

Article

Regulation Without Transformation: Are China's Low-Carbon Policies Effective for Carbon Abatement, and Can They Be Sustained?

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Abstract

We evaluated the effectiveness and long-term sustainability of China's low-carbon policies using a comprehensive policy intensity index and satellite-based CO₂ emissions. We found that both command-and-control and market-based measures have significantly reduced emissions across China but mainly via scale effects (i.e., contraction of industrial activity) rather than technique effects (i.e., more green invention patents granted and an increase in carbon total factor productivity) or composition effects (i.e., industrial upgrading and clean energy transition). Furthermore, command-and-control policies are associated with less green innovation, while market-based policies lead to limited gains in industrial restructuring and, unexpectedly, also show a negative association with clean energy adoption. Using a unique dataset of millions of business registration records and county-level CO₂ emissions, we also uncovered substantial intra-national carbon leakage at the city level, with emissions relocating to provincial border areas where enforcement is weaker, thus exacerbating emission inequality among jurisdictions. Furthermore, our novel transfer learning projections indicate that current policies may lose their efficacy in nearly 47% of cities under foreseeable economic and structural changes, exposing the fragility of contraction-led carbon abatement. These results underscore the need to move beyond the short-term suppression of outputs toward a durable, innovation-driven pathway of decarbonization.

Keywords: carbon abatement; carbon leakage; clean energy transition; green innovation; transfer learning

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1. Introduction

The worsening global climate crisis is placing unprecedented pressure on governments to adopt truly effective decarbonization strategies. Now the world's largest carbon dioxide emitter, China faces the dual challenge of maintaining robust economic growth while still meeting two ambitious climate targets: peak carbon emissions by 2030 and carbon neutrality by 2060. To reach them, China has rolled out an array of low-carbon policies, consisting chiefly of command-and-control (e.g., industrial closure mandates, sector-specific emission limits) and market-based policies (e.g., emissions trading pilots, green

subsidies). However, compared with developed countries, China faces a tighter timeline and greater difficulty in fulfilling its carbon peaking and carbon neutrality targets, which place exceptionally high demands on the efficiency of emission reductions. Put differently, China's low-carbon policies must go beyond simply achieving emission cuts; they must also drive industrial and energy structural transformations while also fostering a technology-driven, enduring mode of decarbonization.

Research on low-carbon policies in advanced Western economies, such as the EU emissions trading system and California's cap-and-trade program, would suggest they have succeeded in achieving durable emission reductions [1–3]. Yet, we should not overlook opposing views. For instance, Sinn [4] argued that environmental regulations could actually augment carbon emissions (called the "green paradox"), perhaps due to either improperly designed carbon taxes or delays in the implementation of certain administrative measures. Later, Smulders et al. [5] highlighted how the early introduction of environmental regulations can lead to a rise in carbon emissions, while Ritter and Schopf [6] reported that pursuing green policies is capable of accelerating the extraction and consumption of fossil fuels, resulting in higher carbon emissions. Such debates are likely rooted in various complex social conditions characterizing different regions. For example, using OECD countries' data, Jiang and Ma [7] discovered a nonlinear relationship between environmental regulation and the carbon emission network: when the former is at a low level, an innovation suppression effect prevails, but once the regulation reaches a certain threshold, there begins to emerge an innovation compensation effect. In China, where much more extensive heterogeneity is found across its regions in terms of socioeconomic, cultural, and natural factors, such dynamics are probably even stronger. For instance, using provincial-level data, several researchers have independently identified stark regional disparities in the impact of environmental regulation on carbon emissions [8–10]. Yet, most evaluations of low-carbon policy effectiveness in China have focused on policy-oriented investigations that take a regional perspective, leaving a dearth of comprehensive national-level analyses. This glaring knowledge gap may inadvertently invite biased perceptions of the overall efficacy of China's low-carbon policies to date.

To rectify the lack of comprehensive evidence on the performance of China's low-carbon policy framework, this study conducted a nationwide evaluation at the fine-grained city-level scale. We sought to address three interrelated questions: (1) Have China's low-carbon policies—encompassing both command-and-control and market-based types—achieved even the minimum objective of reducing carbon emissions nationally? (2) If emission reductions have ensued, which operative mechanisms were responsible; that is, were outputs merely curbed, or did policies also somehow induce pronounced structural transformation and technological innovation? (3) Can these policies be sustained over time, both nationally and regionally? By answering these outstanding questions, our aim is not only to assess policy effectiveness but also to uncover the pertinent structural and institutional factors explaining the observed patterns.

Our research rests on a suite of complementary analyses. First, we carry out a city-level, national-scale empirical assessment of both policy types (i.e., command-and-control and market-based) for the 2007–2017 period, providing comprehensive coverage rarely seen in the existing literature. Second, we decompose the policies' carbon-reducing effects into three dimensions (i.e., technique, composition, and scale effects), leveraging methods adapted from decomposition-related literature in environmental economics. Third, we check for domestic leakage by examining the impact of policies on carbon emissions in provincial border areas versus central areas and by comparing values for an urban carbon emissions Gini index, thus introducing a novel spatial lens to environmental governance. Fourth, we used transfer learning to simulate forward-looking policy resilience, allowing us to evaluate whether current policy frameworks will remain effective under projected

socioeconomic shifts; this ex-ante approach is hard to find in climate policy research. Overall, this research delivers several policy-relevant insights. For China's low-carbon transition to succeed, it will require a coherent and adaptive policy architecture, one that blends regulatory mandates with targeted financial support, aligns carbon pricing with energy reforms, harmonizes enforcement in boundary areas, and embeds adaptation to technological and economic evolution.

2. Literature Review and Theoretical Framework

Existing studies on the impact of carbon regulation on carbon emissions in China are predominantly policy-oriented, in that they usually take policies, such as the carbon emission trading scheme and the low-carbon city pilot policy, as entry points. Those studies often rely on difference-in-difference (DID) models to evaluate the emission-reduction effects and to explore the underlying mechanisms involved. In contrast, research that directly quantifies the effects of regulatory stringency (i.e., policy intensity) is still relatively scarce. For example, Liu et al. [11] and Huo et al. [12] found that China's low-carbon city pilot policy has been effective in reducing carbon emissions; Hu et al. [13] and Wu [14] reported that China's carbon emission trading scheme could significantly augment carbon abatement. Moreover, other research has argued that those policies may not even be effective. For instance, Zhang et al. [15] showed that the impact of China's low-carbon city pilot policy on urban carbon emissions and their intensity is actually not significant. Yet, given the complexity and diversity of natural and socioeconomic conditions across China's different regions, conclusions drawn from policy-oriented research are not widely generalizable, and their applicability to informing nationwide carbon reduction efforts is limited.

Relative to whether low-carbon policies have achieved emission reductions, understanding the mechanisms by which they enable carbon abatement is of greater importance. Drawing on the decomposition framework of Grossman and Krueger [16] and Antweiler et al. [17], we analyze policy effectiveness through three distinct channels. The scale effect achieves abatement by curtailing high-carbon production activities due to increased compliance costs. The composition effect reduces emissions by driving structural shifts toward cleaner sectors and energy types. Finally, the technique effect, grounded in the Porter hypothesis [18], posits that regulation stimulates innovation to lower emission intensity per unit of output. Previous research focused on China is usually concerned with technique effects and industrial structure upgrading with respect to composition effects. For example, Chen et al. [19] and Pan et al. [20] revealed that its low-carbon city pilot policy could promote technological progress; Sun et al. [21] and Zhao et al. [22] provided similar, corroborative evidence vis-à-vis the country's carbon emission trading scheme. Qiu et al. [23] and Wang et al. [24] found that the low-carbon city pilot policy could encourage the upgrading of urban industrial structure; Liu and Sun [25] and Jiang et al. [26] provided complementary evidence supporting the carbon emission trading scheme. However, conclusions regarding the transition to clean energy remain controversial. For instance, Lee et al. [27] found that the low-carbon city pilot policy could hasten energy transformation, while Zhang et al. [28] argued that the carbon emission trading scheme impedes the development of renewable energy. Achieving sustained carbon emission reductions requires the combined action of composition effects and technique effects: the former steers and reshapes the industrial and energy structure toward a low-carbon configuration, while the latter improves production processes and technologies to lower the emission intensity per unit of output. The scale effect, in contrast, can only deliver short-term gains; it lacks the capacity to secure long-term abatement without undermining economic vitality.

Furthermore, fairness issues caused by low-carbon policies also deserve inquiry. According to the pollution haven hypothesis proposed by Copeland and Taylor [29],

differences in the stringency of environmental regulations can lead to the relocation of pollution-intensive industries from developed countries to developing countries. When applied to carbon emissions, Ma and Zhang [30] and Jiang et al. [31] revealed that China's low-carbon city pilot policy and carbon emission trading scheme resulted in more carbon emissions in adjacent cities of pilot cities, a phenomenon termed "carbon leakage". In the context of nationwide research, we argue that administrative border regions warrant special attention in particular. In China, ecological and environmental governance is organized primarily at the provincial or prefectural level, with responsibilities delineated by administrative boundaries in the absence of an integrated coordination mechanism across jurisdictions. Interprovincial border areas—characterized by multiple governing entities, unclear divisions of authority and responsibility, and institutional fragmentation—are thus prone to becoming "governance vacuums". To be more precise, these regions often fall under the management of several provinces, with environmental policy formulation and implementation constrained by each jurisdiction's own vested peculiar interests. Under the "promotion tournament" theory, the career advancement of local officials depends heavily on quantifiable performance indicators, especially short-term economic metrics such as GDP (gross domestic product), investment attraction, and fiscal revenue. Border areas, which are usually geographically remote from administration centers and possess limited resource endowments and economic foundations, rely much more on investment promotion and industrial relocation to achieve their growth targets in the face of intense regional competition. In this dynamic context, local governments are more inclined to relax environmental standards and reduce enforcement frequency so as to lower firms' compliance costs and enhance their investment appeal. Such a strategy leaves environmental regulation policies vulnerable to substantial implementation flexibility in those border regions, where lax enforcement is likely prevalent.

In summary, while the existing literature has extensively evaluated specific policies, our comprehensive synthesis suggests five critical gaps remain unaddressed. First, regarding spatial resolution, previous assessments are mostly "policy-oriented" evaluations of economically advanced pilot regions, or they rely on provincial-level data, leading to sample selection bias that fails to assess the "average" effect across China's diverse landscape. Second, concerning policy measurement, the prevailing methodological approach typically utilizes binary policy dummies to represent regulation. Such simplifications are unable to capture the continuous variation in enforcement stringency across different jurisdictions. Third, in terms of mechanism identification, most studies confirm that emissions are decreasing but do not systematically analyze the underlying processes. They often overlook the pivotal distinction between short-term "scale effects" (output contraction) and sustainable "technique effects" (green innovation). Fourth, with respect to spatial leakage and equity, research is still mainly focused on international or interprovincial transfers, leaving the phenomenon of intra-national leakage toward provincial border areas largely unexplored. Finally, considering sustainability assessment, the evaluations are overwhelmingly retrospective and rely solely on historical datasets. Hence, they fail to examine whether current policy frameworks will stay resilient or face diminishing returns under future economic and structural shifts. Table 1 below compiles the chief differences between this study and prior representative studies in those five-dimensional aspects.

To fill these knowledge gaps, this study contributes to the literature in four specific ways. First, in terms of scale and representativeness, unlike studies limited to pilot zones, we carry out the first nationwide, city-level evaluation, using a comprehensive policy intensity index and satellite data. Our work covers 284 cities, thereby rectifying the bias of past regional studies. Second, concerning mechanism decomposition, we explicitly decouple "contraction-led" reductions from "transformation-led" reductions. By isolating scale, technique, and composition effects, we are able to provide empirical evidence on the

fragility of China’s current abatement model. Third, with respect to spatial equity, we identify a novel form of “intra-national carbon leakage” by focusing on provincial border areas as “governance vacuums”. Doing so adds a neglected equity dimension to the pollution haven hypothesis. Finally, regarding methodological innovation, we introduce transfer learning into climate policy evaluation. This novel ex-ante analysis is capable of showing whether existing measures are likely (or not) to remain effective in the future, thus complementing the predominantly retrospective orientation of most prior research. By combining these elements, our unique study delivers evidence-based insights into how China’s low-carbon transition can shift from short-term output suppression to a durable, innovation-driven pathway. The findings presented here do more than advance our empirical understanding of environmental regulation in large emerging economies. They have immediate, practical implications for the design of more coherent, equitable, and adaptive low-carbon policies worldwide.

