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Does Energy Quota Trading Alleviate Regional Carbon Distortion? Evidence from a Quasi-Natural Experiment in China

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Evidence from a quasi-natural experiment in China

Abstract

Global climate action increasingly requires balancing ambitious decarbonization with sustained economic growth, in which carbon distortion—the misallocation of carbon-emission capacity across economic activities—is a key manifestation of this tension. This study asks whether market-based energy governance can alleviate regional carbon distortion. We exploit the 2016 launch of China's Energy Quota Trading (EQT) pilot as a quasi-natural experiment and apply a difference-in-differences design to provincial panel data for 2010–2022. The EQT policy significantly reduces carbon distortion, and the effect strengthens over time and survives instrumental-variable, synthetic-DID, double/debiased machine learning (DDML), placebo, and alternative-sample robustness checks. Mechanism analyses show that green technological innovation and industrial upgrading are two transmission channels. The moderating-effect analysis shows that better transportation infrastructure, higher human capital, and greater informatization strengthen the distortion-mitigating effect of EQT. These findings indicate that market-based environmental governance can improve carbon allocation efficiency at relatively low economic cost, offering implications for improving market-based energy governance during the low-carbon transition.

Keywords: Energy quota trading; Carbon distortion; Resource misallocation; Green technological innovation; Industrial upgrading; China

1. Introduction

Global efforts to address climate change and advance toward carbon neutrality have become a defining part of the sustainable development agenda (IPCC, 2023). As the world's largest developing economy and a major carbon emitter, China has set the dual-carbon goals of peaking emissions by 2030 and achieving carbon neutrality by 2060 (Mallapaty, 2020), which together require decarbonizing without sacrificing sustained economic growth. From an economic perspective, there are generally two major levers for reconciling these objectives: advancing low-carbon technology and improving the allocation of scarce carbon-related resources (Du et al., 2023). Technological innovation, although essential for long-run decarbonization, requires substantial investment and lengthy adjustment processes. Reallocating emission capacity away from low-productivity, carbon-intensive activities toward more productive uses, by contrast, can deliver comparatively immediate and low-cost gains in both environmental and economic performance. The efficiency of such reallocation therefore shapes the economic cost of China's climate transition. Hence, there is an urgent need to give full play to the decisive role of market-based governance institutions in energy allocation.

Against this backdrop, carbon distortion has drawn growing attention. Carbon distortion refers to the inefficient allocation of carbon emission capacity across economic activities, whereby carbon-related resources deviate from their productivity-maximizing distribution due to market frictions, institutional constraints, and environmental externalities (Su & Chen, 2024). Because carbon emissions are

intrinsically linked to energy consumption and production activities, the environmental capacity associated with carbon emissions can be viewed as a scarce productive resource whose allocation influences aggregate productivity and economic efficiency (Chen, 2009; Shapiro & Walker, 2018; Rozenberg et al., 2020). Under efficient allocation, carbon-related resources should be allocated across economic activities such that their marginal products are equalized. In reality, however, the absence of effective price signals and institutional barriers to factor mobility often prevent this optimal allocation, causing scarce environmental capacity to remain concentrated in relatively low-productivity and carbon-intensive activities. Excessive carbon distortion not only increases the economic costs of emissions reduction but also weakens incentives for technological upgrading and structural transformation (Aghion et al., 2016). Alleviating carbon distortion has become an increasingly important pathway toward improving the allocation of carbon-related resources and achieving low-carbon development at lower economic cost (Tombe & Winter, 2015). Given that CO_2 emissions mainly originate from fossil fuel combustion, a market mechanism that adjusts the pricing and allocation of energy-use rights provides an institutional entry point for correcting such distortions.

Market-based environmental governance has long been regarded as an effective means of correcting resource misallocation and internalizing environmental externalities (Goulder & Parry, 2008; Narassimhan et al., 2018). Among various market-based instruments, EQT operates directly at the upstream stage of energy allocation, rather than imposing end-of-pipe regulations after emissions occur, thus

providing a distinctive advantage in addressing the root cause. In July 2016, the Energy Quota Trading (EQT) pilot program was initiated by China in the provinces of Zhejiang, Fujian, Henan and Sichuan. By creating a market for tradable energy consumption quotas under an overall energy consumption constraint, the EQT policy introduces price signals into the allocation of energy resources and provides economic incentives for firms to optimize energy use (Zheng et al., 2024). Different from regulatory mandates, market-based tools offer greater flexibility and allow market participants to adjust production and investment decisions according to relative prices (Fowlie et al., 2012). Through the trading of energy quotas, enterprises can either improve energy efficiency and reduce energy consumption or acquire additional quotas through the market, thereby achieving compliance at a lower cost (Shi et al., 2020). Given that fossil energy use directly affects carbon emissions, EQT may generate low-carbon effects at lower cost, particularly when coordinated with complementary market-based instruments such as the carbon emissions trading system (Pan & Dong, 2023). By changing the price and opportunity cost of energy-use rights, EQT may reshape the distribution of carbon-emission capacity across economic activities and thereby alleviate carbon distortion.

Existing studies on EQT suggest that market-based energy governance can improve energy efficiency and facilitate low-carbon transitions (Zhou et al., 2024; Cheng et al., 2025). However, whether these policy benefits further extend to the allocation efficiency of carbon-related resources remains insufficiently examined. This gap limits a comprehensive understanding of the effects of EQT, particularly

whether its benefits go beyond emission reduction and energy-efficiency improvement to include a more efficient allocation of limited carbon-emission capacity. Meanwhile, traditional studies on resource misallocation have primarily employed production-function approaches to examine distortions in conventional inputs such as capital, labor, and energy, together with the associated efficiency losses (Hsieh & Klenow, 2009; Midrigan & Xu, 2014; Lin & Du, 2015). Yet the carbon emissions accompanying production activities—and the scarce environmental capacity they embody—have rarely been incorporated into the factor-allocation framework. As a result, the allocation efficiency of carbon-related environmental resources and its economic consequences remain insufficiently understood.

In recent years, the emerging literature on carbon distortion has begun to address this issue at both the firm and regional levels. At the firm level, studies have measured carbon misallocation and its associated output losses, but limited micro-level data availability has largely confined the sample period to 2008–2012 (Yang et al., 2023). At the provincial level, studies have further examined regional carbon distortion and its policy determinants, but have mainly focused on instruments that directly price emissions at the output stage, particularly emissions trading systems (Su & Chen, 2024). By contrast, EQT operates through the pricing and reallocation of energy-use rights at the input stage (Che & Wang, 2022). It therefore remains unclear whether the findings from carbon-pricing policies can be extended to EQT and whether an upstream energy-market reform can improve the allocation efficiency of carbon-related resources.

To address this question, we exploit the 2016 provincial rollout of the EQT pilot as a quasi-natural experiment and apply a TWFE-DID model to panel data for 30 Chinese provinces from 2010 to 2022. To reinforce causal identification, we supplement the baseline with an IV approach using historical atmospheric ventilation conditions and the SDID estimator of Arkhangelsky et al. (2021). We further employ double/debiased machine learning (DDML), together with a comprehensive set of robustness checks, to assess the stability of the baseline estimates. We also investigate whether green technological innovation and industrial upgrading act as transmission channels, and examine whether transportation infrastructure, human capital, and informatization moderate the effect of EQT on regional carbon distortion.

Our results indicate that the EQT policy significantly mitigates regional carbon distortion, reducing the carbon distortion index by 0.0029 points. The IV estimates support this finding, while the SDID results yield a similar effect under an alternative construction of the counterfactual group. The DDML estimates remain negative and statistically significant across alternative learners and cross-fitting folds. We also find that green technological innovation and industrial upgrading serve as two important transmission channels. The moderating-effect analysis further shows that favorable complementary regional conditions strengthen the distortion-mitigating effect of EQT. These findings highlight the importance of regional conditions in translating market-based policy incentives into improvements in resource allocation.

