 2007 to 2017. For the analysis, we have matched the carbon emissions data, climate policy data, and socioeconomic data at the county level. Descriptive statistics for these variables are presented in Table 1.

Table 1: Descriptive Statistics

Name of variable	Variable definition	Measurement unit	Average	Standard deviation	Min.	Max.	Number of observations
emission	Carbon emissions	million tons	3.211	3.288	0	56.429	27 320
*emission*_2007	Carbon emissions in 2007	million tons	2.364	2.581	0	47.519	27 320
emission_gdp	Carbon emissions per unit of GDP	Ton/10,000 yuan	2.674	2.596	0	48.316	21 574
emission_pop	Per capita carbon emissions	Ton/person	7.782	10.85	0	215.909	18 848
gdp	Regional GDP	100 million yuan	176.498	295.689	0.751	9270.309	21 574
pop	Year-end total population	10,000 persons	49.645	34.976	1	366.183	18 848
*pop*_2007	Total population at the end of 2007	10,000 persons	48.479	34.577	1.133	305.448	18 780
*pergdp*_2007	Per capita GDP in 2007	10,000 yuan/person	1.486	1.358	0.197	17.107	20 570

5. Regression Analysis

Following the method outlined by Dobkin et al. (2018), we examine the carbon emissions reduction effects of the Low-Carbon Pilot Provinces/Cities and the Carbon Trading Pilot Programs between 2008 and 2017, within the framework of event analysis. First, we apply a non-parametric event analysis method to capture changes in carbon emissions before and after the policy implementation, thereby highlighting the dynamic effects of climate policy. Specifically, we employ the following regression equation:

$$y_{ct}=\alpha+\sum_{r=-4}^{-2}\mu_r Pilot_{crt}+\sum_{r=0}^{3}\mu_r Pilot_{crt}+\sum_{w=-4}^{-2}\tau_w ETS_{cwt}+\sum_{w=0}^{3}\tau_w ETS_{cwt}+X_{c,2007}\gamma_t+\delta_c+\epsilon_{ct} \quad (5)$$

In the above equation, c and t denote county/district and year, respectively. y_{ct} is the core explained variable, specifically representing total carbon emissions (added 1 before taking the natural logarithm).

$Pilot_{crt}$ is the dummy variable corresponding to the relative year of the implementation of the Low-Carbon Pilot Provinces/Cities. Specifically, if the Low-Carbon Pilot Provinces/Cities policy had been implemented for a duration of r years for the province/city where county c is located in year t, then its value is set to 1; otherwise, it is 0.

Similarly, ETS_{cwt} is also the dummy variable for the relative year of the implementation of the Low-Carbon Pilot Provinces/Cities. By the same token, if the Low-Carbon Pilot Provinces/Cities policy had been implemented for a duration of w years for the province/city of county c in year t, its value is 1; otherwise, it is 0.

We have set the policy window to cover the period from four years prior to the pilot program implementation to three years after the implementation. This is because the Carbon Trading Pilot Programs only began to be carried out on a large scale in 2014. There were a total of four years between the year of policy implementation and 2017 (the final phase of the samples), which is the reason for choosing this four-year period.

To ensure consistent time windows before and after the implementation (i.e., ex-ante and ex-post), we have designated a four-year time window and defined $Pilot_{c(-4)t}$ and $ETS_{c(-4)t}$ as the dummy variables for samples that are four or more years earlier from the implementation of the pilot program policy. Such a selection offers a relatively long time window for testing the policy effects, guarantees the consistency of the lengths of the ex-ante and ex-post time windows, and helps avoid the problem of insufficient observations resulting from an overly long timeframe.

The designation of a locality as part of the Climate Policy Pilot Program, as well as the timing of such designation, depends on local socioeconomic factors, which are often correlated with economic performance and carbon emissions. Economically dynamic regions with higher carbon emissions are generally more motivated to implement structural adjustments, making them more likely to be selected for pilot programs earlier than others. Therefore, it is essential to further control for key covariates to obtain more accurate estimates of the effects on emissions reduction. In this paper, we employ an interaction term between predetermined covariates $X_{c,2007}$ for various counties and districts from the previous sample phase (2007), including total population at year-end and per capita GDP, and the dummy variable for year γ_t , using this as a control to account for socioeconomic differences across counties and districts.

The fixed effect δ_c of counties and districts is included to control for time-invariant differences across counties and districts. The fixed effect of year γ_t is included to account for common shocks affecting all counties and districts at the national level. The residual error term ϵ_{ct} is included to address potential heteroscedasticity issues. In the regression analysis, we have clustered standard errors at the district/county level, following the approach of Bertrand et al. (2004).

