energies

MDPI

Article

Data Trading Platforms and Urban Joint Pollution–Carbon Burden: Quasi-Experimental Evidence from China

Xiangxiang Sun [1,2,*] and Junxu Zhou [3]

[1] College of Economics and Management, Minjiang University, No. 200 Xiyuangong Road, Shangjie Town, Minhou County, Fuzhou 350116, China
[2] Fujian Digital Media Economy Research Center, Fujian Social Science Research Base, Minjiang University, Fuzhou 350108, China
[3] College of Accounting, Xijing University, Weiqu Sub-District, Chang'an District, Xi'an 710123, China
* Correspondence: lookxiang@126.com

Abstract

Cities face growing pressure to reduce air pollution and carbon emissions simultaneously, yet the data systems supporting energy and environmental decision-making remain fragmented. This study examines whether city-level data trading platforms, as institutions for organizing data circulation, are associated with changes in urban joint pollution–carbon outcomes. Using a balanced panel of 164 Chinese cities from 2009 to 2023, we construct an outcome-oriented joint pollution–carbon burden indicator from an entropy-weighted pollution index and multisource carbon-emission estimates; lower values indicate better joint performance. The empirical results show that platform establishment is associated with a statistically significant decline in the joint burden. This finding remains consistent across alternative indicator constructions, an unbalanced panel of complete observations, controls for regional trends, treatment assignments verified against original sources, and placebo tests based on random assignment. Further analysis indicates that platform establishment is associated with improvements in energy productivity and industrial upgrading, providing evidence consistent with the proposed production mechanisms. These findings suggest that data marketization may contribute to improved environmental outcomes by facilitating the integration of data circulation into energy management and production decisions.

Keywords: data marketization; data trading platforms; energy productivity; industrial upgrading; joint pollution–carbon burden

Check for updates

Academic Editor: Jing Qiu

Received: 2 September 2026
Revised: 20 October 2026
Accepted: 21 October 2026
Published: 29 October 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license.

1. Introduction

Cities are increasingly expected to deliver a dual transition: cleaner air and lower carbon emissions. Yet the institutions that shape these objectives remain divided across administrative and sectoral boundaries. Air-pollution control and carbon mitigation are often organized through separate policy systems, even though both are rooted in energy use, industrial processes, transport activity, and urban infrastructure. This institutional separation creates a policy puzzle. An institution can alter energy and production decisions without being classified as an environmental policy, while formal environmental regulation may not reach the information and coordination processes through which emissions are generated. The unresolved question is whether a digital market institution designed to circulate data can also become an instrument of joint pollution–carbon reduction.

This question is particularly salient in the marketization of data. Data trading platforms are commonly presented as market-making institutions for the digital economy. They define

data products, clarify rights and authorization procedures, support data valuation and listing, and reduce frictions in data exchange. Their environmental implications, however, remain empirically unresolved. Energy management, emission diagnosis, industrial coordination, and logistics planning all depend on timely and reusable information. If a platform makes such information easier to identify, authorize, combine, and reuse, it may influence the joint pollution–carbon burden even without setting emission standards or mandating abatement technologies.

China's city-level data trading platform pilots provide a useful setting for examining this question. The pilots form part of a broader reform that treats data as a production factor and promotes the market-oriented allocation of data elements. Their formal objective is not to impose emission standards, cap carbon, or subsidize clean technologies. Instead, they seek to make dispersed data resources identifiable, standardized, authorized, valued, listed, transacted, and reusable. The pilots therefore represent a distinct institutional intervention: a data trading platform is not simply more broadband or a larger digital sector, but a local attempt to create rules and intermediaries through which data products can be matched with users.

The environmental consequences of this intervention are theoretically ambiguous. One pathway is an information-allocation effect: data circulation may help firms identify energy waste, compare production processes, adopt cleaner technologies, and coordinate with logistics, utilities, finance, and government agencies. A competing pathway is a digital-scale effect: data centers, platform operations, computing activities, and platform-enabled industrial expansion consume electricity and may generate rebound effects. The central empirical question is therefore whether the information-allocation gains from data marketization outweigh these digital-scale pressures in urban production systems.