Accordingly, this study offers three primary contributions to the existing literature. First, it broadens the evaluation of China's EQT policy from conventional

environmental and productivity outcomes (Wang et al., 2024) to the allocative efficiency of carbon-related resources. By using carbon distortion as the outcome variable, the study introduces an allocative-efficiency perspective into the assessment of energy-use rights trading, allowing its policy consequences to be evaluated not only in terms of emission reduction or productivity improvement, but also in terms of how efficiently limited carbon-emission capacity is distributed across economic activities.

Second, this study extends the emerging literature on carbon misallocation and carbon distortion by broadening the policy settings through which carbon-resource allocation is examined. Yang et al. (2023) incorporate carbon emissions into the resource-misallocation framework and show that distortions in carbon shadow prices generate substantial output losses at the firm level. Their estimates indicate that eliminating such distortions could produce sizeable output gains, highlighting the economic importance of improving carbon allocation efficiency. Su and Chen (2024) subsequently examine carbon distortion at the regional level and provide evidence that emissions trading can mitigate such distortions. Building on this literature, our study shifts attention from output-side carbon-market regulation to input-side market-oriented allocation of energy-use rights. By examining the impact of EQT on regional carbon distortion, this study explores how regional carbon distortion responds to market-based energy reform, thereby enriching the empirical literature on policy determinants of carbon-resource allocation and providing further support for applying the carbon-distortion framework to environmental policy evaluation.

Third, this study provides further evidence on the transmission channels through which EQT affects the allocation efficiency of carbon-related resources. Drawing on the perspectives of technological change and structural transformation (Hu et al., 2020; Guo & Hu, 2024; Yang et al., 2024), the study examines whether EQT promotes green technological innovation and industrial upgrading. The empirical results show that EQT significantly promotes both. Combined with the theoretical links between technological progress, industrial upgrading, and carbon-resource allocation, these findings enrich the understanding of the mechanisms underlying the allocative effects of EQT and add mechanism-based evidence on how market-based energy governance affects the allocation efficiency of carbon-related resources.

This paper is structured in five sections. Following this introduction, Section 2 discusses the institutional context and derives the testable hypotheses. The empirical strategy and data sources are detailed in Section 3, while Section 4 delivers the estimation results and their interpretation. Finally, Section 5 summarizes and discusses the findings, presents policy implications, and outlines limitations and directions for future research.

2. Policy background and hypothesis development

2.1 Institutional background of the EQT policy

On July 28, 2016, the National Development and Reform Commission (NDRC) issued the pilot scheme for the paid use and trading of energy consumption rights, designating Zhejiang, Fujian, Henan, and Sichuan as pilot provinces. The program combines aggregate energy-consumption controls with market-based trading

arrangements to limit total energy use while improving the allocation of energy resources. Under the nationally prescribed cap, local governments allocate initial energy-use quotas to covered enterprises. Quotas within the permitted limit are generally allocated free of charge, whereas excess energy use entails additional compliance costs and unused quotas can be traded in the market. Supported by reporting, auditing, and verification arrangements, the scheme turns energy-use rights into tradable economic assets and introduces market-based price signals into energy allocation.

This institutional design changes firms' incentives by attaching an explicit opportunity cost to energy use, thereby encouraging enterprises to adjust production decisions in response to resource scarcity. Given the close relationship between fossil-energy consumption and carbon emissions, the market-oriented allocation of energy-use rights may also affect the distribution of carbon-emission capacity across economic activities (Pan & Dong, 2022). The EQT pilot therefore provides a quasi-natural experimental setting for examining whether market-oriented energy reform can alleviate regional carbon distortion.

2.2 Hypothesis development

The hypotheses developed below draw on three complementary theoretical perspectives. Property rights theory and the Coase theorem explain how clearly defined and tradable energy-use rights can facilitate the reallocation of scarce resources through market exchange (Coase, 1960). The Porter Hypothesis provides a theoretical basis for the green technological innovation channel by emphasizing that

well-designed environmental regulation can stimulate innovation and improve resource-use efficiency (Porter & van der Linde, 1995). Structural transformation theory, in turn, explains how changes in relative production costs and sectoral returns can induce the movement of productive factors across sectors and reshape the composition of economic activity (Herrendorf et al., 2014). Together, these perspectives provide the theoretical foundations for the direct allocative effect, the green technological innovation channel, and the industrial upgrading channel examined below.

2.2.1 The alleviating effect of the EQT policy on carbon distortion

Carbon distortion refers to a situation in which carbon-related resources are not allocated according to their marginal productivity. This inefficiency is often driven by environmental externalities, administrative protection, and factor-market frictions, which cause the marginal productivity of carbon-related resources to deviate from their implicit economic cost (Hsieh & Klenow, 2009). As a result, carbon-emission capacity remains concentrated in relatively inefficient sectors or firms, preventing carbon-related resources from flowing toward their most productive uses and generating inefficient allocation across economic activities (Tombe & Winter, 2015).

The EQT policy may alleviate such distortions by introducing market-based price signals into the allocation of energy-use rights. According to property rights theory and the Coase theorem, clearly defined and tradable property rights allow market participants to reallocate scarce resources through voluntary exchange, thereby improving allocative efficiency (Coase, 1960). By assigning an explicit economic

value to energy-use rights, the EQT policy converts previously underpriced environmental resources into scarce production factors. Enterprises with relatively high energy efficiency can obtain additional revenue by selling surplus quotas, whereas inefficient energy users must incur higher compliance costs by purchasing additional quotas (Zhou et al., 2024; Shi et al., 2020). These incentives encourage carbon-intensive and low-productivity producers to reduce inefficient energy use while allowing resources to move toward firms capable of generating greater economic output with lower energy consumption.

As quota trading develops, differences in marginal energy-saving or compliance costs across firms may gradually narrow, thereby promoting the reallocation of carbon-related resources toward more productive economic activities. This process improves the alignment between the allocation of carbon-related resources and their marginal productivity, bringing the observed allocation closer to the efficient benchmark and thereby alleviating regional carbon distortion. Therefore, we hypothesize that:

Hypothesis 1. The EQT policy alleviates regional carbon distortion.

2.2.2 Green technological innovation channel

Beyond the direct reallocation of production factors, the EQT policy may also improve carbon allocation efficiency through technological change. According to the Porter Hypothesis, properly designed environmental regulation can stimulate innovation that improves resource efficiency and partly offsets compliance costs (Porter & van der Linde, 1995). By internalizing environmental externalities,

market-based instruments provide continuous incentives for firms to reduce resource consumption and adopt cleaner production practices (Jaffe et al., 2002).

Within the EQT system, the market price of energy-use quotas converts environmental constraints into explicit economic costs, strengthening incentives for energy-intensive enterprises to engage in green R&D in order to maintain profitability (Acemoglu et al., 2012; Calel & Dechezleprêtre, 2016). This induced innovation effect can improve carbon allocation efficiency through two technological pathways. First, green innovation improves internal production efficiency by shifting the production frontier outward. By adopting energy-saving technologies, firms can generate higher economic value-added per unit of energy consumed, thereby improving the productivity of carbon-related resources (Hassler et al., 2021). Second, green innovation generates knowledge spillovers through the diffusion of cleaner technologies. As pioneering firms develop and apply cleaner technologies under quota constraints, these technologies gradually diffuse across the industry (Bloom et al., 2013), narrowing technological gaps among enterprises and promoting the convergence of marginal abatement costs (Bartelsman et al., 2013).

At the aggregate level, green technological innovation reduces technological disparities across firms and improves the efficiency with which carbon-related resources are utilized. As a result, the observed allocation of carbon-related resources moves closer to its efficient benchmark, thereby alleviating regional carbon distortion. Based on this, we hypothesize that:

Hypothesis 2. Promoting green technological innovation is a channel through which

the EQT policy alleviates carbon distortion.

2.2.3 Industrial upgrading channel

The EQT policy may also alleviate carbon distortion through industrial upgrading. Structural transformation theory suggests that changes in relative production costs and sectoral returns can reshape the composition of economic activity by inducing productive factors to move across sectors (Herrendorf et al., 2014). Because energy-intensive industries consume more energy and rely more heavily on carbon-intensive production technologies, they are more exposed to the cost imposed by energy-use quotas (Martin et al., 2014; Shapiro & Walker, 2018). EQT therefore places greater adjustment pressure on energy-intensive activities, reducing their relative profitability and encouraging capital, labor, and other productive factors to shift toward sectors with lower energy dependence and higher value added. Through this sectoral reallocation, EQT can facilitate industrial upgrading, consistent with evidence that low-carbon policy can promote industrial restructuring by reducing the share of high-carbon industries (Zheng et al., 2021).

