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EDITED BY

Otilia Manta,
Romanian Academy, Romania

REVIEWED BY

Iza Gigauri,
University of Georgia, Georgia
Alba Kruja,
Epoka University, Albania

*CORRESPONDENCE

Keqiang Wang,
✉ wkqzy@163.com

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Command-driven vs. market-oriented environmental regulations: impacts on high-quality development of manufacturing industry

Chunxin Lin¹, Keqiang Wang^{1*} and Hongmei Liu²

¹College of Public Finance and Investment, Shanghai University of Finance and Economics, Shanghai, China, ²Business School, Shanghai Normal University, Shanghai, China

The manufacturing industry is a key area of environmental regulation. However, whether command-driven and market-oriented environmental regulations exert heterogeneous impacts on the high-quality development of the manufacturing industry (HQDM) remains underexplored. This study treats the command-driven low-carbon city pilot policy and the market-oriented carbon emissions trading pilot policy as “quasi-natural experiments”. Firm-level data of listed manufacturing enterprises spanning 2003–2021, it adopts the double machine learning method to evaluate the influence of heterogeneous environmental regulations on the HQDM. The findings show that the low-carbon city pilot policy significantly inhibits the HQDM, whereas the carbon emissions trading pilot policy significantly promotes it. The effect of market-oriented environmental regulation on the HQDM is primarily achieved through the mechanism of technological innovation. In regions where both the low-carbon city pilot policy and the carbon emissions trading pilot policy are implemented, both command-driven and market-oriented regulations boost the HQDM, signifying a synergistic effect between them. Further heterogeneity analysis shows that the results for eastern and western areas, state-owned firms, and technology-intensive manufacturing sectors align with the baseline regression results. The conclusions of this study provide important references for the selection of carbon reduction policies, formulating differentiated emission reduction measures.

KEYWORDS

command-driven environmental regulation, market-oriented environmental regulation, low-carbon city pilot policy, carbon emissions trading pilot policy, high-quality development of manufacturing industry, double machine learning

1 Introduction

Manufacturing stands as the mainstay of the national economy. Over time, China has evolved into the world's foremost manufacturing powerhouse (Guo and Sun, 2023). However, products produced by the manufacturing industry are often carbon-intensive (Naegele and Zaklan, 2019), making it a major source of carbon emissions (Cao et al., 2021). As a result, the manufacturing industry has become a key field for environmental regulation and low-carbon transformation.

Environmental regulation plays a crucial role in balancing economic development and environmental protection (Ai et al., 2020; Liu et al., 2021). In recent years, curbing carbon emissions has evolved into a shared global objective. As the world's top energy consumer and carbon emitter (Fan et al., 2016), During the 75th United Nations General Assembly, China pledged to reach carbon peak by 2030 and attain carbon neutrality by 2060, demonstrating its commitment as a responsible major power to advancing low-carbon transformation. A series of regulatory measures have been implemented, such as the implementation of low-carbon city pilot policy (LCCP, hereinafter referred to as such) and carbon emissions trading pilot policy (CETP, hereinafter referred to as such). the LCCP are typical command-driven environmental regulation, while the CETP are typical market-oriented ones. Their implementation marks a shift in China's carbon emission regulations from purely command-driven to a combination of command-driven and market-oriented approaches.

An urgent question is whether carbon emission regulations promote the HQDM. How do command-driven and market-oriented environmental regulations¹ differ in their effects on the HQDM? Which type of environmental regulation can more effectively balance low-carbon transition and high-quality development?

To address the above issues, this study uses the command-driven LCCP and market-driven CETP as quasi-natural experiments. Based on microdata from manufacturing listed firms spanning 2003–2021, it applies double machine learning to assess how heterogeneous environmental regulations impact the HQDM. Specifically, What are the similarities and differences in their transmission mechanisms? Do regions with both policies perform better than those with a single policy, resulting in a “1 + 1 > 2” synergy effect? Scientifically answering these questions and clarifying the economic effects and mechanisms of different low-carbon transition methods have significant theoretical implications. Moreover, in the context of global warming, examining the impact of command-driven and market-oriented carbon emission regulations on the HQDM holds considerable practical significance. Empirically, the LCCP hampers the HQDM, whereas the CETP bolsters it—implying market-oriented regulations outperform administrative ones.

This paper potentially makes two marginal contributions: Firstly, it investigates the distinct impacts of command-driven and market-oriented environmental regulations on the HQDM by leveraging China's LCCP and CETP as quasi-experimental settings. Unlike previous studies that primarily used proxy variables to measure heterogeneous environmental regulations, this approach avoids subjective bias in the selection of measurement indicators. Moreover, it enriches the research on the economic effect of environmental regulation by considering both LCCP and CETP together. Secondly, It employs the double

machine learning (DML) method to identify the policy effects of heterogeneous environmental regulations. the DML is particularly advantageous in high-dimensional settings with complex covariate structures, which can avoid the pre-selection of control variables (Yang J. et al., 2020; Zhang et al., 2022; Bodory et al., 2022; Farbmacher et al., 2022). This differs from previous methods that primarily relied on approaches such as DID, PSM-DID, triple difference (DDD), and spatial DID (SDID).

2 Literature review

The study primarily covers literature on the economic effects of command-driven and market-oriented environmental regulations, as well as methods for evaluating policy effectiveness.

Scholars have extensively investigated the economic effects of environmental regulation, but academia has yet to reach a consensus, resulting in two opposing hypotheses. The first is the “compliance cost” theory proposed by neoclassical economics, which contends that environmental regulations raise firms' production and operational costs, hampering economic growth (Gray, 1987; Lanoie et al., 2011). The second is the “innovation compensation” hypothesis proposed by Porter, which believes that appropriate environmental regulation not only avoids negative impacts on the economy but can also promote technological innovation in enterprises and stimulate economic growth (Porter and Linde, 1995). Some scholars' research supports this perspective (Zhang et al., 2011; Zhou and Tang, 2021; Chen et al., 2022; Zheng et al., 2023). Environmental regulations are generally classified into command-driven and market-oriented regulation. This paper will next review the economic effects of these two types of environmental regulations.

2.1 The economic effects of command-driven and market-oriented environmental regulations

Existing studies on command-driven environmental regulation focus on evaluating specific policies, using quasi-natural experiment designs and methods such as DID, DDD and PSM-DID. For instance, Zhang and Zhao (2023) found sulfur dioxide emission control policies enhanced firms' technological innovation; Shao et al. (2024) showed the Top 10,000 Energy - Intensive Enterprises Initiative reduced pollutant emissions; Cai et al. (2016) revealed the Two-Zone Emission Control Policy lowered FDI. Regarding low-carbon pilot policies, Chen et al. (2021) and Qiu et al. (2021) demonstrated positive impacts on firms' TFP and cities' GTFP. Basu et al. (2025) demonstrated that under the policy frameworks of the U.S. Superfund Program and the Clean Air Act, relevant environmental regulations significantly reduced the average pollution exposure levels among the elderly population.