Existing studies examine the environmental consequences of explicit low-carbon policies and the economic value of data circulation, but they have not established whether a concrete market institution for data circulation is associated with measurable changes in the joint pollution–carbon burden. To address this gap, we use the staggered establishment of city-level data trading platforms as a quasi-experimental setting. The two-way fixed-effects model is used as a benchmark and is complemented by the Borusyak–Jaravel–Spiess imputation estimator and a Callaway–Sant'Anna outcome-regression estimator, together with event-study diagnostics, randomization placebos, alternative outcome constructions, an unbalanced-panel check, source-audited treatment coding, and selection reweighting.

The estimates indicate that data trading platform adoption is associated with a statistically significant reduction in the joint pollution–carbon burden. This pattern suggests that data marketization may have environmental consequences beyond the expansion of digital activity, particularly when data circulation becomes connected to energy management and production decisions.

This study contributes to the literature on environmental engineering and policy in three ways. First, it extends research on the environmental implications of institutional change beyond policies explicitly designed for pollution control or carbon mitigation. By examining the establishment of urban data trading platforms, the study provides empirical evidence on the relationship between data marketization and the joint burden of air pollution and carbon emissions, highlighting the potential environmental relevance of institutions primarily designed to facilitate data circulation. Second, it advances the empirical assessment of environmental outcomes by adopting an integrated measure of pollution and carbon burdens rather than examining either dimension in isolation. The use of alternative standardized and rank-based measures further assesses the robustness of the findings across different approaches to measuring joint environmental outcomes. Third, it provides evidence on potential production-side pathways and the conditions associated

with heterogeneous environmental responses. By examining energy productivity, industrial upgrading, and differences in baseline environmental pressure, the study offers insights into how data marketization may be linked to urban environmental performance through changes in production activities and industrial structure.

2. Literature Review and Hypotheses

2.1. Data Trading Platforms as Environmental Information Infrastructure

China's data market reform has evolved from broad factor market reform toward more specific institutions for data circulation. The 2020 central policy on factor market allocation placed data alongside land, labor, capital, and technology in the reform agenda; subsequent national guidance in 2021 called for market-oriented allocation and more standardized data market arrangements; and the 2022 data-institution policy emphasized data rights, circulation, transactions, security, and governance [1–3]. Data trading platform pilots sit at this intersection. Their formal purpose is to organize data circulation, while their environmental relevance depends on whether energy, production, emissions, and logistics information becomes usable across organizational boundaries.

A data trading platform is not simply broadband, a data center, or an e-government database. It is a market-making institution that registers, classifies, authorizes, values, lists, and matches data products. This distinction separates the treatment from generic digital infrastructure and motivates the treatment coding.

The environmental relevance follows from fragmented information. Firms hold process data, utilities hold energy data, agencies hold monitoring data, and logistics and technology providers hold operational data. Market rules may reduce the cost of matching these resources with environmental and production applications.

The treatment therefore captures institutionalized data exchange rather than connectivity alone. Its environmental effect depends on whether platform rules become connected to production, energy, and monitoring decisions. Figure 1 provides spatial context for the empirical setting.