Industrial upgrading can, in turn, alleviate carbon distortion by changing where existing carbon-emission capacity is used. Under a distorted industrial structure, a disproportionate share of carbon-related resources may remain tied to low-productivity and energy-intensive sectors. Structural transformation does not necessarily require an increase in aggregate factor endowments or available carbon-emission capacity; rather, allocative efficiency can improve when existing productive factors and the associated carbon-emission capacity move toward sectors

in which they generate greater economic value (Du et al., 2021). As higher-productivity sectors expand and inefficient energy-intensive sectors contract, the mismatch between the sectoral distribution of carbon-emission capacity and its productive use is reduced. Related evidence shows that structural transformation in manufacturing can reduce carbon emissions by shifting economic activity away from resource-intensive production (Li et al., 2019). This reallocation process can therefore contribute to alleviating regional carbon distortion. Accordingly, we propose:

Hypothesis 3. Industrial upgrading serves as an additional pathway through which the EQT policy alleviates carbon distortion.

3. Empirical strategy and data

3.1 Measurement of carbon distortion

According to neoclassical allocation theory, resource allocation is efficient when the value of a factor's marginal product equals its corresponding factor price. Any deviation between the two implies that resources are not allocated to their most productive uses, resulting in allocative inefficiency and factor distortion. Following the factor misallocation measurement approach of Hsieh and Klenow (2009) and recent studies on carbon distortion (Yang et al., 2023), this study measures regional carbon distortion by comparing the marginal product of carbon emissions with its implicit factor price.

To estimate the marginal product of carbon emissions, carbon emissions are incorporated into an extended Cobb–Douglas production function as an additional production factor alongside capital and labor. Although carbon emissions are

commonly viewed as an undesirable by-product of economic activities, they are intrinsically linked to energy consumption and industrial production under existing technological conditions. Consequently, carbon emissions can be interpreted as a necessary input accompanying economic output and can therefore be incorporated into the production framework. This treatment is consistent with previous studies (e.g., Chen, 2009; Shapiro & Walker, 2018; Rozenberg et al., 2020). The production function is specified as follows:

$$Y_{it}=A_{it}K_{it}^{\alpha}L_{it}^{\beta}C_{it}^{\gamma} \tag{1}$$

where Y_{it} denotes real output of province i in year t; A_{it} represents total factor productivity; K_{it}, L_{it}, and C_{it} denote capital input, labor input, and carbon emissions, respectively; and α, β, and γ are the corresponding output elasticities. Taking logarithms yields:

$$\ln Y_{it}=\ln A_{it}+\alpha\ln K_{it}+\beta\ln L_{it}+\gamma\ln C_{it} \tag{2}$$

Equation (2) is estimated using a panel fixed-effects framework that controls for both province-specific and year-specific heterogeneity. Based on the estimated carbon output elasticity $\hat{\gamma}$, the marginal product of carbon emissions is calculated as:

$$MPC_{it}=\hat{\gamma}\frac{Y_{it}}{C_{it}} \tag{3}$$

The estimated (MPC_{it}) reflects the additional economic output generated by one additional unit of carbon emissions and therefore captures the productive value of carbon-related resources under prevailing production technologies. The carbon distortion index is then constructed by comparing the estimated marginal product of carbon emissions with its implicit factor price. Specifically:

$$DI_{it}=\left|1-\frac{MPC_{it}}{P_{it}^{C}}\right| \tag{4}$$

where (P_{it}^{C}) denotes the proxy for the implicit factor price of carbon emissions. Because directly observed carbon prices are unavailable at the provincial level for most of the sample period, following Su and Chen (2024), we use the natural logarithm of annual provincial budgetary expenditure on environmental protection as a proxy for the implicit factor price of carbon emissions. The rationale is that the implicit price of carbon reflects the economic costs associated with carbon constraints and emission-reduction activities, while environmental protection expenditure captures, to some extent, the economic resources devoted to these activities. In particular, such budgetary expenditure is closely related to carbon-reduction projects and provides financial support for the establishment and operation of carbon markets, the development of carbon-reduction technologies, and other low-carbon transition initiatives. These activities contribute to reducing carbon emissions and promoting low-carbon development. Accordingly, provincial environmental protection expenditure provides an observable proxy for the economic cost associated with carbon emissions and is used to approximate the implicit factor price of carbon.

Since the purpose of this study is to assess the magnitude of carbon misallocation rather than distinguish between the overpricing and underpricing of carbon-related resources, the carbon distortion index is defined as the absolute proportional deviation between (MPC_{it}) and (P_{it}^{C}). A larger value of (DI_{it}) therefore represents a greater departure from the efficient allocation benchmark and a higher degree of regional carbon distortion. For estimation of the extended production function, real output is

measured by real gross regional product (GRP); capital input is constructed using the perpetual inventory method (Wang & Szirmai, 2012); labor input is proxied by the number of employed persons; and carbon input is measured by total provincial carbon dioxide emissions. Detailed variable definitions are reported in Table 1.

[Insert Table 1 about here].

3.2 Baseline TWFE-DID model specification

We evaluate the effect of EQT on regional carbon distortion using the 2016 pilot rollout as the policy shock within a two-way fixed effects difference-in-differences framework. The baseline model is specified as follows:

$$DI_{it}=\alpha+\beta EQT_{it}+\gamma Control_Var_{it}+ProvinceFE+YearFE+\varepsilon_{it} \quad (5)$$

In the model, the variable DI_{it} denotes the carbon distortion index of province i in period t, while EQT_{it} is the treatment indicator for the EQT pilot. The pilot was launched across four provinces—Sichuan, Zhejiang, Henan, and Fujian—in 2016, with the remaining provinces serving as the comparison group. Accordingly, EQT_{it} equals 1 for the four pilot provinces in 2016 and subsequent years, and 0 otherwise.

The estimate of primary interest, β, quantifies the causal effect of the EQT initiative on carbon distortion. Should this estimate be negative and statistically distinguishable from zero, it would indicate that the policy curbs carbon distortion and improves the efficiency of carbon resource allocation. ProvinceFE and YearFE are included to absorb fixed provincial attributes and temporal shocks common to all jurisdictions. Standard errors are clustered at the provincial level to account for within-province correlation and heteroscedasticity.

Following closely related studies on EQT and carbon distortion (Du et al., 2023; Su & Chen, 2024; Cheng et al., 2025), we control for a set of regional characteristics that may affect carbon-resource allocation. Economic development captures differences in productivity, technology, and production patterns that may influence the productive use of carbon-related resources. Government intervention may affect resource allocation through fiscal and administrative channels, while trade openness can reshape regional production and factor allocation through market competition and technology diffusion. Energy structure reflects regional dependence on carbon-intensive energy sources and therefore directly influences the relationship between energy use and carbon emissions. Urbanization and population density further capture differences in energy demand, economic agglomeration, and the spatial concentration of production activities. Detailed definitions and measurements of these variables are reported in Table 2.

[Insert Table 2 about here].

3.3 Data sources and descriptive statistics

The study uses a balanced panel of 30 Chinese provinces from 2010 to 2022, excluding Taiwan, Macao, Hong Kong, and Tibet because of data availability. The variables used to measure carbon distortion and construct the set of controls are compiled from the China Statistical Yearbook, China Energy Statistical Yearbook, China Statistical Yearbook on Environment, and provincial statistical yearbooks. A small number of missing values are filled by linear interpolation. Descriptive statistics for the main variables used in the empirical analysis are reported in Table 3.

[Insert Table 3 about here].