Table 1. Comparative summary of representative works vis-à-vis the present study.

Study	Spatial Resolution	Policy Measurement	Mechanism Identification	Spatial Leakage/Equity	Forward-Looking Assessment
Liu et al. [11]	City (pilot cities)	Binary policy dummy	Multi-channel mediation (industry, energy, innovation)	Regional heterogeneity (East vs. non-East)	Retrospective; policy suggestions only
Huo et al. [12]	City	Binary policy dummy	Industry upgrade, R&D, TFP	Not modeled	Short-term effects found, with long-term rebound
Hu et al. [13]	Province × industry	Binary policy dummy	Technical efficiency, industrial structure	Institutional heterogeneity only	Retrospective evaluation only
Pan et al. [20]	City (selected pilots)	Binary policy dummy	Innovation heterogeneity	No spatial modeling	Linkages to carbon neutrality (ex post)
Sun et al. [21]	City	Binary policy dummy	Porter effect, cost crowding-out	Spatial DID (spillovers modeled)	Limited long-term discussion
Zhang et al. [28]	Province	Binary policy dummy	Energy intensity and green tech (mediation)	Spatial Durbin model (inter-provincial spillovers)	No forward-looking analysis
Jiang et al. [31]	City	Binary policy dummy	Energy efficiency and decarbonization	SDID; carbon leakage identified	Effects decay after 5 years
Lee et al. [27]	City	Binary policy dummy	TFP mediation, PT moderation	SDID (spillovers tested)	Restricted to the sampling period only
Present study	Nationwide city-level (n = 284 cities)	Continuous policy intensity index	Scale–composition–technique decomposition	Intra-national leakage at provincial borders (equity focus)	Forward-looking ex-ante assessment via transfer learning

3. Methods and Materials

3.1. Study Area, Selection of Metrics, and Data Sources

To comprehensively determine how China’s low-carbon policies have affected carbon emissions across the country, we selected 284 cities based on their availability of data.

The low-carbon policies intensity (*PI*) (here and henceforth, the word in parentheses after each variable is its abbreviated form, which will be used in Tables 2–10) data came from Dong et al. [32]. Using a phrase-oriented NLP algorithm and text-based prompt learning, they constructed a low-carbon policy intensity index for China, quantified by policy level, objective, and instrument. This process is based on the low-carbon policy inventory compiled for China’s manufacturing industries, containing 7282 national-, provincial- and prefecture-level policies spanning 2007 to 2022. Another advantage of using the work of Dong et al. [32] is that they classified different kinds of policies and calculated their corresponding intensity, which eased our analysis. To obtain more thorough results, we investigated the impact of total, command-and-control, and market-based low-carbon policies.

The CO₂ emissions data were obtained from Chen et al. [33]. They applied a particle swarm optimization–back propagation algorithm to unify the scale of satellite imagery—DMSP/OLS (Defense Meteorological Satellite Program/Operational Line-Scan System)

and NPP/VIIRS (National Polar-Orbiting Partnership/Visible Infrared Imaging Radiometer Suite)—from which they estimated the CO₂ emissions of 2735 Chinese counties during a 30-year period (1997–2017).

Moreover, it was necessary to include control variables in our model testing to properly account for plausible effects of other pertinent factors in play:

- (1) Economic development (*gdp*). In general, residents in economically developed areas tend to care more about environmental quality [34]; we used per capita GDP as the measure of economic development.
- (2) Industrial structure (*indus*). Pollution is usually greatest in the industrial sector, so we included that as a control variable, expressed here as the natural logarithm of secondary industry added value.
- (3) Population density (*pden*). This metric, according to Verhoef and Nijkamp [35] and Glaeser and Kahn [36], could impact CO₂ emissions via scale or agglomeration effects; to represent it, we used the number of persons per square kilometer.
- (4) Urbanization level (*urb*). The expansion of infrastructure during the urbanization process also consumes a substantial amount of energy and emits more CO₂ [37]; to express this, we used the urban population proportion.
- (5) Fiscal decentralization (*decent*). Fiscal decentralization directly affects local governments' fiscal autonomy, which can alter the trade-off between economic development and environmental protection. Under well-established regulatory and institutional frameworks, decentralization can enhance the provisioning of green public goods and spur the adoption of low-carbon technologies to reduce carbon emissions [38]. Conversely, in contexts where performance evaluation is biased toward economic development and environmental constraints are weak, decentralization tends to attract high-carbon industries, leading to increased emissions [39]. Here, we used the ratio of local general public budget revenue to the national total as the measure of fiscal decentralization.
- (6) Government support (*scir*). Allocating fiscal expenditures to science and technology can accelerate regional technological progress [34], which in turn could help to meet carbon abatement goals. The rate of fiscal expenditure on science and technology was used here to convey the scale of government intervention.
- (7) Degree of openness (*open*). The pollution haven hypothesis states that a high level of openness may attract developed countries to relocate energy-intensive and high-emission industries to countries or regions with weaker environmental standards, thereby increasing carbon emissions there [40]. By contrast, the pollution halo hypothesis suggests that foreign investment and trade can introduce advanced green technologies, managerial expertise, and environmental standards, which collectively could reduce carbon emissions [41]. Hence, we used the ratio of foreign direct investment to GDP to gauge the degree of openness.

Unless stated otherwise, the data for these variables used in our study came from the *China City Statistical Yearbook* and China's national economic development and statistical bulletins for each city, from 2007 through 2017. This period was the longest possible given the limited data availability.

3.2. Baseline Regression

We fit the following econometric model as the baseline regression:

$$Carbon_{it} = a_0 + a_1 PI_{it} + x_{it}\beta + \gamma_t + \mu_i + \varepsilon_{it} \quad (1)$$

where $Carbon_{it}$ is the CO₂ emission level of city i in year t ; a_0 is the fitted regression's y-intercept; PI_{it} is the low-carbon policies intensity (for either the command-and-control or market-based policies, or in total) of city i in year t ; a_1 is the corresponding regression coefficient; x_{it} denotes a given control variable for city i in year t , for which β is its corresponding coefficient value; γ_t is the year, a fixed effect; μ_i refers to a given city, also set as a fixed effect; and ε_{it} is the model's error term (i.e., unexplained variance).

3.3. Minimizing Endogeneity

Many factors can influence carbon emissions. Although a wide range of variables are controlled for in our analysis, the regression model may still suffer from endogeneity issues caused by omitted variable bias. To address that, we employed the bounds test approach proposed by Oster [42] and the doubly debiased LASSO estimation method developed by Guo et al. [43] for testing and correction, respectively.

The Oster bounds test leverages the correlation between observed variables and the coefficient of the key explanatory variable to infer the correlation between unobserved variables and the latter, providing an estimate for the magnitude of omitted variable bias and computing a bias-adjusted estimator. If zero does not lie within the interval formed by the adjusted estimator and original estimator, this indicates that omitted variable bias is unlikely to have undermined the credibility of the baseline regression results. The doubly debiased LASSO method corrects bias through a two-stage procedure. In the first stage, an initial estimation is made by applying a 'trim transform' to compress the singular values of the design matrix, this mitigating the impact of high-dimensional noise and confounding factors. In the second stage, the correction step constructs an orthogonalized estimator via the projection of residual direction to further eliminate any remaining biases.

In addition, an interaction effect detected between carbon emissions and the low-carbon policies would imply the existence of endogeneity in our model. To resolve that problem, we derived instrumental variables (IV) for low-carbon policies from three dimensions (culture, climate, and nature), followed by a two-stage least squares regression (2SLS) analysis.

As a key pillar of traditional Chinese cultural heritage, Confucianism embodies profound ideas regarding environmental protection and sustainable development. To validate this instrument, we consider both relevance and exclusion restrictions. For example, Confucius advocated "fishing only with a line and not with a net, and shooting birds only with an arrow tied to a string, avoiding those nesting" (*The Analects*), which shows opposition to excessive fishing and hunting and reflects an awareness of why protecting the ecological chain is vital. Mencius asserted that "if farming follows the proper seasons, there will be more grain than can be consumed; if fine-meshed nets are not used in ponds, there will be more fish and turtles than can be eaten; if trees are felled only at the proper time, there will be more timber than can be used" (*The Mencius*); this emphasizes the rational use of natural resources in accordance with natural rhythms and regenerative capacities. Therefore, in those regions where Confucian culture is more deeply rooted, greater attention may be paid to environmental protection efforts. For exclusion restriction, a valid potential concern is that historical culture might influence carbon emissions through channels other than environmental regulation, such as via human capital accumulation or economic preferences. Yet, our model explicitly controls for economic development, industrial structure, and science expenditures. Conditional on these controls, it

is reasonable to argue that the historical density of Confucian academies could influence current CO₂ emissions. This would happen primarily by fostering a social norm legitimizing and strengthening environmental governance (i.e., the policy channel), rather than through omitted economic confounders. Further, as historical relics, the number of academies is predetermined and insulated from reverse causality from current emissions shocks. Here, we use the per capita number of Confucian academies and temples, which meets the requirements of both relevance and exogeneity, as the instrumental variable for the cultural dimension (IV1). Climate and natural factors are usually not affected by human activities but are nonetheless relevant to regional environmental planning. Therefore, we used annual average humidity and the air circulation coefficient as instrumental variables for the climate (IV2) and natural (IV3) dimensions, respectively.

Despite employing rigorous estimation methods, we must acknowledge several lingering sources of endogeneity as well as measurement limitations inherent to observational studies. Regarding spatial spillovers, the Stable Unit Treatment Value Assumption (SUTVA) may be violated if pollution control in one city shifts its emissions to neighboring cities. However, we explicitly address this “leakage” concern in Section 3.5 by identifying the relocation of emissions to provincial border areas, treating these spillovers as a distinct mechanism of policy evasion rather than mere statistical noise. Regarding measurement noise, although using satellite-based DMSP/VIIRS data can introduce potential errors in comparison to ground monitoring, this independent remote approach is the only way to avoid the systemic “self-reporting bias”. The latter arises when local governments may underreport emissions to meet their targets. Here, we assumed any remaining measurement noise was largely random, which would attenuate our estimates rather than generate spurious significance. Regarding policy anticipation and simultaneity, some firms may react to policy rumors before implementation or face overlapping mandates. Though annual data resolution limits our ability to fully isolate anticipation effects, our separate regression of command-and-control versus market-based intensities helps to disentangle the effects of distinct policy instruments. Lastly, regarding instrument validity, our instrumental variables passed standard diagnostic testing (Kleibergen–Paap and Hansen J statistics). Nonetheless, we conservatively interpret the resulting IV estimates as Local Average Treatment Effects (LATE). This is preferable because it reflects the impact of policies driven by exogenous geographic and cultural factors, supporting the causal direction even when precise point estimates vary.

3.4. Mechanism Analysis

As discussed in Section 2, a mechanism analysis of low-carbon policies affecting carbon abatement was conducted from the perspectives of technique, composition, and scale effects. That is, we investigated the impact of low-carbon policies on corresponding factors of those three effects to learn how low-carbon policies have contributed to carbon abatement in China.

When measuring technological progress, total factor productivity (TFP) and patent-based indicators are two commonly used proxy variables. Firstly, TFP, originating from the growth accounting framework of Solow [44], denotes the residual output growth after accounting for capital and labor inputs and is generally viewed as a reliable, comprehensive measure of technological advancement and efficiency improvements [45]. Secondly, patent data, due to their institutionalized recording and cross-country comparability, are widely utilized to track the intensity of innovation output and technological creation [46], being significantly associated with productivity gains at both macro and micro levels. Accordingly, TFP and patents are considered common and complementary approaches for gauging technological progress, with the former reflecting the overall contribution of technology to outputs and the latter capturing the observable outcomes of innovation activity.