The coefficients corresponding to the Low-Carbon Pilot Provinces/Cities and the Carbon Trading Pilot Programs are denoted as μ_r and τ_w, respectively. In the equation above, μ_r and τ_w represent the dynamic effects on the relevant variables of the counties and districts of the Low-Carbon Pilot Provinces/Cities and Carbon Trading Pilot Programs before and after the implementation of the relevant policies relative to non-pilot counties and districts. It is important to note that, unlike the separately estimated carbon emission reduction effects of these two types of policies, μ_r and τ_w capture the carbon emission reduction effects when the other policy is given. In the following sections of this paper, we will compare the differences between the estimated results when considering each policy individually and when both policies are considered simultaneously.

The identification assumption of the non-parametric event analysis method is that, after controlling for relevant variables, the implementation time of a pilot policy is unrelated to the level of the explained variable. Previous studies typically used the parallel trend test to bolster confidence in this identification assumption. However, the selection of pilot programs is not entirely random, and researchers cannot fully control for unobservable variables that may influence the selection process. Consequently, it is likely that the ex-ante parallel trend assumption may not hold. To address this, we adopted a parametric event analysis method to more accurately estimate the effects of the pilot policies. Based on the estimated results from equation (5), we chose a linear function to model the ex-ante trend. Specifically, the following regression equation is used to estimate the effects of the Low-Carbon Pilot Provinces/Cities and the Carbon Trading Pilot Programs.

$$y_{ct}=\alpha'+\rho r+\sum_{r=0}^{3}\mu'_r Pilot_{crt}+\sum_{w=-4}^{-2}\tau'_w ETS_{cwt}+\sum_{w=0}^{3}\tau'_w ETS_{cwt}+X_{c,2007}\gamma_t+\delta_c+\epsilon'_{ct} \quad (6)$$

$$y_{ct}=\alpha''+\sum_{r=-4}^{-2}\mu''_r Pilot_{crt}+\sum_{r=0}^{3}\mu''_r Pilot_{crt}+\psi w+\sum_{w=0}^{3}\tau''_w ETS_{cwt}+X_{c,2007}\gamma_t+\delta_c+\epsilon''_{ct} \quad (7)$$

In equation (6), we focus on the coefficient μ'_r, which represents the policy effect after the implementation of the Low-Carbon Pilot Provinces/Cities, based on the ex-ante trend ρ relative to the period prior to the policy implementation. In equation (7), we focus on the coefficient τ''_w, which captures the policy effect after the implementation of the Carbon Trading Pilot Programs, based on the ex-ante trend ψ relative to the period before the policy implementation.

In the case of the parametric event analysis method, the identification assumption is that the implementation time of the pilot policy is uncorrelated with change in the explained variable, which is generally easier to satisfy compared to the identification assumption of the non-parametric event analysis method. To assess the validity of this assumption, we will examine the linear fit of the ex-ante trend. This will help test the confidence in the identification assumption for estimation using the parametric event analysis method. For rigor, we define the results from the parametric estimation as the baseline regression outcome, following the approach of Dobkin et al. (2018) and Chen and Lan (2020), while presenting the non-parametric estimation results in the accompanying chart.

6. Regression Analysis Results

6.1 Baseline Regression Results

Table 2 presents the results of our non-parametric event analysis. Columns (1) and (3) show the estimated results when considering either the Low-Carbon Pilot Provinces/Cities or the Carbon Trading Pilot Programs separately. Columns (2) through (4) display the results of the non-parametric event analysis for both policies simultaneously. To mitigate multicollinearity, we use the one-year ex-ante effect as the baseline group in all our non-parametric event analyses. The regression coefficient represents the difference in the explained variable for a given ex-ante (or ex-post) year relative to the year immediately preceding the policy implementation.

Table 2: Results of the Non-Parametric Event Analysis

	ln (1+carbon emissions)			
	Low-Carbon Pilot Provinces/Cities		Carbon Trading Pilot Programs	
	(1)	(2)	(3)	(4)
Four-year ex-ante effect	-0.006 (0.006)	-0.004 (0.006)	0.047*** (0.004)	0.041*** (0.004)
Three-year ex-ante effect	-0.006 (0.004)	-0.002 (0.004)	0.011*** (0.002)	0.004** (0.002)
Two-year ex-ante effect	0.000 (0.001)	-0.000 (0.001)	0.012*** (0.001)	0.006*** (0.001)
Current-year effect of policy implementation	0.000 (0.002)	0.000 (0.002)	-0.005*** (0.001)	-0.005*** (0.001)
One-year ex-post effect	-0.016*** (0.003)	-0.008** (0.003)	-0.012*** (0.004)	-0.002 (0.004)
Two-year ex-post effect	-0.019*** (0.003)	-0.011*** (0.003)	-0.012** (0.005)	-0.002 (0.005)
Three-year ex-post effect	-0.036*** (0.004)	-0.028*** (0.004)	-0.022*** (0.006)	-0.013** (0.006)
Fixed effect of district/county	Controlled	Controlled	Controlled	Controlled
Fixed effect of year	Controlled	Controlled	Controlled	Controlled
The other pilot policy	Not controlled	Controlled	Not controlled	Controlled
Control variables	Controlled	Controlled	Controlled	Controlled
Observations	20570	20570	20570	20570

Notes: The data in columns (1) and (4) are based on the same regression equation. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Numbers in parentheses are standard errors. The control variables include the interaction terms between the population at the end of 2007 and the year dummy variable, as well as between regional per capita GDP in 2007 and the year dummy variable. The same applies to the other columns.