4. Empirical results

4.1 Baseline estimates

Table 4 presents the benchmark estimation results. Across the four model specifications, the EQT coefficient is negative and statistically significant in every case. In the preferred specification reported in Column (4), the coefficient is −0.0029 and significant at the 1% level, providing evidence that EQT reduces regional carbon distortion. Relative to the sample mean, this estimate corresponds to a reduction of about 0.29%, implying that EQT improves the matching between carbon-related resource use and regional productivity. This finding is also consistent with the property-rights and Coasean mechanism discussed in Section 2.2.1: by assigning an explicit economic value to energy-use rights, EQT strengthens price signals, increases the cost of inefficient energy use, and encourages resources to shift toward more productive activities. Taken together, the baseline estimates provide support for Hypothesis 1.

[Insert Table 4 about here].

4.2 Parallel trends and dynamic effects

The DID design relies on the assumption that treated and untreated provinces would have followed comparable trends in carbon distortion before the policy. We examine this condition and the evolution of the treatment effect using the following event-study specification (Beck et al., 2010):

$$DI_{it}=\alpha+\sum_{T=-6,T\neq-1}^{6}\rho_T EQT_{it}^{T}+\gamma Control_Var_{it}+ProvinceFE+YearFE+\varepsilon_{it} \quad (6)$$

where T measures the number of years relative to the introduction of EQT. The year immediately before implementation (T = −1) is omitted as the reference period. The event-time indicators equal one when province i is observed in relative year T, and zero otherwise, while the corresponding coefficients capture the treatment effect at each event time. The remaining controls and fixed effects are identical to those in the baseline model.

Fig. 1 reports the event-study estimates. Before the policy, the coefficients remain close to zero and show no systematic upward or downward pattern, providing support for the parallel-trends assumption. After implementation, the coefficient becomes significantly negative at T = 0 and continues to decline over the subsequent six years. This pattern suggests that the distortion-reducing effect of EQT appears immediately after implementation and strengthens gradually over time.

[Insert Fig. 1 about here].

4.3 Additional identification strategies

Although the baseline DID estimates indicate that EQT reduces regional carbon distortion, two concerns remain. Pilot assignment may be correlated with unobserved time-varying provincial factors, and the small number of treated provinces may make the results sensitive to the choice of control group. We therefore use an instrumental variable approach to address policy endogeneity and the synthetic difference-in-differences (SDID) estimator to construct an alternative counterfactual.

4.3.1 Instrumental variable approach

To mitigate concerns about potential endogeneity arising from non-random pilot assignment and omitted time-varying factors, we employ a two-stage least squares (2SLS) approach. Using historical atmospheric ventilation conditions as an instrument, this section examines whether the distortion-mitigating effect of EQT remains robust after accounting for potential endogeneity in policy assignment.

Following Hering and Poncet (2014), we construct the instrument using historical atmospheric ventilation conditions. The historical ventilation measure is defined as the natural logarithm of the average air circulation coefficient over 1980–2000, where the air circulation coefficient is based on 10-m wind speed and boundary-layer height from ECMWF data. Because this historical measure is time invariant and would be absorbed by province fixed effects, it is interacted with a linear time trend to generate within-province variation.

The economic reasoning is as follows. On the one hand, poorer historical ventilation limits pollutant dispersion and may increase local environmental-governance pressure as environmental constraints become more stringent over time. Provinces with poorer historical ventilation conditions may therefore be more likely to adopt market-based energy regulation, supporting the relevance of the instrument. On the other hand, the historical ventilation measure predates both the estimation period and the introduction of EQT and mainly reflects persistent geographical and meteorological conditions. It is therefore unlikely to be affected by contemporaneous carbon distortion or subsequent EQT implementation. The identification further assumes that, conditional on the control variables and

province and year fixed effects, the interaction between historical ventilation conditions and the time trend affects regional carbon distortion only through its influence on EQT adoption.

Table 5 reports the 2SLS results. The first-stage coefficient is negative and statistically significant, indicating that provinces with poorer historical ventilation conditions are more likely to implement EQT as the time trend progresses. In the second stage, the coefficient on EQT remains significantly negative, suggesting that its distortion-mitigating effect persists after accounting for potential endogeneity in pilot assignment.

[Insert Table 5 about here].

4.3.2 Synthetic difference-in-differences estimation

Because only four provinces were selected as EQT pilots, the TWFE-DID estimate may be sensitive to the composition of the control group. An equally weighted control group may provide an inaccurate counterfactual if untreated provinces differ from the pilot provinces in their pre-policy carbon-distortion trends. We therefore apply the SDID estimator developed by Arkhangelsky et al. (2021), which combines the conventional DID framework with the synthetic control method (Abadie et al., 2010) by jointly estimating unit and time weights. This procedure improves pre-treatment balance and constructs a control group that more closely matches the treated provinces before the policy. The estimated average treatment effect on the treated is −0.0026, close to the baseline TWFE-DID estimate. Fig. 2 also shows a good pre-treatment fit and a clear post-policy divergence between the treated

and synthetic control groups.

[Insert Fig. 2 about here].

4.4 Robustness checks

4.4.1 Spatial placebo test

Although the model includes province and year fixed effects and a set of observable controls, omitted regional characteristics may still influence the estimated treatment effect. The DID coefficient can be written as:

$$\hat{\beta}=\beta_{true}+\gamma\frac{cov(EQT_{it},\mu_{it}|\chi)}{var(EQT_{it}|\chi)} \tag{7}$$

where β_{true} denotes the true effect of the policy, while the second component reflects possible bias associated with unobserved factors μ_{it}. We therefore implement a spatial placebo exercise. Given 30 provinces and four treated units, we conduct an exhaustive spatial permutation test by considering all $\binom{30}{4} = 27{,}405$ possible treatment assignments. The baseline DID specification is re-estimated for each assignment, producing 27,405 placebo coefficients, $\hat{\beta}_j$, j=1,...,27,405. Fig. 3 summarizes their distribution and associated p-values. Most placebo estimates are centered close to zero and fail to reach statistical significance at the 5% level. In comparison, the actual estimate of −0.0029 is located in the left tail of the distribution. The exact permutation p-values are 0.0249 for the one-sided test and 0.0348 for the two-sided test. These findings support the robustness of the baseline result to alternative spatial treatment assignments.

[Insert Fig. 3 about here].

4.4.2 Changing the timing of policy intervention

We further conduct a timing placebo test to check whether the baseline estimate captures pre-existing trend differences or anticipatory responses rather than the actual effect of EQT. Specifically, we assign a pseudo-treatment year of 2013, three years before the formal policy implementation, and re-estimate the baseline DID specification. The year 2013 is chosen because it lies sufficiently before the 2016 policy launch to avoid potential anticipation effects, while still retaining adequate pre- and post-period observations within the 2010–2022 sample window. As shown in Column (1) of Table 6, the estimated coefficient is statistically insignificant, suggesting that the baseline result is unlikely to be driven by unobserved time-varying factors.

4.4.3 Propensity score matching

The selection of EQT pilot provinces may reflect pre-existing regional characteristics, which could reduce comparability between treated and untreated provinces. To improve balance on observable characteristics before policy implementation, we combine propensity score matching with the DID framework. Following Rosenbaum and Rubin (1983), propensity scores are obtained from a logit model using the pre-policy averages of the baseline covariates, including lnPGDP, Gov, Opening, lnEnergy_Str, Urban, and lnDensity. Each pilot province is then matched with three non-pilot provinces using nearest-neighbor matching.

Table 6, Column (2), presents the matched-sample estimate. The EQT coefficient continues to be negative and statistically significant at the 1% level, implying that the baseline finding is maintained once the treated and control groups are made more

comparable on observable characteristics.

[Insert Table 6 about here].

4.4.4 Controlling for other policies

The 2010–2022 sample period overlaps with several environmental policy initiatives that may also affect regional carbon distortion. To distinguish the effect of EQT from these concurrent interventions, we extend the baseline TWFE model by separately introducing controls for three major policies.

The first is the carbon emissions trading system (CETS), which was approved in 2011 and gradually entered operation from 2013 onward. Because CETS directly regulates carbon emissions through a market mechanism, it may influence outcomes that are also related to EQT. The second is pollution-rights trading (PTS), which was expanded during the Eleventh Five-Year Plan period and mainly regulates pollutants such as sulfur dioxide and chemical oxygen demand. Since these pollutants are often jointly generated with carbon emissions through fossil-fuel combustion, PTS may also alter carbon-related production and allocation decisions. The third is the national ecological civilization pilot (NECP), launched in 2016 as a broader environmental-governance initiative that may affect industrial structure and resource allocation.