Compared with patent applications, the number of granted patents offers a more accurate representation of the actual level of regional technological progress. Further, compared with utility model patents and design patents, invention patents entail a higher degree of technological sophistication and have a more direct impact on carbon emission reduction. Therefore, we first identified all granted green invention patents, based on the World Intellectual Property Organization's (WIPO) green patent classification list, and then aggregated their counts at the city level to establish an objective measure of city-level green technological progress using patents. For TFP, we calculated China's city-level carbon TFP using the Malmquist productivity index based on the Shephard carbon distance function, incorporating capital, labor, energy, and GDP as desirable outputs, and CO₂ emissions as the undesirable output. In our research, carbon TFP is partitioned into its efficiency change and technological change components, with the former capturing the shift in proximity to the production frontier, while the latter reflects carbon-oriented technological progress. Parameter estimation was carried out through a fixed-effects stochastic frontier analysis model, which can accommodate technological heterogeneity and statistical noise.

Next, we investigated the composition effect from the perspective of both industrial structure upgrading and clean energy transition. In pursuing its carbon peaking and carbon neutrality goals, industrial and energy structure transformations constitute fundamental channels for China. The country's economic growth has historically been driven by energy-intensive, heavy industrial sectors that rely disproportionately on coal and other high-carbon fuels, rendering structural adjustments absolutely essential for decoupling that growth from emissions [47]. Low-carbon policies may precipitate a reallocation of resources from high-emission industries toward advanced manufacturing and service sectors, thereby weakening the carbon intensity [48]. In tandem, such policies may accelerate the shift in the energy mix from coal-dominated consumption toward cleaner energy sources, such as natural gas, hydropower, wind, and solar, which is especially critical because over 50% of China's primary energy supply is coal [49]. These dual structural transitions not only align with China's green development strategy but also provide long-term, sustainable pathways for substantial reductions in emissions. In this study, we used the ratio of value added in the tertiary sector to that in the secondary sector—i.e., the value added of the service industry relative to that of manufacturing or industrial sectors—as the indicator for the degree of industrial structure upgrading. The city-level clean energy data were sourced from Yang et al. [50], who first estimated the renewable electricity consumption for each province, municipality, and autonomous region in China from 2005 to 2021 by using provincial-level data on power generation, interprovincial electricity imports and exports, and renewable power generation. The total electricity consumption was disaggregated into five categories (i.e., thermal, hydro, wind, solar, and nuclear power), according to the expanded provincial energy balance sheets, and each was allocated to the city level. This assignment of power was based on socioeconomic indicators based on sectoral GDP (including industrial, construction, and transportation sectors) and resident population characteristics. Finally, clean electricity consumption data converted into standard coal equivalents for 331 cities were obtained for the nuclear, hydro, wind, and solar power categories. We summed the usage of these four types of clean energy to obtain the total clean energy consumption at the city level. The ratio of that clean energy consumption to total energy consumption was calculated from 2007 to 2017 for each year and city, and this was used as an indicator for measuring its clean energy transition.

The scale effect was studied from the perspective of industrial enterprises. In China, large-scale ones are defined as industrial firms whose annual core business revenue is at least 20 million RMB. These enterprises typically represent relatively huge units possessing more advanced technology and equipment. Since they are responsible for a significant share of carbon emissions, changes in their relevant indicators can reflect the

overall expansion or contraction of industrial activity. As such, they serve well as a straightforward measure of the scale effect. Here we used the number and output value of large-scale industrial enterprises to gauge the urban industrial scale.

3.5. Further Analysis

In line with our reasoning in Section 2, we conducted an additional analysis from the perspective of carbon emission fairness and carbon abatement sustainability.

For carbon emission fairness, the impact of China's low-carbon policies on provincial vis-à-vis non-provincial border areas was quantitatively investigated. We used ArcGIS software (version 10.2) to identify counties located along provincial borders within cities and then pooled the county-level carbon emission data at the city level accordingly. This allowed us to obtain carbon emissions for both provincial border and non-border counties within each city jurisdiction. Next, we examined the impact of low-carbon policies on carbon emissions in these different areas. To attain more comprehensive results, we acquired data on the establishment of new industrial enterprises with high carbon emissions. Specifically, we compiled a dataset of millions of business registration records from China's industrial and commercial enterprises, spanning 2007 to 2017, and parsed those official physical addresses to identify their corresponding counties. Based on its industry classification, it was possible to determine whether an enterprise qualified as a high-carbon emitter, after which the number of such high-carbon enterprises was aggregated at the county level. Specifically, we conducted a meticulous stepwise screening process to identify high-carbon enterprises. First, we selected all firms classified under primary industry categories of manufacturing, construction, production and supply of electricity, heat, gas, and water, and mining. Next, within this subset, we further filtered enterprises by secondary industry classifications including electricity, heat production and supply; gas production and supply; water production and supply; coal mining and washing; oil and natural gas extraction; petroleum processing, coking, and nuclear fuel processing; ferrous metal mining; non-ferrous metal mining; non-metallic mineral mining; mining support activities; ferrous metal smelting and rolling processing; non-ferrous metal smelting and rolling processing; non-metallic mineral products; chemical raw materials and chemical products manufacturing; chemical fiber manufacturing; pharmaceutical manufacturing; general equipment manufacturing; special equipment manufacturing; electrical machinery and equipment manufacturing; computer, communication, and other electronic equipment manufacturing; metal products; railway, shipbuilding, aerospace, and other transportation equipment manufacturing; automobile manufacturing; metal products, machinery, and equipment repair; building installation; housing construction; civil engineering construction; and building decoration and other construction industries. Finally, we excluded enterprises with relatively low carbon emissions, such as those engaged in specialized equipment repair, instrument repair, other machinery and equipment repair, electrical equipment repair, metal product repair, general equipment repair, transportation equipment repair (railway, shipbuilding, aerospace), cultural and office machinery manufacturing, audiovisual equipment manufacturing, computer manufacturing, electronic component and device manufacturing, communication equipment manufacturing, off-road leisure vehicle and parts manufacturing, non-electric household appliance manufacturing, textile, apparel and leather processing equipment manufacturing, food, beverage, tobacco, and feed production equipment manufacturing, as well as salt production. Through this process, we identified all enterprises classified as high-carbon emitters. The final screening resulted in a total of 568,012 enterprises. Next, these county-level data were summed at the city level to obtain the annual counts of high-carbon enterprise registrations in both provincial border and non-border areas within each city. We then evaluated the impact of low-carbon policies on these numbers to investigate the issue of carbon emission

migration within and among Chinese cities. It is important to bear in mind that an imbalance in carbon emissions across regions may not be restricted to interprovincial border areas: it could also manifest within cities. To enhance the comprehensiveness of our conclusions, we used county-level carbon emission data to calculate the city-level carbon emission's *Gini* index and examined the impact of China's low-carbon policies on it. That annual *Gini* index was calculated this way:

$$Gini = \frac{\sum_{i=1}^N \sum_{j=1}^N |y_i - y_j|}{2N^2 \bar{y}} \quad (2)$$

where y_i is the carbon emissions of county i , the N is the number of counties included in a given city, and $\bar{y}$ is the average county-level carbon emissions in a given city.

Going further, we also explored whether the impact of China's low-carbon policies on carbon abatement can be sustained; that is, whether such policies can continue to achieve their intended outcomes when future economic and social conditions change. However, evaluations relying solely on historical data are often insufficient to directly answer this question. Fortunately, the transfer learning approach pioneered by Torrey and Shavlik [51] and Weiss et al. [52] offers a promising way to resolve that issue. The essence of transfer learning lies in reassigning the relationships between variables from a source dataset to a target dataset that shares similar characteristics. This study treats region A as the target dataset and all other regions as the source dataset. If the emission-reduction effect of environmental policies in region A at time t is similar to that in other places at time τ (where t does not necessarily equal τ), then the emission-reduction effect of environmental policies elsewhere at time $\tau + s$ (provided that $\tau + s$ falls within the sample period) may be used to infer the effect in region A at time $t + s$ (so long as $t + s$ lies outside the sample period).

Our application of transfer learning rests on two important assumptions about comparability. We first assumed a "space-for-time" interchangeability. That is, the policy response mechanisms observed in "source" regions (typically at a clearer stage of policy implementation) can effectively model the future trajectory of a "target" region, provided they share fundamental socioeconomic characteristics. We also assumed structural similarity can serve as the prerequisite for knowledge transfer and explicitly address the risk of "negative transfer". The latter occurs when imposing a model from a disparate source region (e.g., a service-oriented city) onto an incompatible target (e.g., a resource-dependent city) weakens prediction performance. To rigorously control for that, we employed the high-dimensional generalized linear model transfer learning framework that was proposed by Tian and Feng [53]. Crucially, this algorithm does not force any transfer blindly. Instead, it applies a data-driven selection mechanism to identify an "informative set" of source cities statistically similar to the target, while automatically discarding source data that would introduce bias (negative transfer). As noted in the results below, transfer attempts were abandoned for cities lacking a suitable match, which ensures the predictions are grounded in valid comparability. Finally, after obtaining the results, they were visualized using ArcGIS software (v. 10.2) in Figure 1.

4. Results

This section presents empirical evidence on the impact of China's low-carbon policies. We begin with baseline regression results in Table 2, which established the average effect of low-carbon policies on CO₂ emissions. Then Table 3 reports a series of robustness checks to verify the stability of those baseline findings, with Table 4 examining potential endogeneity concerns by taking a 2SLS approach. Next, the underlying mechanisms by which low-carbon policies affect emissions were explored. Specifically, Tables 5–7 present

the total effect of technique, composition, and scale effects. Tables 8–10 then examine heterogeneity and extended outcomes. These encompass regional differences, distributional effects on emission inequality, and impacts on the establishment of high-carbon enterprises.

The baseline regression (Table 2) suggested that China's low-carbon policies negatively affected carbon emissions, and this effect is statistically significant. Further, both command-and-control policies and market-based policies had significant negative effects on carbon emissions. Therefore, on the whole, this analysis indicated that China's low-carbon policies could promote carbon abatement.

Table 2. Regression coefficients, statistical significance, total sample size (N), and the goodness of fit (R^2) of fitted econometric models for the impact of China's low-carbon policies on CO₂ emissions. The values in brackets under each coefficient are their cluster-robust standard errors. See the Methods and Materials Section for details. *Cons* means the regression y-intercept. Significance levels: *** 0.01, ** 0.05, * 0.1.

	(1) Total	(2) Command	(3) Market	(4) Total	(5) Command	(6) Market
<i>PI</i>	−0.0442 *** (0.0080)	−0.0204 *** (0.0037)	−0.0138*** (0.0034)	−0.0343 *** (0.0071)	−0.0149 *** (0.0035)	−0.0115 *** (0.0030)
<i>gdp</i>				0.0654 ** (0.0254)	0.0680 ** (0.0265)	0.0656 ** (0.0256)
<i>indus</i>				0.0032 *** (0.0010)	0.0032*** (0.0010)	0.0033 *** (0.0010)
<i>pden</i>				0.0130 (0.0874)	0.0171 (0.0861)	0.0139 (0.0870)
<i>urb</i>				0.1139 * (0.0597)	0.1246** (0.0599)	0.1230 ** (0.0607)
<i>decent</i>				−0.0461 (0.0327)	−0.0490 (0.0334)	−0.0524 (0.0324)
<i>scir</i>				−0.4215 * (0.2424)	−0.4119 * (0.2382)	−0.4152 * (0.2403)
<i>open</i>				−0.3192 (0.3588)	−0.3537 (0.3622)	−0.3143 (0.3620)
<i>Cons</i>	2.9366 *** (0.0326)	2.8212 *** (0.0135)	2.7950 *** (0.0100)	2.0163 *** (0.5158)	1.8722 *** (0.5108)	1.8923 *** (0.5135)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3113	3113	3113	3113	3113	3113
R^2	0.7891	0.7864	0.7867	0.8034	0.8017	0.8022

Our robustness test findings are reported in Tables 3 and 4. According to panel A in Table 3, the Oster bounds test showed that the coefficient does not contain zero (i.e., β -test). Moreover, based on the results of double-debiased LASSO in panel B, the negative effect of low-carbon policies on carbon emissions is still significant, which suggests that omitted variable bias would not change our baseline results. In addition, from the 2SLS regression (Table 4), we can see the p -value of the Kleibergen–Paap LM statistic for three IVs is statistically significant at the 5% level, indicating a strong correlation between instrumental variables and the endogenous variable. In addition, the Hansen J statistics are all insignificant at the 10% level, implying that the instrument variables are jointly exogenous. Hence, the fitted 2SLS regression demonstrated that China's low-carbon policies

could still significantly reduce carbon emissions, confirming the robustness of our baseline results.