A comparison of the coefficients for the Low-Carbon Pilot Provinces/Cities (Carbon Trading Pilot Programs) in columns (1) (3) and (2) (4) reveals that focusing on a single policy without considering the combined effect of both significantly overestimates the emissions reduction results. This also suggests that neglecting other climate policies can impact the consistency of the estimated results, as omitting relevant variables leads to substantial bias. The results in columns (1) and (2) show that when the Carbon Trading Pilot Programs are excluded, the emissions reduction effect of the Low-Carbon Pilot Provinces/Cities is overestimated. Similarly, columns (3) and (4) demonstrate that when the Low-Carbon Pilot Provinces/Cities are ignored, the emissions reduction effect of the Carbon Trading Pilot Programs is also overestimated. Additionally, the identification assumption of the non-parametric event analysis method is not satisfied due to the significant ex-ante trend observed in the estimated results for the Carbon Trading Pilot Programs. Therefore, this coefficient cannot be interpreted as the actual policy effect. As a result, we turn to the parametric event analysis method to more accurately estimate the emissions reduction effects of both climate change mitigation pilot policies, with the baseline regression results presented in Table 3.

Table 3: Baseline Regression Results

	ln (1+carbon emissions)			
	Low-Carbon Pilot Provinces/Cities		Carbon Trading Pilot Programs	
	Non-parametric estimation	Parametric estimation	Non-parametric estimation	Parametric estimation
	(1)	(2)	(3)	(4)
Four-year ex-ante effect	-0.006 (0.007)		0.029** (0.014)	
Three-year ex-ante effect	-0.004 (0.006)		-0.011 (0.007)	
Two-year ex-ante effect	0.001 (0.001)		0.007* (0.004)	
Current-year effect of policy implementation	-0.003* (0.002)	-0.006** (0.003)	-0.032*** (0.011)	0.007** (0.003)
One-year ex-post effect	-0.012** (0.005)	-0.018*** (0.005)	-0.016 (0.012)	0.007 (0.005)
Two-year ex-post effect	-0.011* (0.006)	-0.019*** (0.007)	-0.019 (0.014)	0.011* (0.006)
Three-year ex-post effect	-0.032*** (0.010)	-0.043*** (0.010)	-0.059** (0.024)	0.010 (0.010)
Ex-ante trend		0.002 (0.002)		-0.010* (0.005)
Fixed effect of district/county	Controlled	Controlled	Controlled	Controlled
Fixed effect of year	Controlled	Controlled	Controlled	Controlled
The other pilot policy	Controlled	Controlled	Controlled	Controlled
Control variables	Controlled	Controlled	Controlled	Controlled
Observations	7730	7730	4040	4040

The parametric event analysis method requires the inclusion of the ex-ante temporal trend. However, some counties and districts have never been exposed to a specific pilot policy, meaning their ex-ante temporal trend cannot be defined. Therefore, when evaluating a given policy, we retain only the samples that have experienced that policy, while controlling for the other policy in our regression analysis to avoid bias from omitted variables. Since the samples are no longer representative of the complete samples, the results are not directly comparable to those from the non-parametric event analysis in Table 2. To address this, we present the non-parametric estimated results for the Low-Carbon Pilot Provinces/Cities (Carbon Trading Pilot Programs) based on the new samples in columns (1) and (3), alongside the corresponding parametric estimates in columns (2) and (4), which reflect the baseline regression results for the Low-Carbon Pilot Provinces/Cities and the Carbon Trading Pilot Programs.

According to the results in column (2) of Table 3, after accounting for the impact of the ex-ante trend, there is a significant reduction in carbon emissions in the year of implementation of the Low-Carbon Pilot Provinces/Cities. Furthermore, the longer the duration of policy implementation, the more significant the downward trend in carbon emissions. In the third year of the policy's implementation, emissions decreased by 4.3%. Results in column (4) suggest that, compared with the counterfactual analysis after linear fitting, carbon emissions increased by 0.7% in the year of implementation of the Carbon Trading Pilot Programs, rose by 1.1% two years after the policy's implementation, and showed no significant change in subsequent years. Over the time period covered by our study, carbon emissions decreased by an average of 2.67% per year within three years of implementing the Low-Carbon Pilot Provinces/Cities, while emissions increased by 0.93% per year within three years of implementing the Carbon Trading Pilot Programs. In other words, the Low-Carbon Pilot Provinces/Cities have led to a significant reduction in carbon emissions, while the Carbon Trading Pilot Programs have resulted in a slight increase in emissions in the pilot regions.