The aforementioned studies emphasize the positive socioeconomic effects of command-driven environmental regulations, other research has uncovered their negative impacts. For instance, Carril-Caccia and Milgram Baleix (2024) found that stricter environmental regulations (ER) reduce countries' attractiveness to foreign investors; Benatti et al. (2024) observed

¹ The heterogeneity of environmental regulations studied in this paper refers to the command-driven low-carbon city pilot policy and the market-oriented carbon emissions trading pilot policy. Low-carbon city pilot policy and carbon emissions trading policy are two different types of environmental regulations.

that tightened ER negatively affects the productivity growth of high-polluting firms. Agarwal et al. (2019) used the NOx Budget Trading Program (NBP) as a quasi-natural experiment, finding that housing markets in regulated regions with high manufacturing density were sluggish. Zeng et al. (2023) noted that stricter environmental law enforcement significantly reduced the TFP of high air-polluting enterprises, and Huang et al. (2022) further found that tightened environmental supervision lowered manufacturing firms' productivity. Still other studies have reported no significant effects: Alpay and Kerkvliet (2020) found U.S. pollution regulations had no impact on food manufacturing productivity; Wang et al. (2018) observed water quality regulations exerted no notable effect on the productivity of surviving firms; Lange and Redlinger (2019) found oil sector regulatory policies did not significantly affect oil and gas drilling and production speeds. Evidently, the socioeconomic effects of command-driven environmental regulations remain uncertain, as they may be positive, negative, or non-significant.

Market-oriented environmental regulations research mainly assesses emissions trading and carbon taxes. Dechezleprêtre (2016) found the EU Emissions Trading Scheme (EU ETS) spurred innovation in carbon - mitigation technologies; Naegele and Zaklan (2019) detected no carbon leakage triggered by the EU ETS; Clarkson et al. (2015) linked carbon allowance shortfalls to reduced firm value; Martin et al. (2014) noted carbon taxes had no significant effect on manufacturing revenue. For carbon emissions trading policies, Fan et al. (2016) highlighted efficiency improvements, while Cao et al. (2021) found no impact on coal-fired power plants' coal efficiency. Similarly, studies by domestic and international scholars indicate that market-oriented environmental regulations often yield significant economic effects.

In comparative studies of heterogeneous regulations, proxy variables are commonly employed (e.g., Yang and Green, 2024, using fiscal expenditure ratios for command-driven regulation and pollution fee ratios for market-oriented), which are not only subjective but also inherently susceptible to measurement bias. Additionally, existing literature examines low-carbon initiatives and carbon trading separately, lacking simultaneous analysis of their differential effects. This paper addresses these gaps by treating two policies—the command-driven LCCP and market-oriented CETP—with unified goals—as quasi-natural experiments, avoiding measurement subjectivity to better explore their differential impacts.

2.2 Methods for evaluating policy effectiveness

The methods for evaluating the effects of environmental regulation mentioned above primarily use difference methods such as DID (Zhang and Zhao, 2023; Shao et al., 2024; Qiu et al., 2021), DDD (Cai et al., 2016), and PSM-DID (Chen et al., 2021). These traditional policy evaluation methods share the same limitation: they have restrictions on the dimensions of control variables.

Currently, machine learning methods are rapidly permeating the field of econometrics and have also been increasingly adopted for event evaluation. Chernozhukov et al. (2018) pioneered the Double Machine Learning (DML) for event evaluation. Subsequently, Yang J. et al.

(2020), Zhang et al. (2022), Bodory et al. (2022), and Farbmacher et al. (2022) applied DML in policy evaluation. The DML excels in high-dimensional variable screening, as it circumvents multicollinearity pitfalls inherent in traditional methods when dealing with high-dimensional control variables (Zhang et al., 2022).

3 Theoretical mechanisms

Firstly, the paper analyzes the influence of LCCP and CETP on the HQDM. The specific analysis is as follows: The LCCP constrains pollution emissions from local enterprises by establishing greenhouse gas emission data statistics and management systems and implementing a target-based responsibility system. These measures will directly increase the environmental management costs for businesses. Meanwhile, administrative orders can act as a market signal, leading to an excessive concentration of resources and potential resource misallocation. Furthermore, the LCCP may overly focus on the carbon reduction outcomes, lacking a comprehensive consideration of economic impacts, which could inhibit the growth of the manufacturing industry. Therefore, We posit that the LCCP could dampen manufacturing TFP and impede the HQDM.

In contrast, carbon trading's theoretical foundation of carbon emissions trading lies in Coase's property rights theory. The CETP allocates initial free allowances via historical emissions or carbon intensity. Under the framework of total emission control, carbon emission rights are treated as tradable commodities, enabling market exchanges to incentivize firms to internalize carbon externalities. This mechanism facilitates Pareto-efficient resource allocation. Thus, this paper suggests that CETP can enhance manufacturing's TFP and promote its high-quality development.

When a region implements both the CETP and the LCCP simultaneously, the two policies generate a positive synergistic effect on the HQDM; more precisely, after the CETP is formulated, the LCCP's impact on the HQDM shifts from negative to positive. The formation of this synergistic effect stems primarily from two aspects: first, the combination of the two low-carbon policies can strengthen the publicity and guidance for low-carbon development, deepen low-carbon awareness, and thereby enhance the overall policy implementation effect; second, it can construct a "government-guided, market-led" collaborative governance mechanism—the CETP plays a core role in guiding the optimal allocation of carbon emission rights, while the LCCP serves an auxiliary function to address market failures. Meanwhile, the CETP provides market entities with more emission reduction options, which can alleviate the potential "one-size-fits-all" issue caused by LCCP's administrative intervention, reduce its strong impact on market entities, and ultimately enable the LCCP to promote the HQDM while achieving effective emission reduction. In conclusion, in regions where the CETP and the LCCP are implemented simultaneously, these two types of environmental regulations exert a synergistic effect on the HQDM, with both contributing to the improvement of the HQDM.

Secondly, this paper analyzes the influence mechanisms of LCCP and CETP on the HQDM from the perspectives of innovation effects and resource effects. The specific analysis is as follows.

3.1 Innovation effect

Innovative activities, characterized by long cycles, high investment, and significant risks (Gustavo, 2011), are susceptible to government fiscal incentives and support policies (Borghesi et al., 2015; Montmartin and Herrera, 2015). Both the LCCP and the CETP exert dualistic impacts on the innovation effect of HQDM.

From the “compliance cost perspective”, negative effects manifest as follows: As a command-driven environmental regulation, The LCCP pursues emission reduction by adjusting the energy structures, enhancing energy efficiency, and promoting energy conservation. It also focuses on establishing a low-carbon production system and advocating for low-carbon production methods. These measures will directly increase enterprises’ compliance costs. In carbon emission trading, if enterprises have insufficient quotas and need to purchase from the market, such carbon trading expenditures can crowd out R&D investment, weakening firms’ technological innovation capacity. The increase in costs may crowd out investment in technological innovation, leading to a decline in the innovation capabilities of enterprises.

From the “innovation compensation perspective”, the positive impact is manifested as follows: In the face of cost pressures, enterprises’ investment in innovation may not decrease but may instead increase (Bu et al., 2019). Firms can mitigate policy - induced cost burdens via technological innovation, generating an innovation - offset dynamic that bolsters enterprises’ TFP. In addition, productivity improvement also depends on enterprises’ ability to apply existing innovations and efficient technologies (Albrizio et al., 2017; Daron et al., 2006). The LCCP fosters a collaborative ecosystem for low - carbon tech scaling, facilitating knowledge spillovers and technology diffusion. This action will encourage companies to learn advanced technologies from their peers and expand the use of high-tech innovations (Wang et al., 2018). Unlike command-driven environmental regulation, carbon emission trading’s distinctive edge lies in capping total carbon emissions yet enabling firms to monetize surplus allowances (Clarkson et al., 2015), thus creating enduring economic incentives for technological innovation.