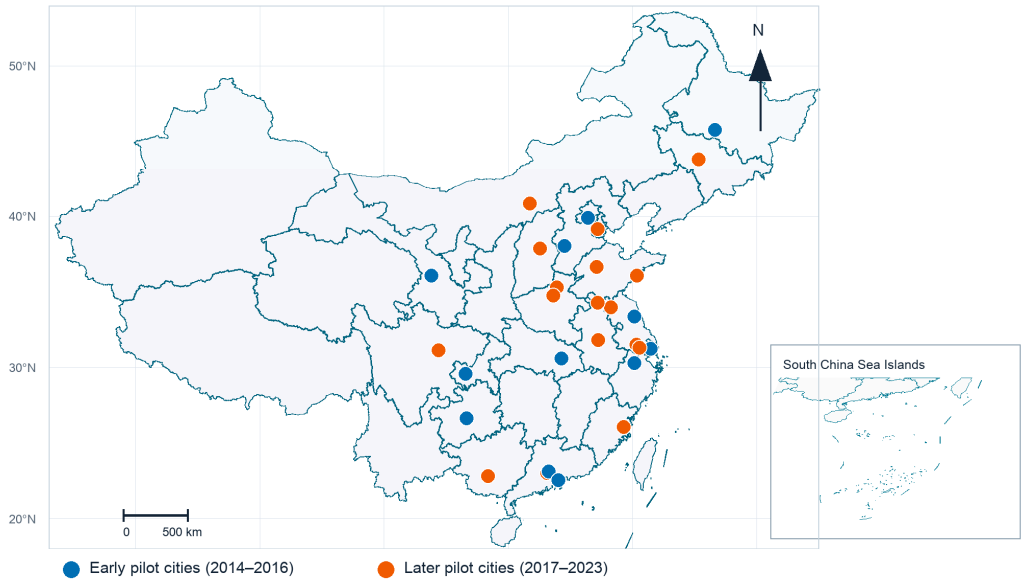


Figure 1. Spatial distribution and adoption timing of treated data trading platform cities. Notes: The map shows the 29 treated cities in the 164-city balanced panel. Blue and orange markers denote first treatment in 2014–2016 and 2017–2023, respectively.

2.2. Related Research and Contribution

Four strands of research are relevant to this study, but they do not yet answer the same institutional question. The first concerns explicit environmental policy. Research on China's low-carbon city pilots shows that climate-oriented interventions can affect energy use, industrial structure, and carbon–smog outcomes [4–6]. Related city-level studies further connect carbon–smog governance with greenhouse-gas accounting in low-carbon urban planning [5,7]. This literature establishes that city-level institutions can generate coordinated environmental consequences. Its interventions, however, are typically designed explicitly to regulate emissions, energy use, or abatement. It therefore leaves open whether an institution established to organize data circulation can affect the same environmental margins without setting an emission standard, imposing a carbon price, or prescribing a specific abatement technology.

The second strand concerns the economics and governance of data. Data are partly non-rival and reusable, so their social value depends not only on collection but also on the rules governing access, rights, authorization, pricing, and reuse [8,9]. Information intermediaries can improve the design and pricing of information products, while digital technologies can reduce search, replication, tracking, and verification costs [10–12]. These contributions explain why data market institutions may have allocative effects beyond the firms that trade data directly. They do not, however, establish that improved circulation changes environmental performance. The unresolved link is therefore not whether data have economic value, but whether institutionalized data exchange changes the information available for energy management, production decisions, environmental monitoring, and green investment.

The third strand is the digitalization-environment literature, which provides an important counterpoint to a purely efficiency-based account. Digital systems may reduce resource use through monitoring, coordination, process optimization, and improved matching, but they also require electricity and may stimulate additional production and demand [13–16]. The sign of the environmental effect is therefore theoretically ambiguous. Yet most existing studies measure ICT penetration, broadband, computing infrastructure, or aggregate digital activity. They rarely distinguish the scale of digital activity from the institutional conditions under which data are authorized, exchanged, and reused. A data trading platform represents a different policy margin from broadband expansion or data-center investment: it may alter the allocation and usability of information without being reducible to the physical scale of digital infrastructure. This distinction is central to evaluating whether data marketization is associated with environmental improvement or with an offsetting digital-demand response.

A fourth, related body of literature examines environmental information disclosure, transparency, and smart urbanism. Credible information can strengthen monitoring, public scrutiny, and accountability, while data-intensive urban systems can support more continuous forms of policy coordination [17–21]. Data trading platforms extend this concern from disclosure to circulation. They are not simply systems that reveal information from an authority to the public; they create rules and intermediaries through which data products can be classified, authorized, valued, matched, and reused across firms, agencies, utilities, and service providers. Whether this market-making function generates measurable city-level environmental consequences remains unresolved. Treating platforms as information institutions, rather than as generic digital-development indicators, is therefore important for both interpretation and empirical design.

Taken together, the literature leaves a specific gap. Environmental-policy studies show that city-level institutions can change joint pollution–carbon outcomes, but they focus on interventions with an explicit environmental mandate. Data-economics and governance

studies explain why institutions can make non-rival information more usable, but rarely follow data circulation into environmental outcomes. Digitalization–energy studies document both efficiency and rebound possibilities, but usually do not identify the institutional margin of data exchange. This study brings this literature into one empirical question: can a non-environmental market institution for data circulation become part of the information infrastructure of urban environmental governance? We address this question by evaluating China's data trading platform pilots and testing whether the joint pollution–carbon burden, energy productivity, and industrial upgrading move in directions consistent with an information-allocation pathway. The contribution is not to assume that digitalization is inherently green, but to evaluate a specific institutional channel through which data marketization may enter environmental and production decisions while leaving open the possibility of offsetting digital-scale effects.