Each policy indicator is added separately to the baseline specification. Columns (1)–(3) of Table 7 show that the coefficient on EQT remains negative and statistically significant at the 1% level in all three cases. The estimated EQT effect is therefore preserved after accounting for these overlapping environmental policies.

[Insert Table 7 about here].

4.4.5 Alternative samples and specifications

To gauge whether our core finding is driven by sample composition, outlier treatment, or the inclusion of COVID-19 years, we run several robustness checks. Estimates in Table 8 show that the EQT coefficient continues to be negative and statistically significant in every test. First, we drop Beijing, Chongqing, Tianjin, and Shanghai, as their administrative rank and economic size are considerably different from those of regular provinces. Second, each continuous variable is winsorized at the 1% level to mitigate the impact of extreme values and possible measurement error. Third, we restrict the estimation window to 2010–2019, so observations influenced by the COVID-19 shock are omitted. The negative EQT effect survives all these specifications, indicating that the main result is robust to these alternative sample treatments.

[Insert Table 8 about here].

4.4.6 Alternative learners and cross-fitting folds

To lessen reliance on any single parametric form, we further apply the double/debiased machine learning (DDML) framework proposed by Chernozhukov et al. (2018). We first partial out province and year fixed effects, and then fit a partially linear DDML model with standard errors clustered by province. The baseline specification combines random forests with five-fold cross-fitting. Robustness checks are conducted by varying the number of folds (three and ten) and by using Lasso in place of the random-forest learner.

The estimates are summarized in Table 9. Under the benchmark specification, the DDML coefficient is −0.0029 and significant at the 5% level, closely matching the TWFE-DID estimate. Using three- and ten-fold cross-fitting produces coefficients of −0.0022 and −0.0025, respectively, showing little sensitivity to the fold structure. The Lasso specification generates a larger estimate in absolute magnitude (−0.0066), which is also significant at the 5% level. The larger Lasso estimate may arise from its linear and sparsity restrictions, in contrast to the greater flexibility of random forests in approximating nonlinear relationships. Importantly, all specifications yield a negative and statistically significant EQT coefficient. Taken together, these results suggest that the estimated effect is not driven by the choice of learner or cross-fitting configuration.

[Insert Table 9 about here].

4.5 Mechanism analysis

The effects of EQT are not confined to the direct exchange of energy-use quotas. By assigning an explicit market value to energy-use rights, EQT reshapes the incentives and constraints facing firms and may, in turn, induce technological adjustment at the firm level and structural transformation at the regional level. Building on the hypotheses developed in Section 2.2 and following the two-step mechanism analysis proposed by Jiang (2022), we first examine whether EQT significantly affects green technological innovation and industrial upgrading. We then draw on established theory and existing evidence to explain how these changes may improve the efficiency with which carbon-related resources are used and allocated.

4.5.1 Green technological innovation

Green technological innovation (GTI) is proxied by green patent applications, following Du et al. (2023). To account for differences in regional population size, GTI is defined as the natural logarithm of green patent applications per 10,000 residents. Table 10, Column (1), reports a positive EQT coefficient significant at the 1% level, providing evidence of increased regional green innovation following the policy. This finding is consistent with the Porter Hypothesis discussed in Section 2.2.2. Once energy-use rights acquire an explicit market value, inefficient energy use becomes more costly, strengthening firms' incentives to improve production processes and develop energy-saving and cleaner technologies.

Green technological innovation can alleviate carbon distortion by improving the productivity with which energy and carbon-related resources are used within firms. Hassler et al. (2021) show that input-saving technological change can improve the efficiency with which scarce natural resources are utilized. More directly, Li et al. (2025) find that green technological innovation significantly enhances carbon productivity and that improvements in factor allocation constitute an important channel through which this effect occurs. From an allocation perspective, the efficiency of carbon-related resources depends not only on the quantity of resources employed, but also on the productive returns generated from those resources. Bartelsman et al. (2013) further show that differences in resource allocation across heterogeneous producers have important implications for aggregate productivity.

The increase in GTI induced by EQT therefore has implications beyond environmental performance alone. By enabling firms to generate greater economic output from a given level of energy use and associated carbon emissions, technological progress raises the productivity of carbon-related resources and reduces the efficiency losses associated with their inefficient use. The significant positive effect of EQT on GTI, together with the theoretical and empirical evidence linking green innovation to carbon productivity and resource-use efficiency, therefore provides support for the green technological innovation channel proposed in Hypothesis 2.

4.5.2 Industrial upgrading

Following Cheng et al. (2025), we proxy industrial upgrading by the log ratio of tertiary- to secondary-industry value added. The positive and statistically significant EQT coefficient in Column (2) of Table 10 indicates that the policy is associated with greater industrial structure advancement. This result is consistent with the structural transformation argument developed in Section 2.2.3. By increasing the relative cost of energy-intensive production, EQT changes sectoral returns and creates incentives for capital, labor, energy, and other productive factors to move across sectors.

The contribution of industrial upgrading to carbon allocation efficiency arises mainly from this process of intersectoral resource reallocation. Structural transformation is characterized by the movement of economic activity and productive factors across sectors as relative productivity and returns change (Herrendorf et al., 2014). In the context of energy allocation, Du et al. (2023) show that EQT improves

carbon emission efficiency partly by alleviating energy misallocation, indicating that the market-based reallocation of energy factors is an important channel through which EQT improves resource-use efficiency. Related evidence also shows that the rationalization and upgrading of manufacturing structure can help reduce carbon emissions (Li et al., 2019), while industrial upgrading can affect carbon outcomes through improvements in green total factor productivity (Yang et al., 2022).

For the present study, the implication is that industrial upgrading changes not only the composition of regional output, but also the sectoral distribution of energy use and the carbon-emission capacity associated with production. As productive factors move from relatively energy-intensive and low-productivity activities toward sectors capable of generating greater economic value, the excessive concentration of carbon-related resources in inefficient uses can be reduced. The significant positive effect of EQT on ISA, together with evidence on structural transformation, energy-factor reallocation, and productivity improvement, therefore provides support for the industrial upgrading channel proposed in Hypothesis 3.

[Insert Table 10 about here].

4.6 Moderating effect analysis

The effectiveness of EQT in improving resource allocation depends not only on the establishment of a market mechanism, but also on supportive regional conditions that allow market signals to be translated into actual production adjustments. Whether firms can reallocate energy-use rights depends on their ability to move production factors, process market information, and coordinate transactions efficiently. To

examine the role of these underlying conditions, we consider the moderating effects of transportation infrastructure, human capital, and informatization using the following specification:

$$DI_{it} = \alpha + \beta_1 EQT_{it} + \beta_2 Moderator_{it} + \beta_3 (EQT_{it} \times Moderator_{it}) + \gamma Control_Var_{it} + ProvinceFE + YearFE + \varepsilon_{it} \quad (8)$$

To reduce potential simultaneity, the moderating variables are lagged by one period and then mean-centered before constructing the interaction terms. For notational simplicity, $Moderator_{it}$ in Eq. (8) denotes the lagged and mean-centered measure of transportation infrastructure, human capital, or informatization. Transportation infrastructure (RoadInfra) is proxied by the natural logarithm of highway mileage. Human capital (HumanCapital) is measured by the ratio of students enrolled in higher-education institutions to total population, while informatization (Informatization) is measured by the ratio of postal and telecommunication business volume to regional GDP. Control_Var contains the same set of control variables as in the baseline regression. The coefficient β_3 captures the moderating effect of these regional conditions on the relationship between EQT and carbon distortion. Since a lower value of DI indicates less carbon distortion, a negative β_3 implies that a higher level of the corresponding regional condition strengthens the distortion-mitigating effect of EQT. The corresponding regression results are reported in Table 11.