3.2 Resource effect

The LCCP exerts both negative and positive impacts on resource allocation for the HQDM.

In terms of negative effects, as a command-driven environmental regulation, its administrative intervention may cause excessive resource allocation to low-carbon industries and sectors. Driven by the policy’s low-carbon orientation and carbon reduction assessment pressures, enterprises might over-invest in non-productive emission reduction equipment (He et al., 2020), leading to resource misallocation due to excessive resource shifts to low-carbon sectors. Moreover, drawing on the rent-seeking theory (Murphy et al., 1993) and the “grabbing hand” theory of government (Andrei and Vishny, 1994), enterprises may proactively cater to government demands to gain local government support or even allocate resources under government “domination”, which further exacerbates resource misallocation.

On the positive side, improved factor utilization efficiency is reflected in the flow of production factors from inefficient to efficient sectors or enterprises. For individual enterprises, both

policies encourage increased investment in low-carbon, high-efficiency sectors, and clean energy use while reducing input in high-carbon, inefficient sectors and fossil fuel consumption (Chen et al., 2021), thereby enhancing internal resource allocation efficiency. At the industry level, the LCCP imposes stringent emission and technical benchmarks, creating industry barriers and raising entry thresholds for manufacturing. It also increases competitive pressure on enterprises with high carbon reduction costs, forcing some to exit. This leads to resource concentration in enterprises with lower carbon reduction costs and higher productivity, promoting overall industry productivity growth (Cheng et al., 2019).

The CETP bolsters firms’ emission - reduction flexibility by providing clear market price signals (Albrizio et al., 2017). Specifically, market trading reallocates carbon emission rights among enterprises, production factors are redirected from inefficient firms to their high - efficiency counterparts. This optimizes quota distribution, enabling cost - minimal emission reduction (Montgomery, 1972). Notably, the resource effect of carbon emission rights depends on market liquidity. Given China’s carbon market remains in a nascent phase with incomplete mechanisms, it may not yet have a significant resource allocation effect.

In summary, the LCCP may cause resource misallocation (inhibiting HQDM), optimize resource allocation (promoting HQDM), or have no significant impact (with coexisting effects). The CETP can optimize resource allocation to boost HQDM, but its resource allocation effect may be insignificant in the early stage due to immature market mechanisms. The actual policy effects require further verification.

In summary, The influence mechanism of heterogeneous environmental regulations on HQDM are shown in Figure 1.

4 Methodology

4.1 Policy background, sample selection, and data sources

In September 2020, during the 75th UN General Assembly, China announced its 2030 carbon peak and 2060 carbon neutrality targets, emphasizing a commitment to advance low-carbon transitions across economic and social spheres. In response, initiatives like LCCP and CETP have emerged as key policy tools.

The LCCP rolled out in three phases: the first in July 2010 (5 provinces, e.g., Guangdong, Liaoning; 8 cities, e.g., Tianjin, Chongqing); the second in November 2012 (Hainan Province and 28 cities, e.g., Beijing, Shanghai, Guangzhou); and the third in January 2017 (45 cities, e.g., Wuhai, Shenyang, Dalian). While specific goals differ marginally across phases, all aim to curb greenhouse gas emissions and pilot green, low - carbon development models. Key strategies include forging low - carbon industrial ecosystems, optimizing energy structures, advancing energy - efficient buildings and low - carbon mobility.

The CETP started in June 2013 with Shenzhen, subsequently expanding to six regions (e.g., Tianjin, Chongqing). Fujian joined in December 2016, making it the eighth pilot. The national carbon market began trading in July 2021. The policy implementation involves determining covered enterprises via historical emissions or carbon intensity benchmarks, allocating initial free allowances, and allowing enterprises to trade allowances in the market. Pilot

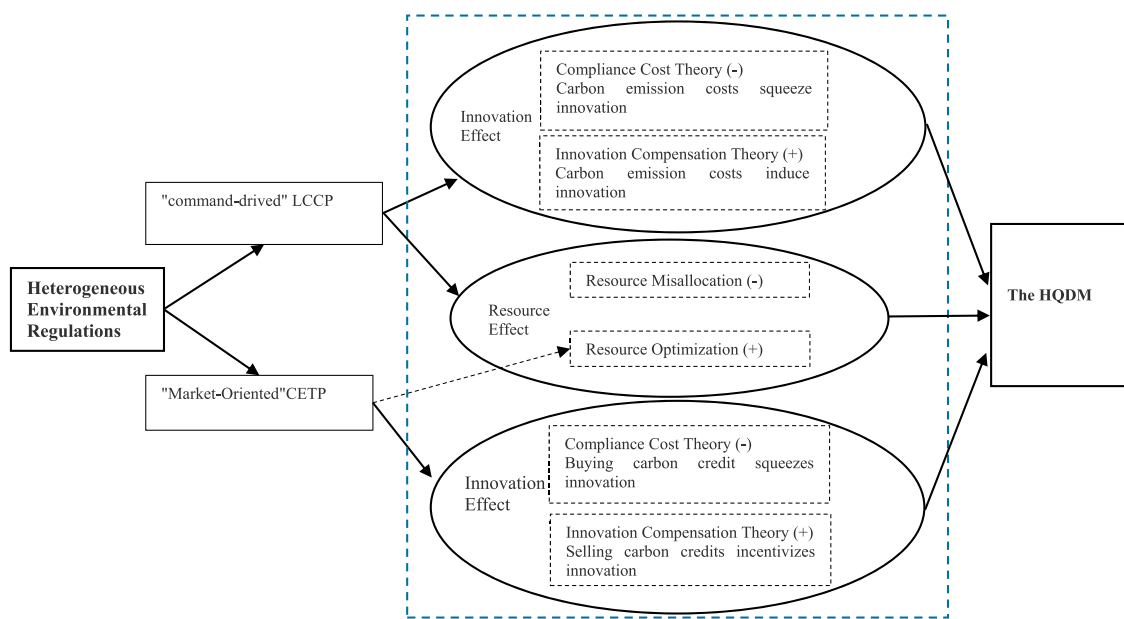


FIGURE 1
The influence mechanism of heterogeneous environmental regulations on the HQDM.

markets have a 40%–60% carbon emissions coverage rate (Ma et al., 2023) and operate independently with no cross-market trading.

The research sample comprises A-share listed firms on Shanghai and Shenzhen exchanges, spanning 2003–2021. Including 2021 arises from the July 2021 launch of the national carbon market, with pilot markets coexisting during the transition period and policy effects being delayed (Ma et al., 2023). Abnormal samples (e.g., ST/*ST companies, those with significant data gaps) were excluded, and missing data were filled using linear interpolation. Data were sourced from CSMAR database and the China City Statistical Yearbook. The policy time nodes are set as 2010, 2013, and 2017 for the three low-carbon pilot batches; for carbon trading, Shenzhen starts in 2013, Beijing, Tianjin, Shanghai, Chongqing, Hubei, and Guangdong in 2014, and Fujian in 2017.