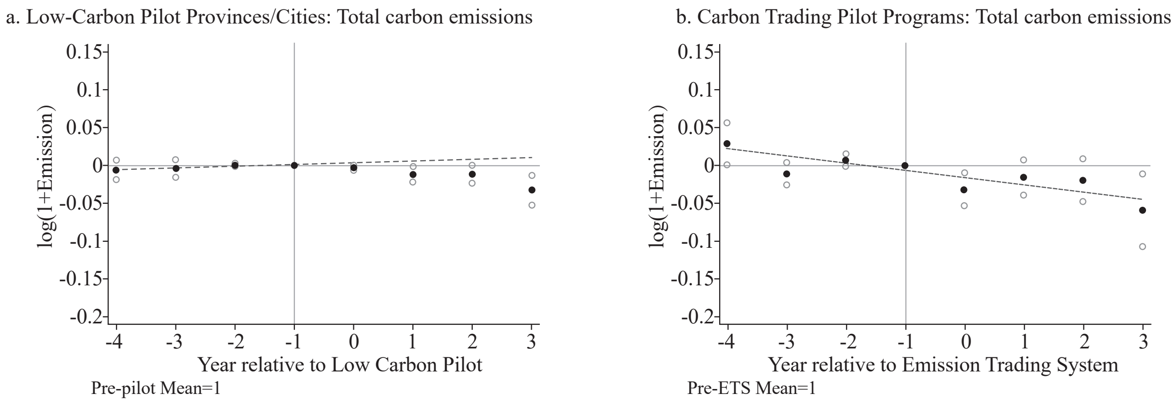

Figure 2: Results of Event Analysis: Carbon Emissions

Notes: Solid dots represent the estimated coefficients μ_r or τ_w from the non-parametric event analysis, while hollow dots indicate the 95% confidence intervals for these coefficients. The dashed lines represent the ex-ante trend of total carbon emissions, estimated using the parametric event analysis method, and correspond to the estimated levels from the non-parametric event analysis.

Source: Drafted by authors according to empirical results.

Our baseline regression results show that the Low-Carbon Pilot Provinces/Cities have significantly reduced carbon emissions in the pilot regions, while the Carbon Trading Pilot Programs have resulted in a slight increase in carbon emissions. Next, we will examine the mechanisms through which the Low-Carbon Pilot Provinces/Cities and the Carbon Trading Pilot Programs influence carbon emissions and explore the reasons behind the differences in their emissions reduction effects.

To test the robustness of our baseline regression results, we conducted a series of robustness checks (detailed in the Online Appendix). These tests include controlling for the energy conservation and emissions reduction targets outlined in the "Five-Year Plans", introducing relevant industrial and energy-related control variables, accounting for more granular differences in ex-ante characteristics, and replacing the proxy variable for carbon emissions. Additionally, we examined heterogeneous treatment effects following the approach of Sun and Abraham (2021). The results of these robustness tests suggest that our conclusions are not affected by the factors mentioned above.

6.2 Mechanism Analysis

The change in carbon emissions can be decomposed into two components: the "technical effects", which refer to changes in carbon emissions intensity, and the "scale effect", which reflects changes in economic output (Jaraitė et al., 2022). To explore the mechanisms through which Low-Carbon Pilot Provinces/Cities and Carbon Trading Pilot Programs influence carbon emissions, we examine how these two types of pilot programs affect both carbon emissions intensity and regional GDP. Table 4 presents the parametric and non-parametric estimation results of the mechanism analysis. Figure 3 illustrates the impact of the two types of climate policies on carbon emissions intensity and regional GDP, based on non-parametric estimates, and shows the ex-ante linear trend of the explained variable obtained from the parametric estimation. The results indicate that both the impact of Low-Carbon Pilot Provinces/Cities on carbon emissions intensity and regional GDP, as well as the impact of the Carbon Trading Pilot Programs on carbon emissions, exhibit a significant ex-ante trend, which is effectively captured by the linear function. Therefore, we primarily rely on the parametric estimation results in Table 4 for our analysis.