Table 3. Results of robustness test for the baseline regression. The values in brackets under each coefficient are their cluster-robust standard errors. See the Methods and Materials Section for details. Significance levels: *** 0.01, ** 0.05, * 0.1.

Panel A: Oster Bounds Test	
<i>PI</i>	−0.0343 *** (0.0071)
β -test ($\delta = 1$)	(−0.0244, −0.0343)
Panel B: Double-Debiased LASSO	
<i>PI</i>	−0.0342 *** (0.0053)
Control variables	Yes
City FE	Yes
Year FE	Yes
<i>N</i>	3113

Table 4. Results of 2SLS. The values in brackets under each coefficient are their cluster-robust standard errors. See the Methods and Materials Section for details. *Cons* means the regression y-intercept. Significance levels: *** 0.01, ** 0.05, * 0.1.

	(1) IV1	(2) IV1 IV2	(3) IV1 IV2 IV3
<i>PI</i>	−0.5104 ** (0.2372)	−0.5048 ** (0.2218)	−0.5021 *** (0.1766)
<i>gdp</i>	0.0201 (0.0295)	0.0206 (0.0286)	0.0209 (0.0258)
<i>indus</i>	0.0014 (0.0015)	0.0014 (0.0014)	0.0014 (0.0013)
<i>pden</i>	−0.0440 (0.1166)	−0.0433 (0.1159)	−0.0430 (0.1161)
<i>urb</i>	−0.1258 (0.1420)	−0.1230 (0.1340)	−0.1216 (0.1173)
<i>decent</i>	0.0682 (0.0718)	0.0668 (0.0681)	0.0662 (0.0615)
<i>scir</i>	−0.6587 (0.4419)	−0.6559 (0.4358)	−0.6545 (0.4250)
<i>open</i>	−0.1019 (0.3770)	−0.1045 (0.3747)	−0.1058 (0.3764)
K-P LM P-val	0.0356	0.0616	0.0231
Hansen J P-val		0.8744	0.9875
<i>N</i>	3113	3113	3113

Although our baseline regression results do show that China's low-carbon policies were effective at carbon abatement, the findings of our mechanism tests (i.e., technique, composition, and scale effects) in Tables 5–7 are cause for concern. First, according to column 1 in Table 5, China's low-carbon policies had a significant negative relationship with green innovation. Also, the results in columns 2 and 3 reveal that command-and-control policies have had a significant negative effect on green innovation, but the effect of market-based policies was not significant. Likewise, according to the results in columns 4, 5, and 6, we find that command-and-control policies exerted a significant negative effect on

carbon TFP, yet total policies or market-based policies did not have any discernible positive effect. Secondly, from Table 6, it is evident that China's low-carbon policies did not promote industrial structure upgrading (column 1), nor did command-and-control policies (column 2), whereas market-based policies (column 3) do show a weak positive effect (significant at the 10% level). As for the clean energy transition, both low-carbon policies and command-and-control policies lacked a significant effect (columns 4 and 5), with market-based policies even featuring a significant negative coefficient (column 6). Thirdly, according to Table 7 results, China's low-carbon policies (total, command-and-control, and market-based) have significantly reduced the number of industrial enterprises. Intriguingly, total and market-based policies negatively affected the output value of industrial enterprises in a significant way. Therefore, it is suggested that China's low-carbon policies could reduce carbon emissions through a scale effect but not a technique or composition effect, which cannot be sustained indefinitely (i.e., over the long term).

Table 5. Regression coefficients, statistical significance, total sample size (N), and the goodness of fit (R^2) of fitted econometric models for the technique effect of China's low-carbon policies. The values in brackets under each coefficient are their cluster-robust standard errors. See the Methods and Materials Section for details. *Cons* means the regression y-intercept. Significance levels: *** 0.01, ** 0.05, * 0.1.

	Green Innovation			Carbon TFP		
	(1) Total	(2) Command	(3) Market	(4) Total	(5) Command	(6) Market
<i>PI</i>	−0.1400 *** (0.0391)	−0.0802 *** (0.0249)	−0.0069 (0.0187)	−0.0008 (0.0028)	−0.0031 * (0.0016)	0.0015 (0.0012)
<i>gdp</i>	−0.0636 (0.0668)	−0.0538 (0.0688)	−0.0521 (0.0684)	−0.0036 (0.0036)	−0.0036 (0.0036)	−0.0047 (0.0041)
<i>indus</i>	−0.0020 (0.0046)	−0.0021 (0.0045)	−0.0015 (0.0046)	0.0006 *** (0.0002)	0.0006 *** (0.0002)	0.0004 ** (0.0002)
<i>pden</i>	0.4509 (0.3105)	0.4677 (0.3071)	0.4657 (0.3121)	−0.0157 (0.0120)	−0.0156 (0.0120)	−0.0147 (0.0103)
<i>urb</i>	0.8725 *** (0.3041)	0.9078 *** (0.3089)	0.9381 *** (0.3111)	−0.0073 (0.0124)	−0.0082 (0.0124)	−0.0012 (0.0098)
<i>decent</i>	−0.0772 (0.1826)	−0.0822 (0.1814)	−0.1096 (0.1827)	−0.0002 (0.0113)	0.0007 (0.0113)	0.0008 (0.0091)
<i>scir</i>	8.3931 *** (2.6112)	8.4227 *** (2.6521)	8.4564 *** (2.6669)	0.0312 (0.0497)	0.0329 (0.0502)	0.0109 (0.0443)
<i>open</i>	−2.0408 (1.3385)	−2.2057 (1.3627)	−2.0923 (1.3558)	0.0446 (0.0524)	0.0410 (0.0532)	0.0251 (0.0461)
<i>Cons</i>	−0.5862 (1.9417)	−1.0963 (1.9075)	−1.3764 (1.9406)	1.0910 *** (0.0753)	1.0984 *** (0.0742)	1.0756 *** (0.0680)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3113	3113	3113	3113	3113	3113
R^2	0.7044	0.7039	0.7029	0.4032	0.4037	0.4530

Table 6. Regression coefficients, statistical significance, total sample size (N), and the goodness of fit (R^2) of fitted econometric models for the composition effect of China's low-carbon policies. The values in brackets under each coefficient are their cluster-robust standard errors. See the Methods and Materials Section for details. *Cons* means the regression y-intercept. Significance levels: *** 0.01, ** 0.05, * 0.1.

	Industrial Structure Upgrading			Clean Energy Transition		
	(1) Total	(2) Command	(3) Market	(4) Total	(5) Command	(6) Market
<i>PI</i>	0.0029 (0.0069)	−0.0070 (0.0049)	0.0048 * (0.0027)	−0.0602 (0.0398)	0.0127 (0.0131)	−0.0366 ** (0.0161)
<i>gdp</i>	0.0613 * (0.0347)	0.0607 * (0.0346)	0.0623 * (0.0351)	−0.3233 ** (0.1346)	−0.3170 ** (0.1311)	−0.3272 ** (0.1360)
<i>indus</i>	−0.0337 *** (0.0018)	−0.0338 *** (0.0018)	−0.0338 *** (0.0018)	−0.0200 *** (0.0051)	−0.0197 *** (0.0051)	−0.0197 *** (0.0051)
<i>pden</i>	0.2201 *** (0.0593)	0.2197 *** (0.0592)	0.2211 *** (0.0596)	−0.0468 (0.1992)	−0.0397 (0.1966)	−0.0498 (0.1978)
<i>urb</i>	−0.0820 (0.0914)	−0.0865 (0.0922)	−0.0800 (0.0923)	0.3860 (0.3574)	0.4219 (0.3657)	0.3901 (0.3584)
<i>decent</i>	0.0298 (0.0376)	0.0329 (0.0381)	0.0296 (0.0376)	0.2741 * (0.1416)	0.2551 * (0.1389)	0.2658 * (0.1388)
<i>scir</i>	−0.3431 (0.3527)	−0.3480 (0.3543)	−0.3400 (0.3543)	−2.9733 ** (1.3232)	−2.9370 ** (1.3090)	−2.9777 ** (1.3228)
<i>open</i>	−0.9085 * (0.5498)	−0.9159 * (0.5521)	−0.9158 * (0.5506)	2.1533 ** (0.8362)	2.1418 ** (0.8282)	2.1913 *** (0.8391)
<i>Cons</i>	0.6338 (0.4335)	0.6799 (0.4290)	0.6171 (0.4373)	4.8974 *** (1.5810)	4.4843 *** (1.5205)	4.7959 *** (1.5628)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3113	3113	3113	3113	3113	3113
R^2	0.7965	0.7966	0.7966	0.5836	0.5829	0.5843

Table 7. Regression coefficients, statistical significance, total sample size (N), and the goodness of fit (R^2) of fitted econometric models the scale effect of China's low-carbon policies. The values in brackets under each coefficient are their cluster-robust standard errors. See the Methods and Materials Section for details. *Cons* means the regression y-intercept. Significance levels: *** 0.01, ** 0.05, * 0.1.

	Number of Industrial Enterprises			Output Value of Industrial Enterprises		
	(1) Total	(2) Command	(3) Market	(4) Total	(5) Command	(6) Market
<i>PI</i>	−0.0897 *** (0.0176)	−0.0518 *** (0.0099)	−0.0381 *** (0.0095)	−0.0378 ** (0.0159)	0.0004 (0.0117)	−0.0141 * (0.0074)
<i>gdp</i>	0.2747 *** (0.0942)	0.2824 *** (0.0415)	0.2731 *** (0.0943)	0.4211 ** (0.1851)	0.4248 ** (0.1866)	0.4210 ** (0.1853)
<i>indus</i>	0.0148 *** (0.0040)	0.0133 *** (0.0036)	0.0153 *** (0.0040)	0.0342 *** (0.0037)	0.0344 *** (0.0037)	0.0344 *** (0.0037)
<i>pden</i>	−0.0177 (0.2248)	0.0587 (0.2173)	−0.0176 (0.2244)	0.2077 (0.1580)	0.2122 (0.1598)	0.2083 (0.1587)
<i>urb</i>	0.0067 (0.1883)	0.2078 (0.1887)	0.0246 (0.1920)	0.1756 (0.1622)	0.1948 (0.1638)	0.1846 (0.1626)
<i>decent</i>	0.2197 ** (0.1043)	0.0288 (0.0898)	0.2046 ** (0.1033)	0.3673 *** (0.0982)	0.3581 *** (0.0979)	0.3607 *** (0.0968)

<i>scir</i>	1.4320 (0.9167)	1.1842 (0.9340)	1.4409 (0.9244)	2.8304 *** (0.9475)	2.8494 *** (0.9622)	2.8360 *** (0.9623)
<i>open</i>	4.7146 *** (0.8074)	4.6433 *** (0.8359)	4.7419 *** (0.8106)	2.4773 *** (0.6617)	2.4605 *** (0.6683)	2.4853 *** (0.6651)
<i>Cons</i>	2.6048 (1.7145)	2.0758 * (1.1750)	2.3374 (1.7291)	−5.3281 *** (1.7308)	−5.5562 *** (1.7417)	−5.4547 *** (1.7236)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	3113	3113	3113	3113	3113	3113
<i>R</i> ²	0.3041	0.3054	0.3036	0.8712	0.8709	0.8711

Our further analysis on fairness issues regarding carbon emissions also produced notable results. According to Table 8, China’s total low-carbon policies and market-based policies could significantly promote carbon abatement in cities’ provincial border areas (column 1 and 3), but the effect of command-and control policies is not significant (column 2); however, the effects of low-carbon policies in non-provincial border areas are all significant (column 4, 5, and 6). In addition, there is evidence that China’s total low-carbon policies and market-based policies significantly stimulated the urban Gini index of carbon emissions (see column 1 and 3 in Table 9), but not so for command-and-control policies. Furthermore, as per Table 10, we uncovered evidence for leakage: either total low-carbon policies or market-based policies significantly promoted the establishment of high-carbon enterprises in provincial border areas but not in non-provincial border areas. That is, China’s low-carbon policies have unintentionally shifted emissions to urban boundaries, which is arguably an unfair outcome.