4.2 Research method

This study applies Double Machine Learning (DML) to assess how heterogeneous environmental regulations influence manufacturing high-quality development (HQDM). Unlike traditional nonparametric regression methods, DML accommodates high-dimensional nuisance functions with numerous covariates, obviating the need for pre-selecting control variables (Yang G. et al., 2020; Zhang et al., 2022; Bodory et al., 2022; Farbmacher et al., 2022).

Referring to Robinson (1988) and Chernozhukov et al. (2018), the following partial linear model is established.

$$Y_{it} = \beta_1 P_{it} + g_0(X_{it}) + U_{it}, E[U_{it}|X_{it}, P_{it}] = 0 \quad (1)$$

$$P_{it} = m_0(X_{it}) + V_{it}, E[V_{it}|X_{it}] = 0 \quad (2)$$

In the equation, Y_{it} is the outcome variable; P_{it} as both the explanatory variable and a policy dummy variable; X represents control variables. $g_0(X_{it})$, $m_0(X_{it})$ are unknown functions estimated via machine learning. U_{it} and V_{it} are error terms with zero conditional means. Equation 1 is the main equation, and Equation 2 is the auxiliary equation.

By using machine learning to predict $g_0(X_{it})$, we obtain its estimated value $\hat{g}_0(X_{it})$, which is then substituted into Equation 1 to derive Equation 3:

$$Y_{it} - \hat{g}_0(X_{it}) = \beta_1 P_{it} + error_{it} \quad (3)$$

Then, using ordinary least squares (OLS), we obtain the OLS estimator $\hat{\beta}_1$ for β_1

$$\hat{\beta}_1 = \left(\frac{1}{n} \sum_{i=1}^n P_{it}^2 \right)^{-1} \frac{1}{n} \sum_{i=1}^n P_{it} [Y_{it} - \hat{g}_0(X_{it})] \quad (4)$$

Substituting $Y_{it} = \beta_1 P_{it} + g_0(X_{it}) + U_{it}$ from Equation 1 into Equation 4 yields Equation 5:

$$\begin{aligned} \hat{\beta}_1 &= \left(\frac{1}{n} \sum_{i=1}^n P_{it}^2 \right)^{-1} \frac{1}{n} \sum_{i=1}^n P_{it} [\beta_1 P_{it} + g_0(X_{it}) + U_{it} - \hat{g}_0(X_{it})] \\ &= \beta_1 + \left(\frac{1}{n} \sum_{i=1}^n P_{it}^2 \right)^{-1} \frac{1}{n} \sum_{i=1}^n P_{it} U_{it} \\ &\quad + \left(\frac{1}{n} \sum_{i=1}^n P_{it}^2 \right)^{-1} \frac{1}{n} \sum_{i=1}^n P_{it} [g_0(X_{it}) - \hat{g}_0(X_{it})] \end{aligned} \quad (5)$$

Rearranging terms gives:

$$\sqrt{n}(\hat{\beta}_1 - \beta_1) = \underbrace{\left(\frac{1}{n} \sum_{i=1}^n P_{it}^2 \right)^{-1} \frac{1}{\sqrt{n}} \sum_{i=1}^n P_{it} U_{it}}_{=a} + \underbrace{\left(\frac{1}{n} \sum_{i=1}^n P_{it}^2 \right)^{-1} \frac{1}{\sqrt{n}} \sum_{i=1}^n P_{it} [g_0(X_{it}) - \hat{g}_0(X_{it})]}_{=b} \quad (6)$$

In the equation, the term “a” adheres to a normal distribution centered at zero. Substituting $P_{it} = m_0(X_{it}) + V_{it}$ which is from Equation 2 into the “b” part of Equation 6 yields Equation 7:

$$\mathbf{b} = (\mathbf{E}P_{it}^2)^{-1} \frac{1}{\sqrt{n}} \sum_{i=1}^n m_0(X_{it}) [g_0(X_{it}) - \hat{g}_0(X_{it})] + o_p(1) \quad (7)$$

Due to regularization bias in machine learning, the convergence rate of $g_0(X_{it}) - \hat{g}_0(X_{it})$ to 0 is typically slower than that of $\frac{1}{\sqrt{n}}$, with its convergence rate denoted as $n^{-\varphi_g}$, i.e., $\varphi_g < \frac{1}{2}$. Since $m_0(X_{it}) \neq 0$, as $n \rightarrow \infty$, the magnitude of “b”, which is $\sqrt{nm}^{-\varphi_g} \rightarrow \infty$. Consequently, even with large samples, $\sqrt{n}(\hat{\beta}_1 - \beta_1)$ will not converge to 0 in probability, and $\hat{\beta}_1$ will not converge to β_1 . This results in a bias in the estimation of β_1 . To correct this estimation bias, orthogonalization methods need to be introduced.

Specifically, first use machine learning to predict the residuals V_{it} of auxiliary Equation 2 again to obtain their estimates $\hat{V}_{it}$. Then, treat $\hat{V}_{it}$ as an instrumental variable for P_{it} to finally obtain the estimate $\hat{\beta}_1$ for β_1 , as shown in Equation 8.

$$\hat{\beta}_1 = \left(\frac{1}{n} \sum_{i=1}^n \hat{V}_{it}^2 \right)^{-1} \frac{1}{n} \sum_{i=1}^n \hat{V}_{it} [Y_{it} - \hat{g}_0(X_{it})] \quad (8)$$

We then obtain Equation 9:

$$\sqrt{n}(\hat{\beta}_1 - \beta_1) = \underbrace{\left(\frac{1}{n} \sum_{i=1}^n \hat{V}_{it}^2 \right)^{-1} \frac{1}{\sqrt{n}} \sum_{i=1}^n \hat{V}_{it} U_{it}}_{=a} + \underbrace{\left(\frac{1}{n} \sum_{i=1}^n \hat{V}_{it}^2 \right)^{-1} \frac{1}{\sqrt{n}} \sum_{i=1}^n [m_0(X_{it}) - \widehat{m}_0(X_{it})] [g_0(X_{it}) - \hat{g}_0(X_{it})]}_{=b} \quad (9)$$

In the equation, the term “a” adheres to a normal distribution centered at zero and $[m_0(X_{it}) - \widehat{m}_0(X_{it})]$ and $[g_0(X_{it}) - \hat{g}_0(X_{it})]$ represent the prediction biases of machine learning concerning $m_0(X_{it})$ and $g_0(X_{it})$. Let the convergence rate of $[m_0(X_{it}) - \widehat{m}_0(X_{it})]$ is $n^{-\varphi_m}$, then the convergence rate of $[g_0(X_{it}) - \hat{g}_0(X_{it})]$ is $n^{-\varphi_g}$. The convergence rate of the interaction term of the two error terms $[m_0(X_{it}) - \widehat{m}_0(X_{it})] [g_0(X_{it}) - \hat{g}_0(X_{it})]$ is $n^{-(\varphi_m + \varphi_g)}$ which is faster than that of a single prediction bias, either $n^{-\varphi_m}$ or $n^{-\varphi_g}$. In this case, it is also faster than $\frac{1}{\sqrt{n}}$, meaning $\varphi_m + \varphi_g > \frac{1}{2}$. As $n \rightarrow \infty$, the magnitude of “b” approaches $\sqrt{nm}^{-(\varphi_m + \varphi_g)} \rightarrow 0$, causing $\sqrt{n}(\hat{\beta}_1 - \beta_1)$ to converge to 0 in probability, making $\hat{\beta}_1$ an unbiased estimator of β_1 . In summary, predicting $g_0(X_{it})$ and V_{it} , via double machine learning (DML) circumvents the dimensionality curse induced by high - dimensional controls, yielding an unbiased estimator of β_1 .