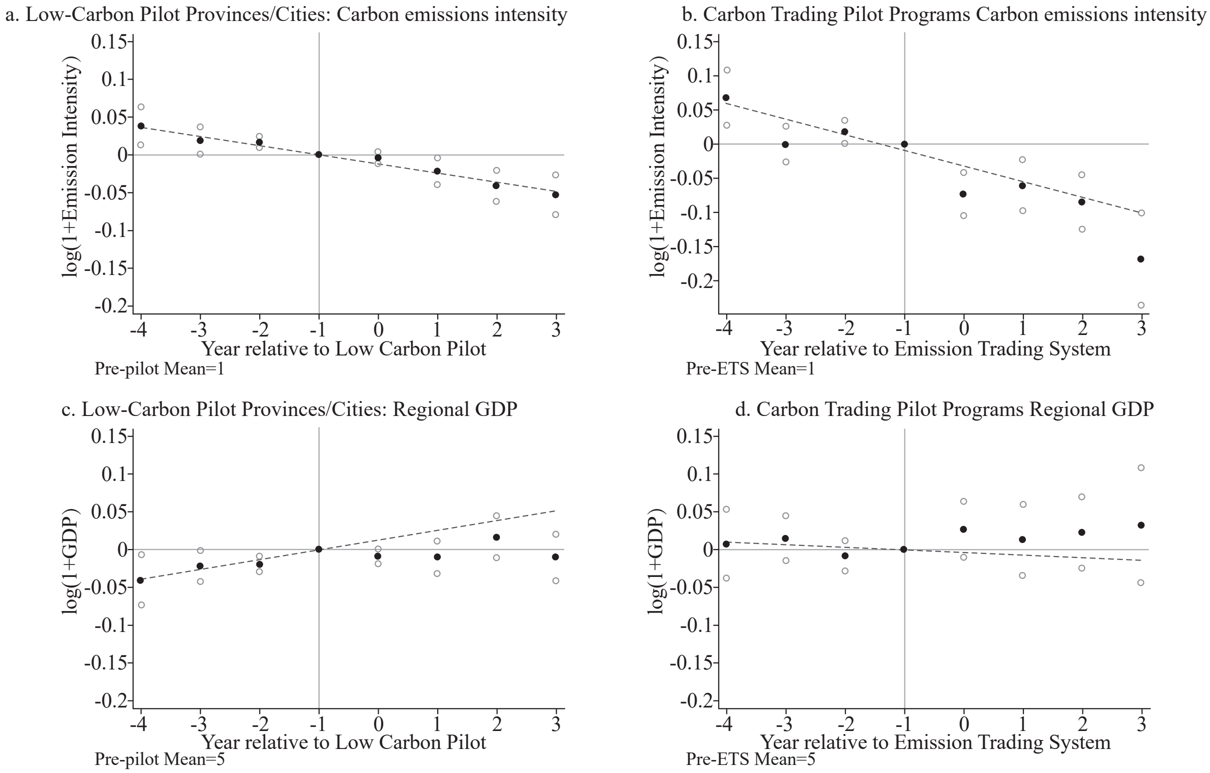

Figure 3: Results of Event Analysis: Carbon Emissions Intensity and Regional GDP

Notes: Solid points represent the estimated coefficient μ_r or τ_w from the non-parametric event analysis method, while hollow points indicate the 95% confidence interval of the coefficient. The dotted lines illustrate the ex-ante trend of the explained variable, as estimated using the parametric event analysis method, and align with the estimated level from the non-parametric event analysis method.

Source: Drafted by the authors according to the empirical results.

The results in column (2) of Table 4 show that after fully accounting for the ex-ante trend, the implementation of the Low-Carbon Pilot Provinces/Cities did not lead to any significant change in carbon emissions intensity. On the other hand, column (6) indicates a statistically significant 2.2% reduction in regional GDP in the year of implementation in the Low-Carbon Pilot Provinces/Cities. Moreover, this restrictive effect persisted over time, with the restrictive effect on regional GDP in the Low-Carbon Pilot Provinces/Cities reaching 6.1% in the third year after policy implementation. Over the three years following the policy's implementation, there was little to no significant change in carbon emissions intensity, either statistically or economically, while regional GDP declined at an annual average rate of 3.87%. This suggests that the reduction in emissions in the Low-Carbon Pilot Provinces/Cities was primarily driven by a contraction in overall economic output, rather than by a straightforward decrease in carbon emissions intensity.

The results in column (4) suggest that, during the initial phase of implementation, the Carbon Trading Pilot Programs had a limited impact on reducing carbon emissions intensity. It was only two years after the policy was introduced that carbon emissions intensity decreased by 1.5%, and by the third year, the reduction had reached 3.1%. Over the three years following the implementation of the Carbon Trading Pilot Programs, the pilot regions saw an average annual reduction of 1.83% in carbon emissions intensity, indicating a growing share of clean production in these areas.

However, as shown in column (8), the implementation of the Carbon Trading Pilot Programs was followed by a significant increase in regional GDP, with the effect on production growing over time. Within three years of policy implementation, regional GDP increased by an average of 3.13% per year. This means that the Carbon Trading Pilot Programs both increased carbon emissions intensity and stimulated regional production, with the latter effect being more evident. The combined outcome for both carbon emissions intensity and regional production was a modest increase in carbon emissions in the pilot regions.