4.6.1 Transportation infrastructure

The interaction between EQT and transportation infrastructure is significantly negative. Transportation networks provide the physical basis for factor reallocation. When transportation conditions are weak, high spatial frictions constrain the

movement of production factors and make it more difficult for firms to reorganize input sourcing or relocate production activities in response to changes in energy costs. Better transportation infrastructure relaxes these constraints. By lowering logistics costs and improving factor mobility, it facilitates the allocation of energy-use rights toward more productive uses by allowing them to be combined more efficiently with complementary inputs. As a result, the price signals generated by EQT are more likely to translate into actual adjustments in production and resource allocation, rather than being offset by rigidities in local factor markets.

4.6.2 Human capital

The interaction between EQT and human capital is also significantly negative, highlighting the role of cognitive and managerial capacity in the adjustment process. Although EQT changes the relative cost of energy use, it does not prescribe how firms should respond. Firms must still choose among different adjustment strategies, such as purchasing additional quotas, substituting inputs, or reorganizing production processes. A stronger human-capital base improves firms' ability to interpret these price signals and assess the trade-offs among alternative responses. Beyond identifying the appropriate response, human capital also facilitates its implementation through stronger managerial and organizational capabilities. It therefore helps ensure that market incentives are translated into substantive changes in energy use and input allocation rather than being treated merely as additional compliance costs.

4.6.3 Informatization

The interaction between EQT and informatization is significantly negative,

underscoring the importance of information transmission for market efficiency. A quota market cannot function effectively if participants are unable to observe prices in a timely manner or identify potential trading partners. Informatization reduces these frictions by improving the timeliness and accessibility of market information. It enables firms to respond to changing market conditions before adjustment opportunities are lost and lowers the cost of finding suitable counterparties. As information asymmetry declines, differences in firms' valuations of energy-use rights are more likely to be converted into actual transactions, allowing the quota market to play a stronger role in correcting carbon distortion.

Overall, these findings suggest that establishing an energy quota market is only the first step toward improving resource allocation. The effectiveness of EQT also depends on complementary regional conditions that enable firms to obtain information, make appropriate adjustments, and reorganize production. The policy benefits of market-based energy regulation can therefore be strengthened not only through better market design, but also through improvements in transportation infrastructure, human capital, and the information environment.

[Insert Table 11 about here].

5. Conclusion and policy implications

5.1 Conclusion

The 2016 EQT rollout introduced a market mechanism into the allocation of energy-use rights. Using province-level observations for 30 Chinese provinces from 2010 to 2022, we assess whether this reform alleviates regional carbon distortion. The

preferred estimate is negative and statistically significant, corresponding to a reduction in carbon distortion of roughly 0.29% relative to its sample mean. Although modest in magnitude, this improvement is economically meaningful given the persistence of carbon-resource misallocation and the substantial adjustment frictions involved in reallocating emission capacity across economic activities. The event-study results further show that the effect strengthens over time, suggesting that the allocative gains from EQT accumulate gradually rather than arising from a short-lived policy response. The main finding remains robust across instrumental-variable estimation, synthetic difference-in-differences, double/debiased machine learning, placebo tests, PSM-DID, controls for concurrent policies, and alternative samples and specifications.

The analysis further identifies two important channels through which EQT contributes to improved carbon allocation. By promoting green technological innovation, EQT enhances the productivity with which energy and carbon-related resources are used, while industrial upgrading facilitates the movement of productive factors and associated carbon-emission capacity toward more productive activities. The effectiveness of this market-based mechanism also depends on complementary regional conditions. Better transportation infrastructure facilitates factor mobility, stronger human capital improves firms' ability to respond to market signals, and greater informatization reduces information frictions and supports more efficient transactions. Finally, the findings provide a basis for policy practice by highlighting the importance of stronger coordination across environmental resource markets,

improved supporting institutions and regulatory frameworks, and implementation strategies tailored to regional conditions. These measures can facilitate the low-carbon transition and high-quality green development while contributing to broader sustainability goals.

5.2 Discussion

The findings extend the existing literature on EQT from carbon outcomes to the underlying allocation of carbon-related resources. Du et al. (2023) show that EQT improves carbon-emission efficiency, with green technological innovation, energy allocation, and transportation networks playing important roles. Cheng et al. (2025) further find that energy-use rights trading reduces carbon emissions through technological innovation and industrial upgrading. Our results build on these studies by showing that EQT also reduces the misallocation of carbon-emission capacity itself. The technological, structural, and allocative adjustments documented in previous studies therefore have implications not only for emission reduction or carbon efficiency, but also for how efficiently scarce carbon-related resources are distributed across economic activities.

This study also contributes to the emerging literature on carbon distortion. Yang et al. (2023) highlight the economic losses associated with inefficient carbon allocation, while Su and Chen (2024) provide direct evidence that carbon emissions trading can mitigate regional carbon distortion. Unlike the carbon emissions trading system examined by Su and Chen (2024), which directly prices emissions at the output stage, EQT operates further upstream by introducing market-based price

signals into the allocation of energy-use rights. Our findings therefore show that carbon distortion can be alleviated not only through the direct pricing of emissions, but also through the market-based reallocation of energy inputs closely associated with carbon emissions.

The baseline estimate of −0.0029 corresponds to approximately 0.29% of the sample mean of the carbon distortion index. This estimate should be understood in the context of the relative rigidity of carbon-resource allocation. Carbon-emission capacity is not a freely adjustable input, but is deeply embedded in existing production technologies, capital stocks, and industrial structures, making its reallocation subject to substantial short-run frictions. Against this background, even marginal improvements in allocation indicate that market mechanisms have begun to relax some of these structural constraints. The progressively strengthening effect observed in the event-study estimates further suggests that the improvement is not merely a short-lived response, but accumulates gradually as firms adjust production and productive factors are reallocated. The estimated effect therefore carries substantive economic significance.

The findings also provide an empirical interpretation of the theoretical framework developed in Section 2.2. From a Coasean perspective, clearly defined and tradable energy-use rights introduce explicit scarcity prices and facilitate the reallocation of resources toward more productive uses. The significant positive effect of EQT on green technological innovation is consistent with the Porter Hypothesis, according to which appropriately designed environmental regulation can stimulate

innovation rather than merely impose compliance costs. Industrial upgrading further extends this adjustment from improvements in resource use within firms to the reallocation of productive factors across sectors. The distortion-mitigating effect of EQT therefore reflects the joint operation of market-based resource reallocation, green technological innovation, and structural transformation.

5.3 Policy implications

5.3.1 Strengthen the market-based allocation of environmental resources

The distortion-correcting effect of EQT highlights the importance of market price signals in allocating scarce environmental resources. Institutional coordination among markets for energy-use rights, pollution-discharge rights, water-use rights, and other environmental resources should therefore be strengthened. More consistent quota accounting, transaction rules, and regulatory standards can reduce overlapping requirements and duplicated compliance costs while providing market participants with clearer scarcity signals. Improving market transparency and transaction efficiency would further allow the allocative advantages of market-based environmental regulation to be realized.

5.3.2 Reinforce green technological innovation and industrial upgrading

The two transmission channels identified in this study also provide clear directions for complementary policies. Targeted green financial instruments, tax incentives, and industry–university–research collaboration can reduce the cost of low-carbon R&D and accelerate the diffusion and commercialization of green technologies. At the same time, institutional barriers that impede the cross-sector

movement of capital, labor, and other productive factors should be reduced. Improving the business environment for high-value-added and less energy-intensive industries can facilitate the movement of productive resources and carbon-emission capacity away from low-productivity, energy-intensive activities.

5.3.3 Adapt policy implementation to regional conditions

The moderating-effect results indicate that the effectiveness of EQT depends partly on regional conditions that support market adjustment. In areas with weak transport connectivity, improving transportation infrastructure can reduce spatial frictions and facilitate factor mobility. Regions with limited human-capital capacity should strengthen the recruitment and training of personnel in energy management and low-carbon production, thereby improving firms' ability to interpret and respond to quota-market signals. Less informatized regions should improve digital trading infrastructure and access to market information to reduce information asymmetry and search costs. Strengthening these complementary conditions can help translate the price signals generated by EQT into effective adjustments in production and resource allocation.