DML boosts estimation precision via cross - fitting: by partitioning the sample, one subset trains models to predict $g_0(X_{it})$ and residuals V_{it} , (generating $\hat{g}_0(X_{it})$ and $\hat{V}_{it}$), while the other subset conducts regression. For partially linear models where covariate functional forms are unknown, DML yields unbiased treatment effect estimates.

4.3 Variable selection

4.3.1 Dependent variable

In this paper, the dependent variable is the indicator of high-quality development of the manufacturing industry (HQDM), which is measured by total factor productivity (TFP).

4.3.2 Explanatory variable

Key policy indicators—*Tlowc* (LCCP) and *Tctrade* (CETP)—act as dummy variables. Drawing on prior research (Demir et al., 2022; Teng et al., 2022; Filippini et al., 2020; Oberfield, 2013; Yang J. et al., 2020), controls cover firm - (micro) and city - level (macro) dimensions. Firm - level controls (14 variables) capture financial attributes (e.g., *Age*, *Size*, *Rate*), while city - level metrics (16 items) span regional growth (*Gdp*), government spending (*Gov*), and market conditions (*Mkr*). Variable definitions and summary statistics are presented in Tables 1, 2.

5 Empirical results

5.1 Benchmark regression tests

Drawing on partial linear model insights, we partition the sample into a 1:4 split (machine learning prediction vs. regression estimation). Following Yang G. et al. (2020), gradient boosting outperforms other algorithms, so we adopt it for policy assessment. Results appear in Table 3.

In baseline regressions (Columns 1 and 3), *Tlowc* exhibits a statistically significant negative effect on listed manufacturers’ TFP (5% level), whereas *Tctrade* shows a positive effect (1% level). When adding interaction and quadratic control terms (Columns 2 and 4): *Tlowc*’s coefficient is -0.0386 (1% significance) implies a 0.0386 average TFP reduction in pilot regions relative to non-pilots; *Tctrade*’s coefficient is 0.0975 (1% significance), which indicates the average TFP of relevant listed manufacturing firms is 0.0975 higher than that of the reference group.

These results suggest command-driven environmental regulations outperform command-driven measures in fostering manufacturing high - quality development (HQDM).

5.2 Robust tests

5.2.1 Sample screening

To address outliers and special samples, we employ trimming and exclude central municipality observations. Tables 4, 5 show *Tlowc* remains negatively significant and *Tctrade* is significantly positive. It is consistent with the baseline findings and confirming result robustness.

TABLE 1 Key variable definitions.

Variable type		Variable symbol		Variable name	Variable meaning
Dependent Variable		TFP		Total Factor Productivity	TFP (LP - estimated)
Explanatory Variables		Tlowc		LCCP	Policy dummy (1 = year of low - carbon pilot rollout onwards, 0 otherwise)
		Tctrade		CETP	Policy dummy (1 = year of carbon trading launch onwards, 0 otherwise)
Control Variables	Enterprise Level	Firm Characteristics	Age	Years Listed	current year–listing year
			Size	Company Size	Total assets
			Soe	Ownership Type	1 = state-owned enterprises, 0 otherwise
			Export	Export Status	1 if the company exports in any year; otherwise 0
			Board	Board Size	Year-end board member count
			dep	Proportion of Independent Directors	Year - end independent director count
			Toph	Ownership Concentration	Largest shareholder ownership ratio
		Financial Status	Rate	Debt-to-Asset Ratio	Total liabilities/total assets
			Kl	Capital Intensity	Net fixed assets/number of employees
			Flow	Liquidity	Operating cash flow-to-assets ratio
			Profit	Return on Capital	Net profit/total assets
			Grow	Growth	Year-on-year growth rate of net assets
			Mva	Market Value	Total market value/total assets
			Inv	Investment	Capital expenditure (fixed/intangible/long - term assets)
	City Level	Regional Development Status	Gdp	Economic Development Leve	GDP/year-end total population
			Urb	Urbanization Level	Urbanization rate
			Stru	Industrial Structure	Secondary-to-tertiary industry value-added ratio
			Pde	Population Density	Population per unit area
			Wage	Income Level	Average wage
			Road	Transportation Infrastructure	Road mileage/year-end total population
			Int	Internet Penetration	Number of internet users
		Government Behavior	Gov	Government Expenditure	Fiscal expenditure/GDP
			Fdi	Foreign Investment Utilization	Actual use of foreign investment/GDP
			Fdp	Fiscal Decentralization	Ratio of budgetary revenue to budgetary expenditure
			RD	Government R&D Investment	Per capita government fiscal expenditure on science and technology
			Exp	Education Investment	Fiscal education expenditure/GDP
			Nsoe	State-Owned Enterprise Reform	Ratio of urban private and individual employment to total employment in the city
		Market Environment	Mkt	Market Environment	Provincial marketization index report in China
			Open	Degree of Openness	Provincial export trade volume/GDP
			Fin	Financial Development Level	Balance of institutional deposits and loans/GDP

The variables Kl, Gdp, Size, Inv, and RD, have been deflated.

5.2.2 Resetting the double machine learning model

This study adopts three methods for robustness checks: adjusting the sample split ratio, algorithm replacement, and model substitution. Specifically, following Chernozhukov et al.

(2018), the sample split ratio is modified from 1:4 to 1:3. For the algorithm replacement, the gradient boosting (gradboost) algorithm is replaced with a stacked regression algorithm—this algorithm assesses policies through a weighted combination of multiple

TABLE 2 Descriptive statistics of key variables.