Table 8. Regression coefficients, statistical significance, total sample size (*N*), and the goodness of fit (*R*²) of fitted econometric models for the impact of China’s low-carbon policies on CO₂ emissions in different kinds of areas. The values in brackets under each coefficient are their cluster-robust standard errors. See the Methods and Materials Section for details. *Cons* means the regression y-intercept. Significance levels: *** 0.01, ** 0.05, * 0.1.

	Provincial Border Areas			Non-Provincial Border Areas		
	(1) Total	(2) Command	(3) Market	(4) Total	(5) Command	(6) Market
<i>PI</i>	−0.0245 *** (0.0093)	−0.0046 (0.0051)	−0.0124 *** (0.0039)	−0.0270 *** (0.0072)	−0.0134 *** (0.0039)	−0.0081 ** (0.0031)
<i>gdp</i>	0.0690 ** (0.0292)	0.0712 ** (0.0299)	0.0681 ** (0.0289)	0.0441 ** (0.0174)	0.0461 ** (0.0181)	0.0445 ** (0.0176)
<i>indus</i>	0.0046 *** (0.0014)	0.0046 *** (0.0014)	0.0047 *** (0.0014)	0.0022 ** (0.0010)	0.0022 ** (0.0010)	0.0024 ** (0.0010)
<i>pden</i>	0.0482 (0.0811)	0.0511 (0.0812)	0.0477 (0.0806)	0.0829 (0.0960)	0.0862 (0.0947)	0.0839 (0.0957)
<i>urb</i>	0.1587 ** (0.0761)	0.1690 ** (0.0763)	0.1622 ** (0.0765)	0.1960 *** (0.0631)	0.2038 *** (0.0632)	0.2039 *** (0.0642)
<i>decent</i>	−0.0632 (0.0498)	−0.0675 (0.0504)	−0.0670 (0.0493)	−0.0214 (0.0373)	−0.0231 (0.0379)	−0.0265 (0.0370)
<i>scir</i>	−0.8066 ** (0.4002)	−0.7967 ** (0.3957)	−0.8060 ** (0.3911)	−0.3572 (0.2876)	−0.3505 (0.2838)	−0.3514 (0.2872)
<i>open</i>	−0.1624 (0.4163)	−0.1793 (0.4196)	−0.1514 (0.4181)	−0.1643 (0.2943)	−0.1934 (0.2969)	−0.1621 (0.2951)
<i>Cons</i>	0.3137 (0.4876)	0.1854 (0.4872)	0.2545 (0.4810)	1.1519 ** (0.5734)	1.0447 * (0.5687)	1.0471 * (0.5714)
City FE	Yes	Yes	Yes	Yes	Yes	Yes

Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3113	3113	3113	3113	3113	3113
R ²	0.7891	0.7864	0.7867	0.8034	0.8017	0.8022

Table 9. Regression coefficients, statistical significance, total sample size (N), and the goodness of fit (R^2) of fitted econometric models for the impact of China's low-carbon policies on the Gini index of CO₂ emissions. The values in brackets under each coefficient are their cluster-robust standard errors. See the Methods and Materials Section for details. *Cons* means the regression y-intercept. Significance levels: *** 0.01, ** 0.05, * 0.1.

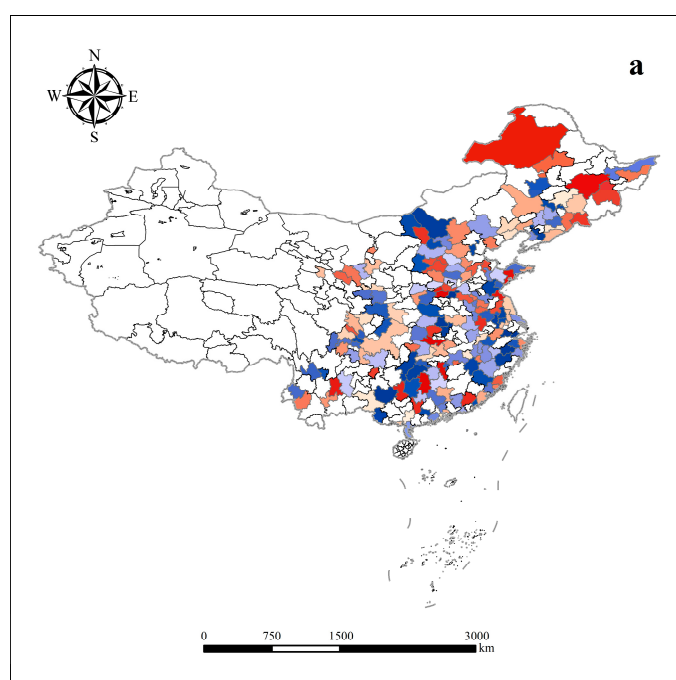
	(1) Total	(2) Command	(3) Market
<i>PI</i>	0.0018 * (0.0009)	−0.0012 * (0.0007)	0.0013 *** (0.0004)
<i>gdp</i>	−0.0099 *** (0.0031)	−0.0101 *** (0.0031)	−0.0097 *** (0.0030)
<i>indus</i>	−0.0001 (0.0002)	−0.0001 (0.0002)	−0.0001 (0.0002)
<i>pden</i>	−0.0034 (0.0114)	−0.0036 (0.0114)	−0.0033 (0.0113)
<i>urb</i>	0.0023 (0.0088)	0.0009 (0.0088)	0.0023 (0.0088)
<i>decent</i>	−0.0048 (0.0056)	−0.0040 (0.0056)	−0.0046 (0.0056)
<i>scir</i>	0.1322 (0.0801)	0.1308 (0.0796)	0.1326 * (0.0799)
<i>open</i>	−0.0721 (0.0532)	−0.0727 (0.0531)	−0.0736 (0.0531)
<i>Cons</i>	0.3991 *** (0.0746)	0.4149 *** (0.0737)	0.4008 *** (0.0730)
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	3113	3113	3113
R ²	0.0715	0.0714	0.0737

Table 10. Regression coefficients, statistical significance, total sample size (N), and the goodness of fit (R^2) of fitted econometric models for the impact of China's low-carbon policies on the establishment of high-carbon enterprises in different kinds of areas. The values in brackets under each coefficient are their cluster-robust standard errors. See the Methods and Materials Section for details. *Cons* means the regression y-intercept. Significance levels: *** 0.01, ** 0.05, * 0.1.

	Provincial Border Areas			Non-Provincial Border Areas		
	(1) Total	(2) Command	(3) Market	(4) Total	(5) Command	(6) Market
<i>PI</i>	0.0549 *** (0.0201)	0.0026 (0.0158)	0.0280 *** (0.0100)	0.0250 (0.0191)	−0.0166 (0.0152)	0.0119 (0.0098)
<i>gdp</i>	−0.0557 (0.0761)	−0.0608 (0.0741)	−0.0535 (0.0766)	0.0879 (0.1060)	0.0712 (0.1003)	0.0751 (0.1021)
<i>indus</i>	0.0027 (0.0027)	0.0026 (0.0027)	0.0024 (0.0027)	0.0048 (0.0031)	0.0041 (0.0031)	0.0042 (0.0031)
<i>pden</i>	0.7920 *** (0.1845)	0.7854 *** (0.1857)	0.7932 *** (0.1852)	1.0729 ** (0.4362)	1.0528 ** (0.4417)	1.0561 ** (0.4423)
<i>urb</i>	0.4967 **	0.4702 **	0.4891 **	0.4870 **	0.4633 **	0.4792 **

	(0.2211)	(0.2218)	(0.2217)	(0.1940)	(0.1943)	(0.1942)
<i>decent</i>	−0.0499	−0.0376	−0.0415	0.1598	0.1558	0.1478
	(0.1248)	(0.1255)	(0.1247)	(0.1120)	(0.1097)	(0.1095)
<i>scir</i>	−0.7965	−0.8225	−0.7975	−0.4228	−0.4374	−0.4178
	(1.3852)	(1.3982)	(1.4006)	(1.0535)	(1.0349)	(1.0351)
<i>open</i>	0.6818	0.7101	0.6567	0.5891	0.7034	0.7030
	(0.7399)	(0.7398)	(0.7435)	(0.9265)	(0.9211)	(0.9197)
<i>Cons</i>	−0.0719	0.2467	0.0586	−1.9921	−1.7197	−1.8726
	(1.2282)	(1.2145)	(1.2360)	(2.6239)	(2.6183)	(2.6416)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	3113	3113	3113	3113	3113	3113
<i>R</i> ²	0.4593	0.4581	0.4597	0.5257	0.5285	0.5286

Figure 1 depicts the transfer learning results for the carbon abatement effect. For 284 Chinese cities examined in this study, we obtained 184 learning results for command-and-control policies and 182 learning results for market-based policies. Comparing them, we see that command-and-control policies can continue to be effective for carbon abatement in 97 cities, with a mean coefficient of -0.0535 ; similarly, market-based policies can continue to be effective in 95 cities, with a mean coefficient of -0.0637 . In other words, according to our estimation, China's command-and-control and market-based policies will cease to be effective for carbon abatement in nearly 47.3% and 47.8% cities, respectively. These findings raise serious concerns about whether current carbon regulation policies in China can be sustained.



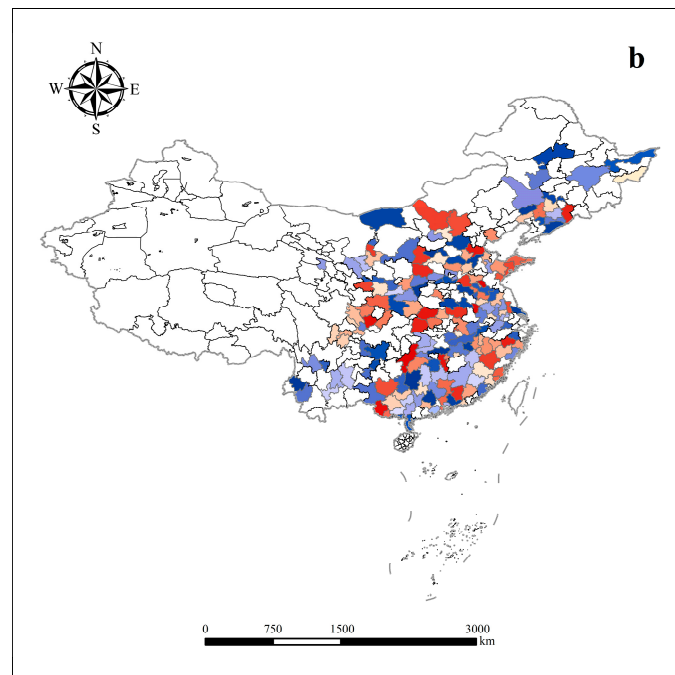


Figure 1. Results of carbon abatement effect transfer learning for (a) command-and-control policies and (b) market-based policies in China. Blue shading indicates regions where low-carbon policies continue to deliver sustained emission reductions, while red shading marks regions where such policies cease to be effective. Increasing color intensity corresponds to stronger effects.