5.4 Limitations and future research

Several limitations should be acknowledged. Carbon distortion is measured using a Cobb–Douglas framework and environmental protection expenditure as a proxy for the implicit carbon price, which may introduce measurement error. Future studies could adopt alternative production functions and more direct pricing measures. Moreover, provincial-level data cannot capture firm- or industry-level responses to

EQT. Micro-level research could further examine heterogeneous adjustments and the interactions between EQT and other market-based environmental instruments.

- **Data Availabilits:**

The processed datasets, variable definitions, and statistical codes are provided as supplementary materials to facilitate the verification and replication of the research findings. Additional data and supporting materials are available from the corresponding author upon reasonable request, subject to applicable data access conditions. The authors agree to provide relevant research materials to the editors and reviewers for academic verification purposes.

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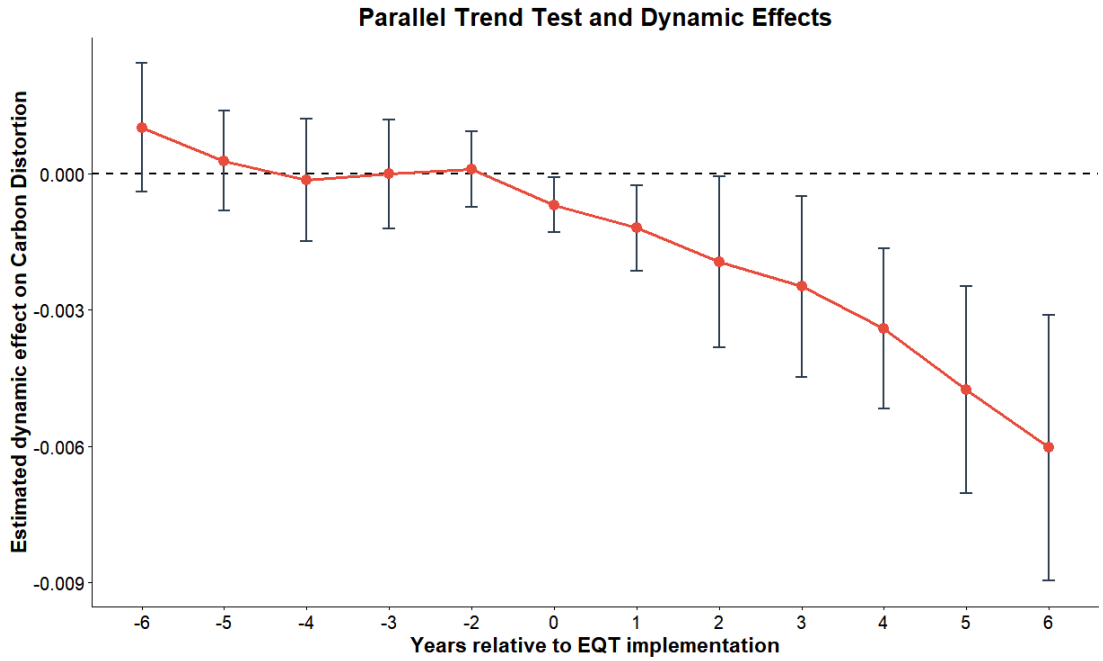


Fig. 1. Parallel Trends Test.

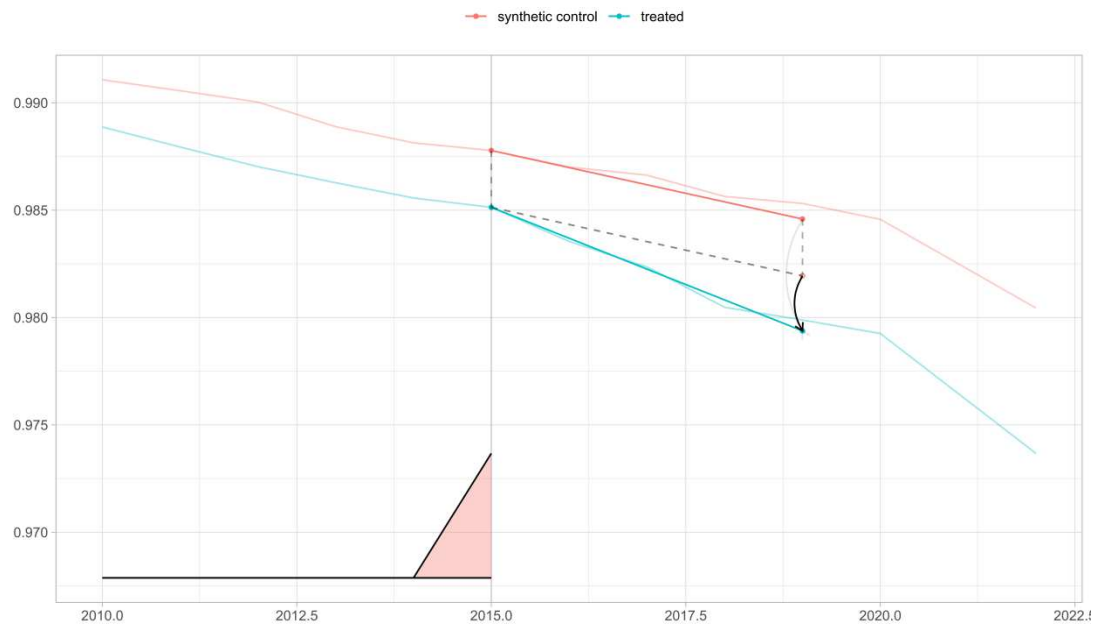


Fig. 2. SDID Estimation Results.

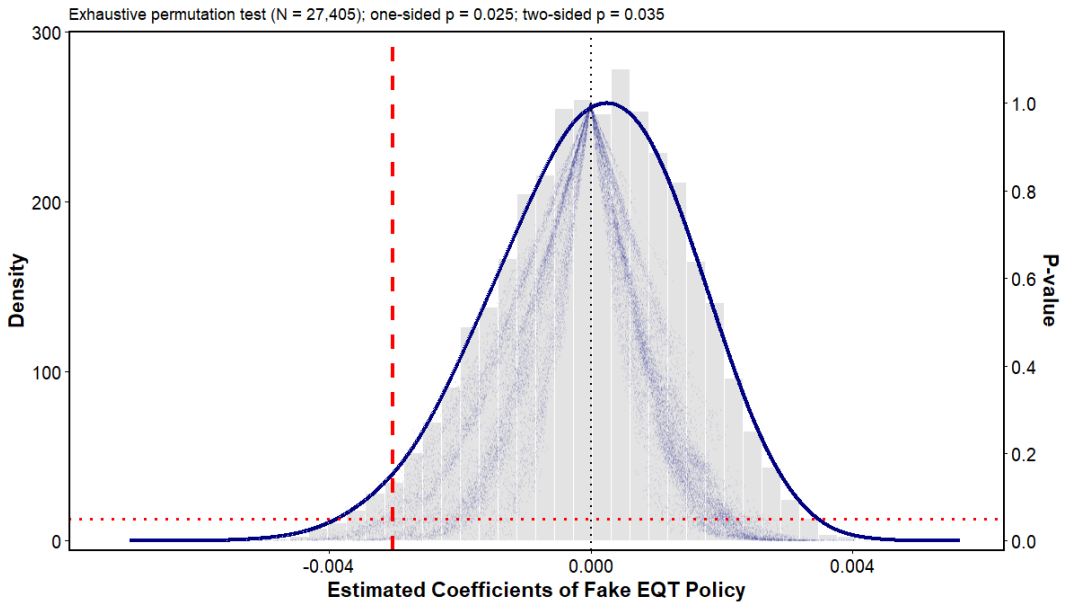


Fig. 3. Placebo test results.

Table 1. Variables for C-D production technology.

Symbol	Variable	Definition
Y	Real output	Real Gross Regional Product (GRP), deflated to the base year
K	Capital input	Real physical capital stock, calculated using the perpetual inventory method
L	Labor input	Total number of employed persons at the year-end
C	Carbon input	Total volume of provincial carbon dioxide emissions
P^c	Market factor price of carbon	Natural logarithm of annual budgetary environmental protection expenditure

Table 2. Description of main variables.