Variable type			Variable symbol	Sample size	Mean	Standard deviation	Minimum	Maximum
Dependent Variable			TFP	7,503	11.4173	0.9003	7.8485	14.8377
Explanatory Variables			Tlowc	7,675	0.2236	0.4167	0.0000	1.0000
			Tctrade	7,675	0.1459	0.3531	0.0000	1.0000
Control Variables	Enterprise Level	Firm Characteristics Regional Development Status	Age	7,675	25.7902	2.9545	20.0000	32.0000
			Size	7,675	126.7634	343.0891	1.2628	9194.1470
			Soe	7,675	0.7104	0.4536	0.0000	1.0000
			Export	7,675	0.0314	0.1744	0.0000	1.0000
			Board	7,675	9.1742	1.8573	0.0000	18.0000
			dep	7,675	0.3633	0.0580	0.0000	0.8000
			Toph	7,675	36.6173	15.4352	3.3904	89.9858
		Financial Status	Rate	7,675	0.4771	0.1797	−0.0872	0.9963
			Kl	7,675	1.8988	2.5821	0.1713	80.4665
			Flow	7,675	0.0421	0.0706	−0.4700	0.4841
			Profit	7,675	0.0302	0.0531	−0.5280	0.3970
			Grow	7,675	0.0634	0.3620	−1.2663	10.3534
			Mva	7,675	203.8824	579.5407	4.5839	25,564.3000
			Inv	7,670	0.0560	0.0731	−0.2736	1.8818
			Gdp	7,656	2.2399	1.1072	0.2475	5.2688
			Urb	7,616	0.6560	0.1932	0.1141	1.0000
			Stru	7,669	1.0908	0.7762	0.1876	32.1235
			Pde	7,656	1131.5980	1318.6980	15.6734	8854.0810
			Wage	7,656	5.6823	3.6751	0.0015	19.7716
			Road	7,342	20.4648	15.3195	1.1475	357.9003
			Int	7,656	273.4573	522.2860	0.0600	9114.0000
	City Level	Government Behavior	Gov	7,675	0.1388	0.0531	0.0353	0.5721
			Fdi	7,249	0.0336	0.0298	0.0000	0.3850
			Fdp	7,656	0.6898	0.2149	0.0256	1.5413
			RD	7,656	0.1485	0.1138	0.0037	0.6874
			Exp	7,656	0.0220	0.0092	0.0012	0.1303
			Nsoe	7,628	0.3895	0.1672	−0.0014	1.3157
		Market Environment	Mkt	7,675	9.2036	19.5322	2.4700	422.0000
			Open	7,468	4.0888	8.2560	0.0252	80.1740
			Fin	7,656	1.3610	0.7149	0.1122	7.4508

machine learning methods, including gradient boosting, random forests (rf), lasso (lassocv), ridge regression (ridgecv), and neural networks (nnet). Furthermore, the model shifts from a local linear model to a more general interactive model.

Results in [Table 6](#) show *Tlowc* remains significantly negative, while that of *Tctrade* stays significantly positive, validating baseline result robustness.

5.2.3 Excluding the impact of simultaneous implementation of two environmental regulations

The implementation timelines for the LCCP and the CETP overlap across multiple periods, and both environmental regulations may significantly impact the TFP of the manufacturing industry. To avoid the issue of omitting important variables when evaluating the policies separately,

TABLE 3 Impact of heterogeneous environmental regulations on the HQDM.

Variable	TFP			
	(1)	(2)	(3)	(4)
<i>Tlowc</i>	−0.0331** (0.0156)	−0.0386*** (0.0176)		
<i>Tctrade</i>			0.1534*** (0.0328)	0.0975*** (0.0342)
Control variable First-order Term	Yes	Yes	Yes	Yes
Control Variables Interaction and Quadratic Terms	No	Yes	No	Yes
Sample Size	6,771	6,771	6,771	6,771

*, **, *** denote significance at the 10%, 5%, and 1% confidence levels, respectively. Standard errors are in parentheses. The same applies below.

TABLE 4 Sample trimming estimation results.

Variable	TFP					
	1%Trimming			5%Trimming		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Tlowc</i>	−0.0333* (0.0180)		−0.0381** (0.0173)	−0.0320* (0.0165)		−0.0337* (0.0159)
<i>Tctrade</i>		0.0901*** (0.0346)	0.0895** (0.0360)		0.0900*** (0.0343)	0.0892** (0.0351)
Control Variable First-order Term	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables Interaction and Quadratic Terms	Yes	Yes	Yes	Yes	Yes	Yes
Sample Size	6,771	6,771	6,771	6,771	6,771	6,771

this paper will further conduct robustness analysis using subsamples. we divide the sample into four policy-assessment groups, with robustness test results in Table 7.

First, Remove cities with the CETP, leaving only low-carbon pilot cities as the treatment group (results in Table 7, columns (1)–(2)).

Second, Remove cities with the LCCP, leaving only carbon emissions trading cities as the treatment group (results in columns (3)–(4)).

Third, we remove cities covered by both policies, and then take cities covered by only one of the two policies as the treatment group (results in columns (5)–(6)).

Finally, Remove cities with only one policy, including only cities with both policies in the treatment group (results in columns (7)–(8)).

From the subsample empirical results in columns (1) to (6), it confirm baseline robustness. Columns (7) and (8) show that *Tlowc*'s coefficient remains significantly positive, indicating that the LCCP significantly promotes the HQDM. The coefficient for *Tctrade* is positive but not significant, implying the CETP have no notable impact on HQDM.

One plausible reason is that cities implementing both low-carbon policies are more conducive to creating an environment for carbon reduction, increasing companies' acceptance and motivation for carbon reduction, and generating a synergistic effect between the two policies. Consequently, the LCCP positively contributes to the HQDM. However, due to the

implementation of the LCCP, companies are required to reduce carbon emissions, which decreases their carbon quota trading in the carbon market. This weakens the impact of the CETP, making its effect on HQDM insignificant.

6 Mechanism and heterogeneity analysis

6.1 Mechanism analysis

6.1.1 Innovation effect

This paper uses R&D intensity (R&D expenditure/operating revenue) as a proxy for technological innovation (Zhou and Tang, 2021). Given the lack of R&D expenditure data prior to 2009, the mechanism test focuses on the second and third pilot policy batches, with corresponding results provided in Table 8.

Table 8, Columns 1–2 assess the 2012 and 2017 LCCP's effects on technological innovation. Results indicate that, after adding the two policy variables, whether controlling for interaction and quadratic terms or not, the *Tlowc*'s coefficient is insignificant. This indicates that the LCCP has no significant impact on technological innovation in manufacturing. In contrast, *Tctrade*'s positive significance suggests the CETP spurs technological innovation. Consistent with prior mechanism logic, the policy's innovation-inducing effect outweighs its crowding-out effect, driving technological innovation.

TABLE 5 Estimation results after removing municipalities.

Variable	TFP					
	(1)	(2)	(3)	(4)	(5)	(6)
Tlowc	−0.0415** (0.0173)	−0.0491** (0.0201)			−0.0401** (0.0174)	−0.0414** (0.0191)
Tctrade			0.1548*** (0.0398)	0.0946** (0.0424)	0.1556*** (0.0392)	0.0559 (0.0410)
Control Variable First-order Term	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables Interaction and Quadratic Terms	No	Yes	No	Yes	No	Yes
Sample Size	5,436	5,436	5,436	5,436	5,436	5,436

6.1.2 Resource effect

This study proxy resource allocation efficiency with capital allocation efficiency (Chen et al., 2021), adopting the “investment level and investment opportunity sensitivity” model to assess heterogeneous environmental regulations’ impact. The model is specified in Equations 10–12:

$$A_{it} = P_{it} \times Roa_{it} \quad (10)$$

$$Invest_{it} = \beta_1 A_{it} + g_0(X_{it}) + U_{it}, E[U_{it}|X_{it}, A_{it}] = 0 \quad (11)$$

$$A_{it} = m_0(X_{it}) + V_{it}, E[V_{it}|X_{it}] = 0 \quad (12)$$

Here, $Invest_{it}$ represents the firm’s investment level, Roa_{it} is the return on assets, which captures the firm’s investment opportunities. P_{it} is the policy dummy variable. The term A_{it} is the interaction term of P_{it} and Roa_{it} , and the definitions of other variables are the same as in models (1) and (2).