5. Discussion

Collectively, our quantitative empirical findings provide strong validation for the phenomenon of “regulation without transformation”. While the amassed evidence confirms that China’s low-carbon policies have successfully enforced “regulation” to significantly curb its CO₂ emissions, the underlying mechanisms point to a critical lack of “transformation”. This study’s decomposition analysis shows that this abatement was driven almost entirely by scale effects (i.e., contraction of industrial output and enterprise numbers), rather than the intended technique effects (i.e., green innovation and TFP growth) or composition effects (i.e., structural upgrading). This surprising dominance of output suppression over technological and structural progress implies that national policy pressure has, in effect, operated as a constraint on economic activity, as opposed to a catalyst for the country’s green transition. This overarching dependence on contraction rather than transformation raises critical questions about the sustainability, efficiency, and equity of China’s decarbonization pathway in the 21st century. The marked discrepancy between our findings and prior policy-oriented studies can be explained, at least partly, by the latter’s inherent sample selection bias, especially when considering the outcomes of market-based policies. Studies reporting significant technique effects of market-based instruments in China have mostly focused on its carbon emission trading scheme pilot cities; these cities are economically advanced and institutionally mature with well-developed innovation ecosystems, best exemplified by Beijing, Shanghai, and Shenzhen. These cities enjoy both a higher absorptive capacity and greater access to complementary resources, enabling firms to readily undergo technological upgrading in response to carbon price signals. In contrast, our dataset covers 284 prefecture-level cities harboring substantial heterogeneity in their economic structure, institutional capacity, and market development, which provides a more accurate and representative estimate of the average national effect of China’s low-carbon policies.

As our regression results show (Table 7), the observed carbon emission reductions in our studied sample of cities are driven mainly by declines in the number and economic output of large-scale industrial enterprises, with no concomitant gains in green invention patents, carbon TFP (total factor productivity), or clean energy uptake (see Tables 5 and 6). This pattern deviates sharply from an optimistic reading of the Porter hypothesis, in which regulation is believed to spur compensating innovation, aligning instead with the regulation-induced contraction literature. The latter finds that, under tight regulatory regimes, the measured TFP tends to drop, with plants induced to shut down or scale back their activities, rather than productivity-enhancing innovation being triggered [54]. Work by Walker [55] has revealed that the Clean Air Act Amendments of the US (implemented in 1990) led to quantifiable declines in polluting firms' TFP, as well as substantial costs in terms of output and employment. More recently, Huo et al. [12] found that the loss in GDP associated with China's pilot low-carbon city policy is around 1.19 trillion RMB, which closely agrees with our observed shrinkage of industrial scale across China during the study period.

From the above mechanism, two corollary implications. First, carbon abatement attained by scale compression is inherently fragile: if fewer emissions are principally a by-product of lower production rather than structural or technological changes, then aggregate emissions remain vulnerable to reversal when either demand recovers or stimulus policies revive industrial activity. Second, that contraction-driven abatement also generates distinct social and economic costs (e.g., job losses, slower productivity growth) without creating a notable domestic comparative advantage in low-carbon technologies, which inevitably weakens the sustainability of environmental policies [56]. This view of ours is supported by several salient facts: Between 2005 and 2020, China's carbon emission intensity plunged by 48.4%, surpassing its pledged target of a 40% to 45% reduction by 2020. Yet, according to the *Statistical Communiqué on National Economic and Social Development*, from 2020 to 2024, carbon emission intensity fell by just 1%, 3.8%, 0.8%, 0%, and 3.4%, respectively, corresponding to an average annual decline of only 1.6%. Hence, the cumulative reduction over this 5-year period was below 10%, well short of the 18% reduction anticipated for 2020 to 2025. These data clearly indicate that a much slower pace of emission reductions is unfolding in China. Pressured by the national "dual control" assessment on energy consumption and intensity, Chinese provinces started rationing electricity and curtailing production through various measures. This had pronounced negative impacts in manufacturing-intensive provinces like Zhejiang, Jiangsu, and Guangdong, where certain energy-intensive enterprises were either abruptly shut down or forced to cut output drastically. However, in response to the COVID-19 pandemic, stimulus measures were introduced that favored energy-intensive industries, which emboldened high-energy-consuming enterprises to instead accelerate production, driving up both their energy consumption and carbon emissions. Moreover, while the national ETS launched in 2021 is arguably a major milestone, it lacks adaptive features (e.g., price floors, auctioning) required to drive genuine technique effects. Without strong price signals to incentivize R&D, firms are likely to continue viewing compliance as just another cost to manage via output adjustments instead of a signal for technological transformation.

Why the contrasting low-carbon policy types failed in China also varies to some extent. Command-and-control policies are linked to diminished green patenting activity and a lower carbon TFP (Table 5). The underlying reason is not simply the new binding rules themselves but rather how they interact with the enforcement domain as well as firms' incentives. The regulatory economics literature suggests that prescriptive, narrowly specified standards limit the choice sets available to firms and increase their short-run compliance costs; since these latter are financed out of cash flow, firms will rationally postpone or underinvest in long-horizon R&D and large capital projects [57]. In the Chinese context

studied here (2007–2017), this pathway mechanism was amplified by three institutional features: First, due to local fiscal and promotion incentives, short-term GDP and employment stabilization became the paramount objective of many subnational governments; hence, strict national standards often translated into selective enforcement or rapid but administratively convenient responses (e.g., capacity cuts, temporary shutdowns) instead of incentivized innovation [58]. Second, modest fossil fuel support in that period (e.g., coal subsidies and other assistance for producers) weakened any private returns to investments in fuel switching or electrification, rendering expensive low-carbon capital projects a less attractive option. Third, capital and credit constraints for many industrial firms meant taking on mandatory retrofits with high upfront costs, these being financially harder to absorb than output adjustments or shutdowns. Taken together, these contextual factors adequately explain why command-and-control policies elicited compliance via contraction in China rather than the Porter effect (i.e., stimulus for innovation).

By contrast, market-based instruments are characterized by a mixed profile in our results. There is a weak positive association with industrial upgrading, yet little if any consistent effect on innovation measures, along with a significant negative relationship to clean energy transition that was unexpected (Table 6). According to other research, market instruments induce technological change only when they deliver credible, sustained price signals and when carbon revenues or complementary policy measures channel resources directly into innovation and infrastructure [59,60]. In practice, early market-based policies that relied heavily on free allocation, were marked by low and volatile allowance prices, or failed to recycle revenue into clean-tech funds, generally yielded limited innovation benefits [1]. The international experience is instructive here: After the EU emissions trading system increased its auctioning and combined allowance revenues with dedicated innovation and modernization funds, there emerged measurable upward effects on low-carbon patenting and investment [61]. Similarly, California's cap-and-trade market for greenhouse gases explicitly ties auction revenue to renewables, energy efficiency, and community projects, forming what is believed to be a crucial component of its recognized structural impacts [3]. In stark contrast to these international precedents, the observed negative association of China's market-based policies with its clean energy transition can be attributed to a systemic "double signal failure". First, a "signal generation failure" has occurred within the carbon market itself. As remarked in other studies, China's pilot projects issued generous free allowances but lacked deep secondary markets [62,63]. This structural flaw muted the carbon price signal, rendering it too weak and volatile to be properly factored into long-horizon project appraisals for renewable energy investments. Second, a "signal transmission blockage" severed the link between carbon pricing and the energy power sector. These policies were not tightly integrated with energy-sector reforms concerning market liberalization and electricity tariffs [64,65]. In consequence, even when regulated firms incurred carbon costs, rigid electricity pricing prevented these costs from being transmitted downstream to create a comparative advantage for clean power. This culmination of internal pricing weakness, coupled with external transmission blockage, meant the carbon market imposed compliance costs without offering the corresponding revenue incentives for renewables. This likely led to signal failure, stalling the sought-after transition.

We do, however, acknowledge that measuring "transformation" requires the careful selection of proxies. Our key finding that policies faltered in spawning technique and composition effects remains robust when considering alternative indicators. While some studies have used patent applications or utility models as proxies, we deliberately focused on green invention patents granted. In the Chinese context, patent application counts are often inflated by strategic filing behaviors seeking government subsidies in lieu of genuine R&D breakthroughs. By adhering to the stricter standard of "granted inventions", we

could filter out this “subsidy-seeking noise” to confirm that the observed lack of innovation reflects a genuine stagnation of technological capabilities and is not a measurement artifact. Likewise, we utilized clean energy’s consumption rather than its installed capacity. Given the well-documented issue of renewable energy curtailment (i.e., idle wind and solar capacity) in China’s electricity grid, using installed capacity would overstate the success of the transition. Our consumption-based metric reliably captures the actual utilization of clean energy, reinforcing this study’s conclusion that market-based policies have yet to successfully close the loop between investment and actual decarbonization.

Our results also revealed a domestic analog to the pollution haven hypothesis for carbon emissions. Namely, we find that China’s provincial border areas—where environmental governance is fragmented and regulatory responsibilities often overlap—underwent widening inequality in CO₂ emissions (Table 8) and the establishment of more high-carbon enterprises (Table 10). Both trends suggest an intra-national carbon leakage dynamic exists, in which emission-intensive production migrates to those jurisdictions with weaker enforcement despite a unified national political system. Documented international experiences have already warned about such a phenomenon: in the EU emissions trading system, Ellerman et al. [2] detected carbon leakage initially concentrated in cross-border industries that then shifted to countries not within the system; in California’s cap-and-trade program, Fowlie et al. [66] found that it prompted electricity imports from neighboring states with more carbon-intensive generation mixes. Such research focused on the leakage between different countries or provinces, as in several studies done in China [67,68]. Building on that, our research extends this body of evidence by explicitly bringing to it a border-region perspective. We show that the leakage phenomenon is not limited to isolated sectoral shifts but can manifest as a broader spatial pattern: Geographically, border areas, especially those limited in fiscal capacity and enforcement resources, tend to lure high-carbon enterprises displaced from stricter central areas. This insight matters because border areas often lie at the nexus of multiple administrative systems, which can complicate the task of coordinated enforcement. In the context of China’s “dual carbon” targets and likely greater regulatory pressure in the coming years, we predict that border regions are at high risk of becoming future domestic pollution havens. Features of these areas, such as their permeable administrative boundaries, generally poor monitoring infrastructure, and outsized dependence on mobile industrial investment, are the very same that create favorable conditions for location-driven leakage.

In addition, our forward-looking transfer learning analysis indicates that, under their current configuration, low-carbon policies would lose their efficacy in about 47% of Chinese cities if current economic and structural conditions change as projected. To better understand this novel empirical finding, we explore aspects of cities where low-carbon policies would or would not reduce future carbon emissions. For command-and-control low-carbon policies, the cities where mitigation effects disappear are concentrated in heavy industrial centers in China’s north and northwest (e.g., Taiyuan, Harbin), accounting for 62% of effective cases in its Northeast region. Conversely, cities where such policies continue to be effective are concentrated in the more developed southern and eastern regions (e.g., Nanjing, Guangzhou), representing 60% of effective cases in East China. For market-based low-carbon policies, we find that the loss of policy effectiveness is most prevalent in manufacturing hubs in the east (e.g., Qingdao, Jinhua), constituting 55% of effective cases in East China; the country’s western and northeastern resource-dependent areas (e.g., Xining, Fushun) are home to 65% of effective cases in Northwest China. These heterogeneous outcomes underscore the influence of interacting geographic, economic, and industrial factors. In the coal- and steel-dependent heavy industrial cities of northern China, high compliance costs and rebound effects triggered by stringent mandates have imperiled command-and-control low-carbon policies to sustain long-term effectiveness

there. In contrast, southern developed cities are benefiting from a stronger enforcement infrastructure and their service-oriented economies, cementing the sustained performance of such policies. For market-based policies, the maturity of China's eastern markets may have facilitated carbon leakage and corresponding unwanted behaviors, thereby weakening their overall efficiency. In its less developed western regions, subsidies along with other incentives for firms have provided fresh stimulus for transformation, albeit from a low baseline scenario. Additionally, our transfer learning approach frequently failed to give predictions in data-scarce remote areas (e.g., Xinjiang, Gansu). Considering the lagging socioeconomic conditions in these regions, the actual national situation—the rate of cities where low-carbon policies can be continuously effective—is probably even worse than our present estimates would suggest. This divergence emphasizes the urgent need to reform and enhance China's low-carbon policies.