Table 4: Results of Mechanism Analysis

	ln(1 + Carbon emissions intensity)				ln(1 + Regional GDP)			
	Low-Carbon Pilot Provinces/Cities		Carbon Trading Pilot Programs		Low-Carbon Pilot Provinces/Cities		Carbon Trading Pilot Programs	
	Non-parametric estimation	Parametric estimation	Non-parametric estimation	Parametric estimation	Non-parametric estimation	Parametric estimation	Non-parametric estimation	Parametric estimation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Four-year ex-ante effect	0.038***		0.068***		-0.041**		0.007	
	(0.013)		(0.021)		(0.017)		(0.023)	
Three-year ex-ante effect	0.019**		-0.000		-0.022**		0.015	
	(0.009)		(0.014)		(0.011)		(0.015)	
Two-year ex-ante effect	0.017***		0.018**		-0.019***		-0.009	
	(0.004)		(0.009)		(0.005)		(0.010)	
Current-year effect of policy implementation	-0.004	0.009	-0.074***	-0.006	-0.009**	-0.022***	0.027	0.020
	(0.004)	(0.006)	(0.016)	(0.009)	(0.005)	(0.008)	(0.019)	(0.015)
One-year ex-post effect	-0.022**	0.002	-0.060***	-0.009	-0.011	-0.035***	0.013	0.029*
	(0.009)	(0.009)	(0.019)	(0.010)	(0.011)	(0.011)	(0.024)	(0.015)
Two-year ex-post effect	-0.041***	-0.006	-0.085***	-0.015*	0.017	-0.020	0.023	0.031***
	(0.010)	(0.012)	(0.021)	(0.008)	(0.014)	(0.014)	(0.024)	(0.010)
Three-year ex-post effect	-0.053***	-0.005	-0.169***	-0.031**	-0.011	-0.061***	0.033	0.034
	(0.013)	(0.018)	(0.034)	(0.016)	(0.016)	(0.023)	(0.039)	(0.021)
Ex-ante trend		-0.012***		-0.023***		0.013**		-0.003
		(0.004)		(0.007)		(0.006)		(0.008)
Fixed effect of district/county	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Fixed effect of year	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
The other pilot policy	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Control variables	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Observations	7401	7,401	3,941	3,941	7,401	7,401	3,941	3,941

Notes: Each column of results corresponds to a regression equation.

To investigate the effect of climate policy on output in greater detail, we re-estimated the model parametrically, using the size and share of the secondary industry in each county as the explained variable. The results closely align with our baseline findings, suggesting that the economic impact of climate policies is predominantly driven by the energy- and carbon-intensive secondary sector.

Based on the analysis above, we find that the Low-Carbon Pilot Provinces/Cities and the Carbon Trading Pilot Programs impact carbon emissions through fundamentally different mechanisms. The Low-Carbon Pilot Provinces/Cities do not exhibit a significant technological effect, but instead show a negative scale effect. Specifically, these regions experience a decrease in GDP while carbon emissions intensity remains steady, leading to a reduction in total carbon emissions. In contrast, the Carbon Trading Pilot Programs are characterized by both technological advancements and skill development that help reduce carbon emissions intensity. The latter effect is more evident, resulting in an overall increase in total carbon emissions despite the improvements in efficiency.

6.3 Heterogeneity Analysis

This section further examines the heterogeneous effects of the pilot climate policies across different regions. In our analysis, we focus on three key attributes at the county and district levels: carbon emissions, carbon emissions intensity, and regional GDP. To ensure that our classification criteria are not influenced by the pilot policies themselves, we divided the samples based on their values from a pre-policy phase, specifically the year 2007. For each attribute, we categorized the samples into two groups: one with values above the median and one with values below the median for total carbon emissions, carbon emissions intensity, or regional GDP. We then conducted a regression analysis using the non-parametric event study method to estimate the heterogeneous effects of the pilot climate policies, with the results presented in Table 5.

As a mandate-based climate policy, the effectiveness of the Low-Carbon Pilot Provinces/Cities is primarily driven by incentives for government officials, rather than being directly linked to the initial carbon emissions levels of the pilot regions. Indirect evidence supporting this conclusion is provided by the results in the first four columns of Panel A in Table 5. Regardless of whether the samples are categorized by the initial amount or intensity of carbon emissions, the Low-Carbon Pilot Provinces/Cities consistently show significant reductions in carbon emissions across all subsample regressions. Since these provinces and cities achieve overall reductions by scaling back output, it is likely that the initial economic conditions of counties and districts have played a role in influencing the emissions reduction outcomes. As shown in columns (5) and (6) of Panel A, the emissions reduction effect is significantly stronger in subsamples with regional GDP below the median, compared to those with GDP above the median. This may be because the opportunity cost of reducing carbon emissions is relatively lower in economically less developed regions, where the pilot areas are more incentivized to cut emissions by reducing output.

Panel B of Table 5 presents the emissions reduction effects of the Carbon Trading Pilot Programs across various subsamples. As shown in the table, the Carbon Trading Pilot Programs have led to an increase in carbon emissions, primarily driven by regions with lower initial carbon emissions intensity. This outcome aligns with the underlying logic of the TPS mechanism for carbon markets, which suggests that the expansion of such programs encourages clean enterprises to boost production, thereby reducing emissions intensity while increasing economic output.