The empirical results, presented in columns (5) to (8) of Table 8, indicate insignificant coefficients for $Tlowc$ and $Tctrade$. This suggests that the LCCP and the CETP do not have a significant impact on firms’ capital allocation efficiency.

Regarding the non-significant impact of the LCCP on firms’ capital allocation efficiency, potential explanations can be derived from mechanism analysis. As a command-driven environmental regulation, the LCCP may cause resource misallocation: government administrative intervention, coupled with firms’ proactive compliance to obtain local government support, ultimately leads to excessive resource reallocation toward low-carbon sectors. At the same time, it can also optimize factor allocation—both within individual firms and across industries—by driving factors to flow from inefficient sectors or enterprises to efficient ones. These two opposing effects, which exert negative impacts and positive impacts on resource allocation for the HQDM, likely offset each other, ultimately resulting in the LCCP’s non-significant influence on capital allocation.

The CETP also exerts no significant impact on firms’ capital allocation efficiency. A plausible explanation, similarly as elaborated in the mechanism analysis, lies in that CETP—a market-based environmental regulation—can optimize resource allocation and reduce carbon emissions through market price signals of carbon emission rights, but this depends on the maturity of market mechanisms. Since China’s carbon emission trading market is still in the initial stage of development, characterized by

underdeveloped market mechanisms, and its pilot carbon markets operate independently of one another with no cross-market carbon quota trading permitted—resulting in its limited market coverage—these are the reasons why the CETP fails to generate a significant resource allocation effect. Meanwhile, Carbon emission rights are quasi-public goods, and the carbon market is a market with quasi-public goods (i.e., carbon emission rights) as its core trading instrument. Given that the non-rival nature of quasi-public goods requires government intervention in supply via “total quantity control” and the definition of exclusive property rights relies on administrative rules, the carbon market cannot meet the core assumptions of a perfectly competitive market—namely, “free entry and exit, homogeneous products, and complete information.” It thus does not qualify as a perfectly competitive market, and its resource allocation efficiency is also constrained.

6.2 Heterogeneity analysis

This paper has demonstrated that the command-driven LCCP inhibits HQDM, while the market-oriented CETP promotes it. Given policy effects differ across firms by ownership and technological intensity, we further explore heterogeneity in these dimensions.

6.2.1 Firm ownership

This paper stratify firms by ownership—specifically state-owned enterprises (SOEs) and non-state-owned enterprises (nonSOEs)—for regression, with results in Table 9.

Table 9 Columns 1–3 show $Tlowc$ remains significantly negative at the 1% level, regardless of whether other interaction terms and quadratic terms are controlled, indicating the LCCP hinders the HQDM of SOEs. Meanwhile, $Tctrade$ ’s coefficient is significantly positive at the 5% level, suggesting CETP boosts HQDM of SOEs. In Columns 4–6, both coefficients are insignificant, indicating that, neither the LCCP nor the CETP exerts a significant impact on the HQDM of non-SOEs.

The possible reason for the heterogeneous effects is that SOEs exhibit a heightened commitment to social responsibilities, and are more proactive in responding to policies. As a result, they implement national policy decisions more effectively, leading to significant

TABLE 6 Estimation results for resetting the double machine learning model.

Variable	TFP					
	Adjusting the sample split ratio (1:3)		Algorithm replacement Stacked regression		Model substitution Interactive model	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Tlowc</i>	−0.0332** (0.0149)	−0.0420** (0.0174)	−0.0750*** (0.0260)	−0.0645*** (0.0230)	−0.0150** (0.0081)	−0.0216*** (0.006)
<i>Tctrade</i>	0.1483*** (0.0327)	0.0935*** (0.0336)	0.0990* (0.0560)	0.0613* (0.0362)	0.0908*** (0.0041)	0.0761*** (0.0069)
Control Variable First-order Term	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables Interaction and Quadratic Terms	No	Yes	No	Yes	No	Yes
Sample Size	6,771	6,771	6,771	6,771	6,771	6,771

TABLE 7 Estimation results for excluding the impact of simultaneous implementation of two environmental regulations.

Variable	TFP							
	Only LCCP		Only CETP		Excluding cities implementing both policies		Cities implementing both policies	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Tlowc</i>	−0.0840*** (0.0210)	−0.0760*** (0.0220)			−0.0800*** (0.0191)	−0.0856*** (0.0221)	0.0226 (0.0429)	0.0948** (0.0443)
<i>Tctrade</i>			0.1000** (0.0470)	0.0930* (0.0560)	0.0902* (0.0492)	0.0355 (0.0486)	0.1368* (0.0716)	0.0513 (0.1217)
Control Variable First-order Term	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables Interaction and Quadratic Terms	No	Yes	No	Yes	No	Yes	No	Yes
Sample Size	4,218	4,218	2,974	2,974	4,732	4,732	4,422	4,422

TABLE 8 Estimation results of mechanism testing.

Variable	<i>Inno</i>				<i>Invest</i>			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Tlowc</i>	0.0010 (0.0050)		−0.0020 (0.0030)	−0.0021 (0.0037)	−0.0075 (0.0298)		−0.0330 (0.0284)	−0.0072 (0.0303)
<i>Tctrade</i>		0.0055 (0.0046)	0.0127*** (0.0049)	0.0080* (0.0050)		0.0143 (0.0346)	−0.0401 (0.0327)	−0.0008 (0.0350)
Control Variable First-order Term	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables Interaction and Quadratic Terms	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Sample Size	3,828	3,828	3,828	3,828	6,768	6,768	6,768	6,768

TABLE 9 Estimation results of heterogeneity in Enterprise's ownership.

Variable	TFP					
	SOEs			Non-SOEs		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Tlowc</i>	−0.0594*** (0.0202)		−0.0598*** (0.0202)	0.0577 (0.0371)		0.0562 (0.0343)
<i>Tctrade</i>		0.0873** (0.0371)	0.0736** (0.0349)		0.0706 (0.0462)	0.0143 (0.0529)
Control Variable First-order Term	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables Interaction and Quadratic Terms	Yes	Yes	Yes	Yes	Yes	Yes
Sample Size	4,842	4,842	4,842	1,929	1,929	1,929

TABLE 10 Estimation results of heterogeneity in technical attribute.

Variable	TFP					
	Labor-intensive		Technology-intensive		Capital-intensive	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Tlowc</i>	0.0620 (0.0399)	−0.0008 (0.0502)	−0.0406* (0.0217)	−0.0447* (0.0250)	−0.0673*** (0.0243)	−0.0451 (0.0276)
<i>Tctrade</i>	−0.1925*** (0.0704)	−0.1176** (0.0526)	0.1324*** (0.0464)	0.1688*** (0.0490)	0.0825** (0.0415)	0.0538 (0.0458)
Control Variable First-order Term	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables Interaction and Quadratic Terms	No	Yes	No	Yes	No	Yes
Sample Size	798	798	3,725	3,725	2,248	2,248

policy effects. Conversely, non-SOEs are more focused on profits and have weaker enforcement of environmental regulations, resulting in less significant policy effects.

6.2.2 Technical attributes

Based on 2012 CSRC industry classification, manufacturing is categorized into labor-intensive, technology-intensive, and capital-intensive sectors.