Moreover, our results reinforce a central insight from the emerging literature on climate policy resilience and adaptive governance: that static regulatory frameworks are ill-suited to dynamic socioeconomic situations [69]. Climate regulation operates in a realm riddled with much uncertainty. Macroeconomic conditions (e.g., industrial composition, energy demand profiles, investment) evolve rapidly, as do technological trajectories (e.g., cost curves for renewables, breakthroughs in storage or hydrogen), more often than not in nonlinear, unpredictable ways [70]. Fixing regulatory architecture at its inception—in terms of carbon prices, allocation rules, technology standards, or sectoral coverage—may fit well with current conditions, yet is apt to gradually drift out of sync as those conditions inevitably change. For example, a carbon price deemed initially sufficient to shift investment decisions in coal-heavy cities may eventually be too low once those cities' marginal abatement costs rise as "low-hanging fruit" plants are closed. Likewise, innovation subsidies designed for the technological frontier may fail to encourage the adoption of next-generation technologies (smart production, AI, robotics, drone delivery, etc.) if cost differentials widen too much. Therefore, flexible adaptation and adjustment mechanisms are pivotal for the long-term implementation of low-carbon policies. A case in point is the EU's market stability reserve, introduced in 2019, which automatically adjusts the supply of the EU emissions trading system allowances based on the surplus volume in the market [71]. The purpose of this embedded mechanism is to stabilize prices and maintain scarcity signals under conditions of fluctuating demand, thereby protecting the credibility of long-term investment signals. In the same vein, other adaptive carbon price floors, capable of being adjusted automatically for inflation, energy price volatility, and abatement cost indices, also exist in New Zealand's emissions trading scheme [72], which could extend the effective lifespan of climate regulations. Such forward-looking adaptive designs, however, have yet to be systematically incorporated into China's framework of national low-carbon policies. Its current carbon pricing pilots and national emissions trading system still lack (in a systematic way) proven automatic adjustment triggers, such as price floors linked to inflation or GDP growth, or the dynamic tightening of carbon caps in response to slower rates of emissions. Similarly, technology support schemes (e.g., feed-in tariffs for clean energy) are usually reformed in abrupt, ad hoc ways, rather than via pre-committed adaptive pathways. The absence of institutionalized recalibration renders it more likely that policies will underperform when confronted with structural change. Until such mechanisms are duly included, China's low-carbon policies, in their current form, risk delivering only transient gains in emission reductions while entrenching structural vulnerabilities, inevitably hindering the attainment of both carbon peaking and neutrality objectives.

Our finding that carbon abatement has relied, so far, on scale contraction rather than technological progress is not unique to China. It serves as a cautionary tale for other industrializing nations (e.g., India, Vietnam) facing the dual pressures of growth and decarbonization. Without mature financial markets to fund green R&D, stringent top-down

mandates will likely force firms into the same “survival mode” condition uncovered in our study—cutting output to minimize immediate compliance costs instead of investing in long-term structural transformation. The identification of provincial border areas in China as “governance vacuums” offers timely, critical insights for federal or decentralized countries worldwide (e.g., the U.S., Brazil, and EU member states). Taken together, our results suggest that without harmonized cross-jurisdictional enforcement, the “pollution haven” effect will likely manifest domestically, undermining national climate targets through internal displacement. In addition, the evidence for command-and-control policies being negatively associated with innovation contributes to the global debate on the Porter hypothesis. This would suggest that, in developing contexts, where firms face capital constraints and soft budget constraints are absent, rigid regulation comes to act as a tax on production rather than a stimulus for innovation. This insight implies that for Global South nations, regulatory instruments must be coupled with explicit technology finance mechanisms to be effective.

6. Policy Implications

Collectively, our findings point to a core challenge in carbon regulation. During the recent study period, China’s low-carbon policies have achieved carbon abatement primarily via industrial-scale contraction; yet, its command-and-control policies were accompanied by a decline in green innovation, while market-based policies did not seem to catalyze its clean energy transition. To address these shortcomings, it is imperative to reconfigure the policy framework in several ways so that temporary emission reductions are converted into sustained, technology-driven decarbonization.

To begin with, command-and-control standards should be redesigned to accelerate, not impede, the upgrading of technology in China. This would entail pairing regulatory mandates with both targeted financing mechanisms and innovation subsidies to jointly lower the upfront capital costs of developing and adopting green technologies. By easing liquidity constraints and matching compliance obligations with investment horizons, firms can better respond to regulatory pressure through efficiency improvements and technology adoption rather than relying on production cuts alone.

Next, market-based instruments must shift decisively toward stronger price signals and revenue recycling strategies. Moving from free allocation to full or majority auctioning should generate stable public revenues, which can then be reinvested in low-carbon infrastructure, energy grid modernization, and fruitful R&D programs. When coupled with transparent, predictable rules to limit carbon price volatility, this will undoubtedly bolster the credibility of long-term investment signals and increase the likelihood that firms make truly transformative—rather than marginal—changes to their production processes. Furthermore, carbon pricing ought to be harmonized with energy-sector reforms. Without its sound integration into electricity market liberalization, tariff adjustments, and renewable grid access, the carbon price signal remains crude and muted. Reforming fossil fuel subsidies, improving dispatch rules for renewables, and ensuring that carbon costs are fully reflected in purchasing power and investment decisions are essential for closing the broken “signal loop” between carbon pricing and real-world decarbonization.

Importantly, intra-national carbon leakage must be tackled, ideally through institutional and enforcement innovations. We recommend establishing “cross-provincial joint enforcement units” for boundary regions. Instead of relying on fragmented local management, these units should operate under a unified command with shared authority to eliminate the “governance vacuums” where high-carbon firms can currently hide. Also, a “carbon archive and traceability system” should be implemented for industrial relocation. When enterprises move operations across jurisdictions, their historical emission records should remain tied to their original registration, as this would deter firms from evading

regulation simply by relocating to looser jurisdictions. Finally, satellite-based monitoring technologies should be formally integrated into official surveillance activities to provide real-time, unbiased surveillance of border areas, given the difficulty in accessing or patrolling them frequently by ground teams.

Finally, policy adaptability must be embraced and embedded as a design principle. To preclude policy obsolescence, instead of blindly relying on discretionary reform, there should be a pre-commitment to adaptive mechanisms. First, as an alternative to fixed prices, China should design and implement a pricing mechanism that automatically indexes the carbon price floor to inflation rates and average abatement costs. This would ensure the price signal remains robust enough to drive innovation in spite of fluctuating economic conditions. Second, to counteract the innovation-stifling effect of command-and-control policies, subsidies should be linked to performance. Financial support ought to be automatically triggered when a city's abatement relies excessively on output contraction as opposed to efficiency gains, thereby actively steering the region back toward a technology-driven transition pathway. Third, we advise shifting to rolling multi-year targets, which can be automatically adjusted according to regional GDP growth and industrial structure changes, to guarantee targets remain ambitious yet achievable without forcing coarse production shutdowns.

To conclude, China's low-carbon transition calls for a coherent and adaptive spatially coordinated policy architecture. A well-calibrated combination of improved command instruments, credible market signals, integrated clean energy policy linkages, cross-border enforcement, and built-in adaptability can steer the basis of abatement from temporary contraction to sustained, innovation-led transformations. By proactively addressing carbon abatement mechanisms and emission fairness issues in tandem, we envision a future low-carbon framework for China that is capable of ensuring its relevant policies remain effective under both current conditions and a changing economic/technological landscape, bringing it closer to carbon peaking and neutrality.

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References

1. Calel, R.; Dechezleprêtre, A. Environmental Policy and Directed Technological Change: Evidence from the European Carbon Market. *Rev. Econ. Stat.* **2016**, *98*, 173–191.
2. Ellerman, A.D.; Marcantonini, C.; Zaklan, A. The European Union Emissions Trading System: Ten Years and Counting. *Rev. Environ. Econ. Policy* **2016**, *10*, 89–107.

3. Borenstein, S.; Bushnell, J.; Wolak, F.A.; Zaragoza-Watkins, M. Expecting the Unexpected: Emissions Uncertainty and Environmental Market Design. *Am. Econ. Rev.* **2019**, *109*, 3953–3977.
4. Sinn, H. Public Policies against Global Warming: A Supply-Side Approach. *Int. Tax Public Finance* **2008**, *15*, 360–394.
5. Smulders, S.; Tsur, Y.; Zemel, A. Announcing Climate Policy: Can a Green Paradox Arise without Scarcity? *J. Environ. Econ. Manage.* **2012**, *64*, 364–376.
6. Ritter, H.; Schopf, M. Unilateral Climate Policy: Harmful or Even Disastrous? *Environ. Resour. Econ.* **2014**, *58*, 155–178.
7. Jiang, Q.; Ma, X. Spillovers of Environmental Regulation on Carbon Emissions Network. *Technol. Forecast. Soc. Change* **2021**, *169*, 120825.
8. Wu, H.; Xu, L.; Ren, S.; Hao, Y.; Yan, G. How Do Energy Consumption and Environmental Regulation Affect Carbon Emissions in China? New Evidence from a Dynamic Threshold Panel Model. *Resour. Policy* **2020**, *67*, 101678.
9. Li, C.; Li, H.; Qin, X. Spatial Heterogeneity of Carbon Emissions and Its Influencing Factors in China: Evidence from 286 Prefecture-Level Cities. *Int. J. Environ. Res. Public Health* **2022**, *19*, 1226.
10. Huang, X.; Tian, P. How Does Heterogeneous Environmental Regulation Affect Net Carbon Emissions: Spatial and Threshold Analysis for China. *J. Environ. Manage.* **2023**, *330*, 117161.
11. Liu, X.; Li, Y.; Chen, X.; Liu, J. Evaluation of Low Carbon City Pilot Policy Effect on Carbon Abatement in China: An Empirical Evidence Based on Time-Varying DID Model. *Cities* **2022**, *123*, 103582.
12. Huo, W.; Qi, J.; Yang, T.; Liu, J.; Liu, M.; Zhou, Z. Effects of China's Pilot Low-Carbon City Policy on Carbon Emission Reduction: A Quasi-Natural Experiment Based on Satellite Data. *Technol. Forecast. Soc. Change* **2022**, *175*, 121422.
13. Hu, Y.; Ren, S.; Wang, Y.; Chen, X. Can Carbon Emission Trading Scheme Achieve Energy Conservation and Emission Reduction? Evidence from the Industrial Sector in China. *Energy Econ.* **2020**, *85*, 104590.
14. Wu, Q. Price and Scale Effects of China's Carbon Emission Trading System Pilots on Emission Reduction. *J. Environ. Manage.* **2022**, *314*, 115054.
15. Zhang, H.; Di Maria, C.; Ghezelayagh, B.; Shan, Y. Climate Policy in Emerging Economies: Evidence from China's Low-Carbon City Pilot. *J. Environ. Econ. Manage.* **2024**, *124*, 102943.
16. Grossman, G.; Krueger, A. Economic Growth and the Environment. *Q. J. Econ.* **1995**, *110*, 353–377.
17. Antweiler, W.; Copeland, B.; Taylor, M. Is Free Trade Good for the Environment? *Am. Econ. Rev.* **2001**, *91*, 877–908.
18. Porter, M.; van der Linde, C. Toward a New Conception of the Environment–Competitiveness Relationship. *J. Econ. Perspect.* **1995**, *9*, 97–118.
19. Chen, H.; Guo, W.; Feng, X.; Wei, W.; Liu, H.; Feng, Y.; Gong, W. The Impact of Low-Carbon City Pilot Policy on the Total Factor Productivity of Listed Enterprises in China. *Resour. Conserv. Recycl.* **2021**, *169*, 105457.
20. Pan, A.; Zhang, W.; Shi, X.; Dai, L. Climate Policy and Low-Carbon Innovation: Evidence from Low-Carbon City Pilots in China. *Energy Econ.* **2022**, *112*, 106129.
21. Sun, Y.; Shen, S.; Zhou, C. Does the Pilot Emissions Trading System in China Promote Innovation? Evidence Based on Green Technology Innovation in the Energy Sector. *Energy Econ.* **2023**, *126*, 106984.
22. Zhao, X.; Lu, W.; Wand, W.; Hu, S. The Impact of Carbon Emission Trading on Green Innovation of China's Power Industry. *Environ. Impact Assess. Rev.* **2023**, *99*, 107040.
23. Qiu, S.; Wang, Z.; Liu, S. The Policy Outcomes of Low-Carbon City Construction on Urban Green Development: Evidence from a Quasi-Natural Experiment Conducted in China. *Sustain. Cities Soc.* **2021**, *66*, 102699.
24. Wang, Z.; Liang, F.; Li, C.; Xiong, W.; Chen, Y.; Xie, F. Does China's Low-Carbon City Pilot Policy Promote Green Development? Evidence from the Digital Industry. *J. Innov. Knowl.* **2023**, *8*, 100339.
25. Liu, Z.; Sun, H. Assessing the Impact of Emissions Trading Scheme on Low-Carbon Technological Innovation: Evidence from China. *Environ. Impact Assess. Rev.* **2021**, *89*, 106589.
26. Jiang, B.; Du, M.; Wang, D. Carbon Emissions Trading, Industrial Structure Upgrading and Green Development: Excess Benefits of Combined Actions. *Econ. Anal. Policy* **2024**, *82*, 480–501.
27. Lee, C.; Feng, Y.; Peng, D. A Green Path Towards Sustainable Development: The Impact of Low-Carbon City Pilot on Energy Transition. *Energy Econ.* **2022**, *115*, 106343.
28. Zhang, M.; Ge, Y.; Liu, L.; Zhou, D. Impacts of Carbon Emission Trading Schemes on the Development of Renewable Energy in China: Spatial Spillover and Mediation Paths. *Sustain. Prod. Consum.* **2022**, *32*, 306–317.
29. Copeland, B.; Taylor, M. Trade and Transboundary Pollution. *Am. Econ. Rev.* **1995**, *85*, 716–737.
30. Ma, Z.; Zhang, P. Heterogeneous Outcomes and Fairness Issues in Environmental Governance: Compelling Evidence from China's Low-Carbon City Pilots. *Environ. Plan. B Urban Anal. City Sci.* **2025**, *52*, 2235–2250.