Variable	Symbol	Definition
Carbon distortion	DI	Carbon distortion index
EQT policy	EQT	Equals 1 for pilot provinces after 2016
Economic development	lnPGDP	Logarithm of real GRP per capita
Government intervention	Gov	Government expenditure / GRP
Trade openness	Opening	Total imports and exports / GRP
Energy structure	lnEnergy_Str	Coal consumption as a share of total energy consumption, in logarithms
Urbanization	Urban	Urban population / total population
Population density	lnDensity	Logarithm of population density

Table 3. Descriptive Statistics

Variable	N	Mean	SD	Min	Median	Max
lnY	390	9.8134	0.9099	7.0424	9.9023	11.7715
lnK	390	10.5430	0.7939	8.0133	10.6494	12.2086
lnC	390	19.4183	0.7384	17.5566	19.3576	20.8872
lnL	390	7.5923	0.7814	5.5452	7.6563	8.8639
P^c	390	2.9655	0.0383	2.8654	2.9631	3.0391
DI	390	0.9875	0.0071	0.9552	0.9890	0.9991
lnPGDP	390	10.8208	0.4874	9.4636	10.8090	12.1547
Gov	390	0.2571	0.1113	0.1050	0.2304	0.7583
Opening	390	0.2765	0.2907	0.0076	0.1462	1.4638
lnEnergy_Str	390	0.6784	0.4112	0.0082	0.5909	4.4364
Urban	390	0.5900	0.1248	0.3381	0.5786	0.9415
lnDensity	390	5.4627	1.2853	2.0543	5.6591	8.2818
LAC	390	13.0046	4.4341	4.7950	12.1089	24.0416
GTI	390	0.6575	0.9497	0.0027	0.2998	5.6200
ISA	390	2.3930	0.1246	2.1323	2.3837	2.8359
HumanCapital	390	0.0205	0.0060	0.0080	0.0201	0.0436
RoadInfra	390	11.6639	0.8528	9.3927	11.9320	12.9126
Informatization	390	0.0596	0.0507	0.0149	0.0363	0.2820

Note: LAC denotes atmospheric ventilation capacity, while HumanCapital, RoadInfra, and Informatization represent human capital, transportation infrastructure, and informatization, respectively.

Table 4. Baseline regression result.

Note:Control Var includes lnPGDP, Gov, Opening, lnEnergy_Str, Urban, and lnDensity. Robust t-statistics in parentheses; ***p<0.01, **p<0.05, *p<0.1.

Variable	(1) DI	(2) DI	(3) DI	(4) DI
EQT	-0.0087***	-0.0031***	-0.0025**	-0.0029***
	(-6.5672)	(-4.4819)	(-2.8417)	(-4.6861)
lnPGDP			-0.0109***	-0.0077***
			(-11.7364)	(-4.3967)
Gov			-0.0037	0.0200***
			(-1.1325)	(4.8013)
Opening			0.0003	0.0014
			(0.2456)	(0.7698)
lnEnergy_Str			0.0052***	0.0020***
			(12.5258)	(4.9877)
Urban			0.0243***	0.0287***
			(5.9291)	(4.6443)
lnDensity			-0.0015***	0.0006
			(-4.8176)	(0.1608)
Control Var	No	No	Yes	Yes
Province FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes
Observations	390	390	390	390
R-squared	0.0977	0.9001	0.6627	0.9144

Table 5. Instrumental variable regression results.

Variable	First-stage regressions (1) EQT	Second-stage regressions (2) DI
LAC×Time	-0.0047**	
	(-2.241)	
EQT		-0.0175**
		(-2.724)
Control Var	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
Kleibergen-Paap rk Wald F statistic		30.829
Stock-Yogo weak ID test critical values:10 % maximal IV size		16.38
N	390	390

Note:Control Var includes lnPGDP, Gov, Opening, lnEnergy_Str, Urban, and lnDensity. Robust t-statistics in parentheses; ***p<0.01, **p<0.05, *p<0.1.

Table 6. Robustness checks: time placebo test and PSM-DID.

Variable	(1) Time Placebo (2013) DI	(2) PSM-DID DI
EQT		-0.0017***
		(-2.8802)
Placebo EQT (2013)	0.0001	
	(0.0655)	
Control Var	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
Observations	390	208
R-squared	0.9736	0.9576

Note:Control Var includes lnPGDP, Gov, Opening, lnEnergy_Str, Urban, and lnDensity. Robust t-statistics in parentheses; ***p<0.01, **p<0.05, *p<0.1.

Table 7. Robustness checks: Excluding other major policies.

Variable	(1) DI	(2) DI	(3) DI
EQT	-0.0028***	-0.0031***	-0.0033***
	(-4.5874)	(-5.0235)	(-5.4590)
CETS	-0.0024***		
	(-4.1517)		
PTS		-0.0012	
		(-0.9512)	
NECP			0.0025***
			(3.9138)
Control Var	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	390	390	390
R-squared	0.9372	0.9341	0.9368

Note:Control Var includes lnPGDP, Gov, Opening, lnEnergy_Str, Urban, and lnDensity. Robust t-statistics in parentheses; ***p<0.01, **p<0.05, *p<0.1.

Table 8. Robustness checks: Alternative sample specifications.

Variable	(1) Excl. Municipalities DI	(2) Winsorized (1%) DI	(3) Pre-COVID Sample DI
EQT	-0.0036*** (-6.7827)	-0.0026*** (-4.8444)	-0.0017*** (-3.6744)
Control Var	yes	yes	yes
Province FE	yes	yes	yes
Year FE	yes	yes	yes
Observations	338	390	300
R-squared	0.9404	0.9466	0.9604

Note:Control Var includes lnPGDP, Gov, Opening, lnEnergy_Str, Urban, and lnDensity. Robust t-statistics in parentheses; ***p<0.01, **p<0.05, *p<0.1.

Table 9. Robustness checks using alternative learners and cross-fitting folds.

	(1) RF	(2) Lasso	(3) RF	(4) RF
EQT	−0.0029**	−0.0066**	−0.0022**	−0.0025**
t-statistic	(−2.5126)	(−2.0991)	(−2.2533)	(−2.1528)
Folds	5	5	3	10
Controls	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	390	390	390	390

Note:Control Var includes lnPGDP, Gov, Opening, lnEnergy_Str, Urban, and lnDensity. Robust t-statistics in parentheses; ***p<0.01, **p<0.05, *p<0.1.

Table 10. Mechanism analysis.

Variable	(1) GTI	(2) ISA
EQT	0.1528***	0.0041**
	(4.4050)	(2.1468)

lnPGDP	0.1951	-0.0252***
	(1.6484)	(-3.8576)
Gov	1.1396***	0.1124***
	(3.8127)	(6.8241)
Opening	-0.6846***	0.0280***
	(-6.6326)	(4.9167)
lnEnergy_Str	-0.0643***	-0.0043***
	(-2.9139)	(-3.5373)
Urban	-0.3894	0.0074
	(-1.1281)	(0.3905)
lnDensity	0.9449***	0.0300**
	(4.4512)	(2.5641)
Control Var	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
Observations	390	390
R-squared	0.9330	0.9743

Note:Control Var includes lnPGDP, Gov, Opening, lnEnergy_Str, Urban, and lnDensity. Robust t-statistics in parentheses; ***p<0.01, **p<0.05, *p<0.1.

Table 11. Moderating effect analysis.

Variable	(1) DI	(2) DI	(3) DI
EQT	-0.0001	-0.0029*	-0.0026**
	(-0.1506)	(-1.966)	(-2.049)
EQT × RoadInfra	-0.0044**		
	(-2.490)		
EQT × HumanCapital		-0.5768***	
		(-3.454)	
EQT × Informatization			-0.0092**
			(-2.730)
Control Var	yes	yes	yes
Province FE	yes	yes	yes
Year FE	yes	yes	yes
Observations	360	360	360
R-squared	0.94143	0.94172	0.93972

Note:Control Var includes lnPGDP, Gov, Opening, lnEnergy_Str, Urban, and lnDensity. Robust t-statistics in parentheses; ***p<0.01, **p<0.05, *p<0.1.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- dataall.csv
- code.r
- VariableDefinitionsRevised.docx