Columns (2), (4), and (6) of Table 10 report results controlling for interaction and quadratic terms. Only *Tlowc* in Column 4 is negatively significant, meaning the LCCP solely exerts a significant negative impact solely on technology-intensive manufacturing, while it has no significant impact on labor-intensive or capital-intensive manufacturing.

Columns (1) and (2) of Table 10 show that the *Tctrade*'s coefficient is significantly negative, suggesting that the CETP inhibits the TFP of labor-intensive manufacturing industries. Columns (3) and (4) reveal that the *Tctrade*'s coefficient is significantly positive, indicating that the CETP promotes the TFP of technology-intensive manufacturing industries. In contrast, column (6) shows that the *Tctrade*'s coefficient is insignificant, implying that the CETP has no significant promoting effect on the TFP of capital-intensive manufacturing industries. A plausible explanation for these findings is that labor-intensive manufacturing

relies heavily on labor rather than technology or equipment and exhibits relatively low profitability. Consequently, compared with capital-intensive and technology-intensive enterprises, labor-intensive manufacturing industries face greater difficulties in improving TFP through technological innovation.

7 Conclusions and policy recommendations

Carbon emissions have become a major challenge facing the globe (Wu et al., 2025), Carbon emission reduction is a core global issue related to humanity's sustainable development. Carbon regulations encompass diverse instruments such as command-driven and market-oriented mechanisms, among which carbon markets have been established and implemented in countries like the UK and the US, accumulating phased practical experience. This paper focuses on practical cases of China's low-carbon policies—specifically the command-driven LCCP and the market-oriented CETP. This study empirically examines their impact on the HQDM and the underlying mechanisms. The analysis is based on microdata of listed manufacturing firms spanning from 2003 to 2021, employing the double machine learning method, and reaches the following research findings.

1. The LCCP significantly inhibits the HQDM, whereas the CETP notably promotes it. Findings stay robust across robustness tests.
2. In regions where both policies are implemented simultaneously, they both enhance the HQDM, demonstrating a synergistic effect.
3. Further mechanism analysis reveals that the CETP can significantly boost technological innovation in listed manufacturing firms yet exerts no notable influence on resource allocation efficiency. Thus, the improvement in TFP of these manufacturing firms is primarily driven by the enhancement of technological innovation. In contrast, the LCCP has no significant influence on either technological innovation or resource allocation efficiency.
4. Heterogeneity tests shows that the regression results for the eastern and western regions, SOEs, and technology-intensive manufacturing are similar to the baseline results. However, the CETP significantly hinders HQDM in the central region and labor-intensive manufacturing. The LCCP has no significant effect on non-SOEs or capital-intensive manufacturing.

Drawing on China's practical experiences, this paper has arrived at the aforementioned research findings and puts forward the following policy recommendations—all in an effort to offer valuable insights for the selection and formulation of carbon emission reduction approaches globally, particularly among developing countries.

7.1 Strengthen the precision of command-driven policies to avoid a “one-size-fits-all” approach

The LCCP exert an overall inhibitory effect on the HQDM. This may be attributed to the strong administrative intervention imposed on the manufacturing industry during LCCP implementation—excessive intervention, to a certain extent, constrains the HQDM. Based on this, when formulating command-driven policies such as LCCP, it is necessary to prioritize the precision of policy objectives: fully take into account the development stages and actual capacity of different industries, formulate differentiated carbon reduction targets, and accompany them with targeted support measures. This will help avoid inappropriate inhibition on the development of the manufacturing industry caused by “one-size-fits-all” policy implementation.

7.2 Prioritize market-oriented environmental regulations as the core to establish a “government-guided, market-led” collaborative governance mechanism

The paper finds that, unlike LCCP, which significantly hinders HQDM, the CETP significantly promotes it. In regions with “dual carbon” policies, both command-driven and market-oriented regulations enhance HQDM, indicating a synergistic effect. It is important to focus on developing market-oriented environmental

regulations and improving related mechanisms to better enhance the synergy between the market and government in environmental governance.

The market-oriented environmental regulations, such as carbon emission trading and carbon tax, can be adopted as core tools, while command-driven environmental regulations serve only as supplementary means to address market failures. Some developing countries may first establish basic rules for low-carbon transition (e.g., setting industry-specific emission reduction targets) through command-driven environmental regulations, and then gradually introduce market mechanisms to avoid long-term reliance on administrative intervention. Additionally, In the process of carbon market development, efforts should be made to promote the legislation of the Carbon Market Management Regulations, while formulating rules for the registration, settlement and compliance of carbon allowances; a “Special Fund for Carbon Market Development” should be established to support the exploration and development of carbon market trading mechanisms.

7.3 Strengthen carbon market construction to activate resource allocation functions

Optimize the carbon market to facilitate efficient resource allocation. Mechanism analysis indicates that the market's allocative function remains underdeveloped, which may be attributed to insufficient market liquidity and inadequate trading activity in carbon quotas. Therefore, refining carbon market trading mechanisms and supporting systems, expand the market's coverage to include more industries and participants, and enhance a unified national carbon market. This will provide institutional support to stimulate carbon market trading and promote efficient resource flow.

It is recommended to promote the expansion of the carbon market in phases: the first phase incorporates high-emission industries such as power, steel, and cement; the second phase extends to moderate energy-consuming industries including chemicals and non-ferrous metals; the third phase gradually covers the entire manufacturing sector. Meanwhile, the participation threshold for small and medium-sized enterprises (SMEs) should be lowered to strengthen their capacity to integrate into the market. Additionally, support should be extended to the technological upgrading of carbon trading platforms, the development of real-time carbon emission monitoring systems for enterprises, and the establishment of a “Carbon Market Information Disclosure Platform”, while third-party institutions should be introduced to conduct data verification.

7.4 Implement differentiated carbon emissions trading policy based on enterprise attributes

Heterogeneity analysis indicates that command-driven LCCP generally inhibit the HQDM. In contrast, market-oriented CETP significantly promotes such development in state-owned enterprises (SOEs), technology-intensive, and capital-intensive manufacturers,

while notably inhibiting it in non-state-owned and labor-intensive manufacturing. Therefore, differentiated carbon quota standards should be considered for manufacturing enterprises with different attributes.

For instance, capital-intensive enterprises—characterized by low dependence on advanced technology and equipment and limited potential to achieve efficiency improvements through technological innovation—should be allocated more carbon quotas. Additionally, Supervision and regulation of non-state enterprises should be strengthened to enhance their proactive response to policies, and a “Hierarchical Management System for Carbon Compliance of Non-SOEs” should be established: For enterprises with delayed carbon compliance, their participation in government project bidding shall be restricted. Additionally, It shall build a low-carbon technology sharing platform and organize technical exchanges, so as to facilitate the green transition of small and medium-sized enterprises.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: The research data was sourced from the CSMAR database (<https://data.csmar.com/>) and the “China City Statistical Yearbook”.

Author contributions

CL: Conceptualization, Data curation, Investigation, Methodology, Software, Writing – original draft. KW: Funding acquisition, Project administration, Resources, Supervision, Validation, Writing – review and editing. HL: Formal Analysis, Project administration, Validation, Writing – review and editing.

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Conflict of interest

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