31. Jiang, J.; Ye, B.; Zeng, Z.; Yang, X.; Sun, Z.; Shao, S.; Feng, K.; Tan, X. Carbon Abatement and Leakage in China's Regional Carbon Emission Trading. *Environ. Sci. Technol.* **2024**, *58*, 17661–17673.
32. Dong, X.; Wang, C.; Zhang, F.; Zhang, H.; Xia, C. China's Low-Carbon Policy Intensity Dataset from National-to-Prefecture-Level over 2007–2022. *Sci. Data* **2024**, *11*, 213.
33. Chen, J.; Gao, M.; Cheng, S.; Hou, W.; Song, M.; Liu, X.; Liu, Y.; Shan, Y. County-Level CO₂ Emissions and Sequestration in China during 1997–2017. *Sci. Data* **2020**, *7*, 391.
34. Lin, B.; Jia, H. Does the Development of China's High-Speed Rail Improve the Total-Factor Carbon Productivity of Cities? *Transp. Res. Part D Transp. Environ.* **2022**, *105*, 103230.
35. Verhoef, E.; Nijkamp, P. Externalities in Urban Sustainability: Environmental versus Localization-Type Agglomeration Externalities in a General Spatial Equilibrium Model of a Single-Sector Monocentric Industrial City. *Ecol. Econ.* **2002**, *40*, 157–179.
36. Glaeser, E.; Kahn, M. The Greenness of Cities: Carbon Dioxide Emissions and Urban Development. *J. Urban Econ.* **2010**, *67*, 404–418.
37. Du, L.; Wei, C.; Cai, S. Economic Development and Carbon Dioxide Emissions in China: Provincial Panel Data Analysis. *China Econ. Rev.* **2012**, *23*, 371–384.
38. Khan, Z.; Ali, S.; Dong, K.; Li, R. How Does Fiscal Decentralization Affect CO₂ Emissions? The Roles of Institutions and Human Capital. *Energy Econ.* **2021**, *94*, 105060.
39. He, Q. Fiscal Decentralization and Environmental Pollution: Evidence from Chinese Panel Data. *China Econ. Rev.* **2015**, *36*, 86–100.
40. Dean, J.; Lovely, M.; Wang, H. Are Foreign Investors Attracted to Weak Environmental Regulations? Evaluating the Evidence from China. *J. Dev. Econ.* **2009**, *90*, 1–13.
41. Zeng, D.; Zhao, L. Pollution Havens and Industrial Agglomeration. *J. Environ. Econ. Manage.* **2009**, *58*, 141–153.
42. Oster, E. Unobservable Selection and Coefficient Stability: Theory and Evidence. *J. Bus. Econ. Stat.* **2019**, *37*, 187–204.
43. Guo, Z.; Čević, D.; Bühlmann, P. Doubly Debiased Lasso: High-Dimensional Inference under Hidden Confounding. *Ann. Stat.* **2022**, *50*, 1320.
44. Solow, R. Technical Change and the Aggregate Production Function. *Rev. Econ. Stat.* **1957**, *39*, 312–320.
45. Hsieh, C.; Klenow, P.J. Development Accounting. *Am. Econ. J.: Macroecon.* **2010**, *2*, 207–223.
46. Griliches, Z. Patent Statistics as Economic Indicators: A Survey. In *R&D and Productivity: The Econometric Evidence*; Griliches, Z., Ed.; University of Chicago Press: Chicago, IL, USA, 1998; pp 287–343.
47. Wang, Q.; Su, M. The Effects of Urbanization and Industrialization on Decoupling Economic Growth from Carbon Emission—A Case Study of China. *Sustain. Cities Soc.* **2019**, *51*, 101758.
48. Zeng, S.; Jin, G.; Tan, K.; Liu, X. Can Low-Carbon City Construction Reduce Carbon Intensity? Empirical Evidence from Low-Carbon City Pilot Policy in China. *J. Environ. Manage.* **2023**, *332*, 117363.
49. Rauf, A.; Zhang, J.; Li, J.; Amin, W. Structural Changes, Energy Consumption and Carbon Emissions in China: Empirical Evidence from ARDL Bound Testing Model. *Struct. Change Econ. Dyn.* **2018**, *47*, 194–206.
50. Yang, G.; Zhang, G.; Cao, D.; Gao, X.; Wang, X.; Yang, S.; Jiang, P.; Zha, D.; Shan, Y. A Comprehensive City-Level Final Energy Consumption Dataset Including Renewable Energy for China, 2005–2021. *Sci. Data* **2024**, *11*, 738.
51. Torrey, L.; Shavlik, J. Transfer Learning. In *Handbook of Research on Machine Learning Applications and Trends: Algorithms, Methods, and Techniques*; Olivas, E.S., Guerrero, J.D.M., Sober, M.M., Benedito, J.R.M., López, A.J.S., Eds.; IGI Global: Hershey, PA, USA, 2010; pp 242–264.
52. Weiss, K.; Khoshgoftaar, T.M.; Wang, D. A Survey of Transfer Learning. *J. Big Data* **2016**, *3*, 9.
53. Tian, Y.; Feng, Y. Transfer Learning under High-Dimensional Generalized Linear Models. *J. Am. Stat. Assoc.* **2023**, *118*, 2684–2697.
54. Greenstone, M.; List, J.A.; Syverson, C. *The Effects of Environmental Regulation on the Competitiveness of US Manufacturing (No. w18392)*; National Bureau of Economic Research: Cambridge, MA, USA, 2012.
55. Walker, R. The Transitional Costs of Sectoral Reallocation: Evidence from the Clean Air Act and the Workforce. *Q. J. Econ.* **2013**, *128*, 1787–1835.
56. Acemoglu, D.; Aghion, P.; Bursztyn, L.; Hémous, D. The Environment and Directed Technical Change. *Am. Econ. Rev.* **2012**, *102*, 131–166.
57. Jaffe, A.; Stavins, R. Dynamic Incentives of Environmental Regulations: The Effects of Alternative Policy Instruments on Technology Diffusion. *J. Environ. Econ. Manage.* **1995**, *29*, S43–S63.

58. Li, H.; Zhou, L.A. Political Turnover and Economic Performance: The Incentive Role of Personnel Control in China. *J. Public Econ.* **2005**, *89*, 1743–1762.
59. Rogge, K.; Reichardt, K. Policy Mixes for Sustainability Transitions: An Extended Concept and Framework for Analysis. *Res. Policy* **2016**, *45*, 1620–1635.
60. Schmidt, T.; Sewerin, S. Measuring the Temporal Dynamics of Policy Mixes: An Empirical Analysis of Renewable Energy Policy Mixes' Balance and Design Features in Nine Countries. *Res. Policy* **2019**, *48*, 103557.
61. Dechezleprêtre, A.; Nachtigall, D.; Venmans, F. The Joint Impact of the European Union Emissions Trading System on Carbon Emissions and Economic Performance. *J. Environ. Econ. Manage.* **2023**, *118*, 102758.
62. Zhang, Z. Carbon Emissions Trading in China: The Evolution from Pilots to a Nationwide Scheme. *Clim. Policy* **2015**, *15*, S104–S126.
63. Stoerk, T.; Dudek, D.J.; Yang, J. China's National Carbon Emissions Trading Scheme: Lessons from the Pilot Emission Trading Schemes, Academic Literature, and Known Policy Details. *Clim. Policy* **2019**, *19*, 472–486.
64. Teng, F.; Wang, X.; Zhiqiang, L. Introducing the Emissions Trading System to China's Electricity Sector: Challenges and Opportunities. *Energy Policy* **2014**, *75*, 39–45.
65. Guo, H.; Davidson, M.R.; Chen, Q.; Zhang, D.; Jiang, N.; Xia, Q.; Kanga, C.; Zhang, X. Power Market Reform in China: Motivations, Progress, and Recommendations. *Energy Policy* **2020**, *145*, 111717.
66. Fowlie, M.; Reguant, M.; Ryan, S. Market-Based Emissions Regulation and Industry Dynamics. *J. Political Econ.* **2016**, *124*, 249–302.
67. He, L.; Chen, K. Does China's Regional Emission Trading Scheme Lead to Carbon Leakage? Evidence from Conglomerates. *Energy Policy* **2023**, *175*, 113481.
68. Zhang, Y.; Qi, L.; Tao, M.; Silva, E.; Zhang, Q. Impact of Carbon Emission Trading on Carbon Transfers in China's Inter-Provincial and International Trade. *J. Environ. Manage.* **2025**, *392*, 126744.
69. Jordan, A.; Huitema, D. Innovations in Climate Policy: The Politics of Invention, Diffusion, and Evaluation. *Environ. Politics* **2014**, *23*, 715–734.
70. Newell, R.G.; Pizer, W.A.; Raimi, D. Carbon Markets 15 Years after Kyoto: Lessons Learned, New Challenges. *J. Econ. Perspect.* **2013**, *27*, 123–146.
71. Perino, G.; Willner, M. Procrastinating Reform: The Impact of the Market Stability Reserve on the EU ETS. *J. Environ. Econ. Manage.* **2016**, *80*, 37–52.
72. Leining, C.; Kerr, S.; Bruce-Brand, B. The New Zealand Emissions Trading Scheme: Critical Review and Future Outlook for Three Design Innovations. *Clim. Policy* **2020**, *20*, 246–264.

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