In regions where initial carbon emissions intensity is below the median, businesses tend to have cleaner production processes. With the implementation of the provincial carbon market, these regions have greater opportunities to expand their market share, creating stronger incentives to ramp up production. Columns (3) and (4) of Table 5 provide empirical support for this explanation: while the Carbon Trading Pilot Programs have only slightly increased carbon emissions in areas with high emissions intensity (above the median), this increase is statistically insignificant. In contrast, for regions with low emissions intensity (below the median), the programs have resulted in a significant rise in carbon emissions.

Table 5: Heterogeneity Test of the Core Attributes of Counties and Districts

	ln (1+carbon emissions)					
	Carbon emissions		Carbon emissions intensity		Regional GDP	
	(1) Above median	(2) Below median	(1) Above median	(2) Below median	(1) Above median	(2) Below median
Panel A: Low-Carbon Pilot Provinces/Cities						
Current-year effect of policy implementation	-0.008**	-0.006	-0.008*	-0.008***	-0.009**	-0.003
	(0.004)	(0.004)	(0.005)	(0.003)	(0.004)	(0.004)
One-year ex-post effect	-0.022***	-0.015**	-0.035***	-0.016***	-0.015**	-0.021**
	(0.008)	(0.007)	(0.010)	(0.005)	(0.007)	(0.009)
Two-year ex-post effect	-0.017*	-0.024***	-0.035***	-0.018**	-0.012	-0.025**
	(0.009)	(0.009)	(0.011)	(0.007)	(0.008)	(0.010)
Three-year ex-post effect	-0.039***	-0.048***	-0.075***	-0.033***	-0.027**	-0.060***
	(0.015)	(0.013)	(0.018)	(0.010)	(0.013)	(0.016)
Ex-ante trend	0.003	0.003	-0.001	0.005*	0.006*	-0.002
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Fixed effect of district/county	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Fixed effect of year	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Control variables	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Observations	3860	3870	3860	3870	3860	3870
Panel B: Carbon Trading Pilot Programs						
Current-year effect of policy implementation	-0.002	0.004	0.005	0.008*	0.003	0.007*
	(0.005)	(0.004)	(0.006)	(0.005)	(0.005)	(0.004)
One-year ex-post effect	0.004	0.003	0.010	0.015**	0.007	0.003
	(0.008)	(0.006)	(0.009)	(0.007)	(0.007)	(0.007)
Two-year ex-post effect	0.003	0.006	0.012	0.017**	0.009	0.007
	(0.010)	(0.007)	(0.011)	(0.009)	(0.009)	(0.008)
Three-year ex-post effect	-0.012	0.001	0.001	0.018	0.005	0.005
	(0.015)	(0.013)	(0.017)	(0.015)	(0.014)	(0.014)
Panel B: Carbon Trading Pilot Programs						
Ex-ante trend	-0.025***	-0.003	-0.017**	-0.012*	-0.003	-0.003
	(0.003)	(0.006)	(0.007)	(0.006)	(0.011)	(0.006)
Fixed effect of district/county	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Fixed effect of year	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Control variables	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Observations	2020	2020	2020	2020	2020	2020

Notes: When we conducted subsample regression according to the amount of carbon emissions in 2007, our control variables did not include the interaction term between the carbon emissions level of 2007 and the dummy variable of year, and the rest are consistent with the baseline regression. Other regressed control variables are fully consistent with the baseline regression.

To further explore the practical applicability of policy instruments, we examined the heterogeneous effects of climate policies on resource-dependent cities and old industrial regions. Our analysis reveals that the policy impact on resource-dependent cities is consistent with the baseline results, indicating that reliance on natural resources does not significantly hinder the implementation of climate policies. In contrast, for old industrial regions, the Low-Carbon Pilot Provinces/Cities did not lead to a reduction in total carbon emissions. This can be attributed to the fact that, in these areas, carbon emissions intensity increased slightly while production output decreased.

However, the Carbon Emissions Pilot Programs under the market mechanism category produced an unexpected outcome: despite an increase in production output, these programs helped significantly reduce carbon emissions intensity, leading to an overall decline in total emissions. This finding suggests the importance of tailoring economic policies to local conditions. In regions facing more complex challenges, government mandates alone may not suffice. Instead, policy innovation is crucial to fully harness the potential for transition and maximize the willingness of local regions to embrace change.

6.4 Cost-Benefit Analysis

We will also conduct a cost-benefit analysis of the baseline results to assess the effectiveness of China's carbon emissions reduction policy. Specifically, we will track changes in GDP and total carbon emissions three years after the policy's implementation to evaluate both the efficiency and long-term impact of the policy beyond its immediate effectiveness.

According to data from the United States Interagency Working Group on Social Cost of Greenhouse Gases, the average social cost of each additional ton of CO_2 emissions was 51 US dollars in 2020. Building on the work of Dong et al. (2023) and Chen et al. (2010), we employ the Social Cost of Carbon (SCC) as a widely used method in climate change economics to quantify both the benefits of carbon emissions reductions and the costs associated with carbon emissions.

Our study revealed that, within three years of implementing the Low-Carbon Pilot Provinces/Cities program, carbon emissions decreased at an annual average rate of 2.67%, while regional GDP declined by an annual average of 3.87%. In contrast, three years after the introduction of the Carbon Trading Pilot Programs, carbon emissions increased by an annual average of 0.93%, while regional GDP grew by an annual average of 3.13%.

Using China's 2013 figures for CO_2 emissions (9.4 billion tons) and GDP (56.88 trillion yuan) at the exchange rate of 1:7 (USD to RMB), the annual net benefit of the Low-Carbon Provinces/Cities program is estimated at -2,111.7 billion yuan. This is calculated as follows: $94.00 \times 2.67\% \times 51 \times 7 - 56.88 \times 10{,}000 \times 3.87\%$.

For the Carbon Trading Pilot Programs, the annual net benefit is 1,749.1 billion yuan, calculated as: $56.88 \times 10{,}000 \times 3.13\% - 94.00 \times 0.93\% \times 51 \times 7$.

From a cost-benefit perspective, the Carbon Trading Pilot Programs demonstrate greater effectiveness than the Low-Carbon Pilot Provinces/Cities. As China is placed with high hopes in the global efforts to address climate change, its climate policies and carbon reduction initiatives exert strong political influence in the international community. However, the SSC (Standardized Sectoral Crediting) approach tends to underestimate the benefits of China's carbon emissions reductions and the associated costs, which represents a limitation in its cost-benefit analysis of emissions reduction efforts.

In the context of this paper, market-based policies appear to be more efficient from a cost-benefit standpoint compared to mandate-based policies. However, this does not imply that mandate-based policies should be discarded in favor of market-based approaches alone. Rather, a nuanced, case-by-case evaluation should be adopted, considering the unique circumstances and goals of each specific context.

7. Concluding Remarks and Policy Recommendations

In this paper, we evaluate the effects of China's pilot climate policies, examining the differing emissions reduction outcomes and mechanisms between the Low-Carbon Pilot Provinces/Cities and the Carbon Trading Pilot Programs, while also explaining the reasons behind these discrepancies. Our findings contribute to a deeper understanding of China's climate policy landscape and offer valuable insights for future climate policymaking.

First, we highlight that the mandate-based policies, particularly those implemented in the Low-Carbon Pilot Provinces/Cities, may lead to short-term reductions in carbon emissions. However, these mechanisms are not sustainable in the long run and may impose significant economic costs. To improve policy effectiveness, we recommend that the central government adopt a more balanced approach, leveraging administrative instruments strategically while setting clear, measurable targets for both total emissions and emissions intensity, rather than focusing solely on overall emissions reduction goals.

Second, the effectiveness of the Carbon Trading Pilot Programs in reducing emissions is closely tied to the design of market-based mechanisms. While these programs have succeeded in lowering carbon emissions intensity through tradable carbon quotas, they have not led to a reduction in total carbon emissions within the pilot regions. Therefore, a key next step in advancing the carbon market is to revise the carbon quota allocation rules and transition from the current Tradable Performance Standards (TPS) system to a more robust cap-and-trade system.

Third, although both the Low-Carbon Pilot Provinces/Cities and the Carbon Trading Pilot Programs contribute to carbon emissions reductions in China, their effects and mechanisms differ. Under China's dual targets of controlling the total amount and intensity of carbon emissions, future policies should be further optimized and adjusted. It is recommended to integrate market-based approaches with mandate-based measures through top-down design and supporting infrastructure development. By reasonably supplementing administrative measures on the basis of a market mechanism as the mainstay, the policies will join to ensure a more comprehensive reduction in total carbon emissions on top of ensuring emissions intensity reduction.

It should be noted that this paper examines a select number of cases from the Low-Carbon Pilot Provinces/Cities and the Carbon Trading Pilot Programs, and the effects of the same policy can vary depending on different contexts. Therefore, we advocate for a "case-by-case" approach when analyzing the impacts of climate policies, as the conclusions drawn here may not be directly applicable to other mandate-based measures or market-based mechanisms.

Furthermore, several key issues regarding the effectiveness of China's climate policies merit further discussion. First, a more in-depth analysis at the sectoral level is needed to develop more targeted and effective climate policies. This includes addressing questions such as how the national carbon market can be implemented across various sectors and how carbon quota transactions should be coordinated between them. Second, leveraging high-quality enterprise data can provide insights into how climate policies affect business operations. Such analysis would help policymakers identify potential barriers to policy implementation, facilitating more informed decision-making and enabling targeted regulatory oversight. CE

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