2.3. Conceptual Framework and Hypotheses

2.3.1. Data Marketization and Joint Pollution–Carbon Burden

Data trading platform pilots differ from environmental regulation because they do not set emission limits or mandate abatement technologies. Their possible environmental effect comes from changing how information enters energy, production, and governance decisions.

The theoretical starting point is that urban pollution–carbon coordination is partly an information-allocation problem. Firms and local governments need to identify energy-intensive processes, feasible technologies, and suitable monitoring or service providers. When production, energy, emissions, logistics, and technology data remain fragmented, these decisions are more difficult. A data trading platform may reduce this constraint by making data products searchable, authorized, standardized, and reusable. The environmental effect is therefore conditional on data entering operational decisions, not on digitalization alone.

This interpretation is consistent with the economics of data: lower search and verification costs can improve matching, but environmental gains require operational use. The expected chain is therefore information access, production-side adjustment, and environmental performance.

The expected net effect is ambiguous because the information-allocation channel competes with a digital-scale channel. ICT expansion and data infrastructure consume electricity, and digitalization may generate rebound effects if efficiency gains stimulate additional production or platform activity [13–15]. Smart-city research likewise cautions that urban data systems improve environmental performance only when digital capacity is translated into operational governance and service delivery [20–22]. Accordingly, the expected environmental improvement from data trading platform pilots depends on whether information-allocation gains exceed digital-scale costs. This conditional prediction motivates the main hypothesis.

H1. *Data trading platform pilots are associated with a lower urban joint pollution–carbon burden.*

2.3.2. Proposed Production-Side Pathways

We focus on two production-side margins through which newly tradable data may enter urban environmental performance: the efficiency with which existing production uses energy and the composition of activities that expand within the city. These margins are conceptually distinct, although they may operate simultaneously.

Energy productivity provides the first testable channel. Fossil-energy use links carbon dioxide with conventional pollution, so producing more output from a given energy input can generate joint environmental benefits. Information on load profiles, equipment perfor-

mance, production schedules, and emission benchmarks can help firms locate avoidable losses and adjust operations. In the public sector, comparable information can support the identification of high-energy users and the targeting of energy-saving interventions.

A data trading platform may affect this margin by making relevant data searchable, authorized, standardized, and reusable across firms, utilities, service providers, and public agencies. By reducing information frictions [8,10,12], data trading platforms may improve energy management and production decisions. If the resulting information is used to reduce avoidable energy waste, the predicted intermediate outcome is higher energy productivity, which is consistent with a lower joint pollution–carbon burden. This reasoning yields the first testable prediction.

H2a. *Data trading platform pilots are associated with higher urban energy productivity.*

Industrial upgrading provides a second, distinct channel. The composition of local production affects environmental burden, and data exchange may alter which firms, services, and technologies are able to match and expand within a city.

The relevant margin is not digital capacity alone. Broadband or computing infrastructure does not guarantee reallocation; data must be accessible and usable in ways that reduce matching frictions among firms, producer-service providers, technology suppliers, and logistics operators. If data marketization supports the expansion of service-oriented and technology-intensive activities relative to energy-intensive activities, environmental performance may improve through a composition effect. This prediction extends evidence that environmental policies can affect outcomes through industrial restructuring [5,23] to a non-environmental market institution.

H2b. *Data trading platform pilots are associated with industrial upgrading.*

Taken together, H2a and H2b identify two intermediate outcomes predicted by the conceptual framework: higher energy productivity and industrial upgrading. Environmental information governance provides the institutional foundation for these pathways by making relevant data more accessible, standardized, and reusable across firms, service providers, utilities, and public agencies. The empirical tests examine whether platform adoption shifts these intermediate outcomes in the predicted directions; they do not estimate mediated shares of the total treatment effect.

Figure 2 summarizes the main association and the two proposed production-side pathways.

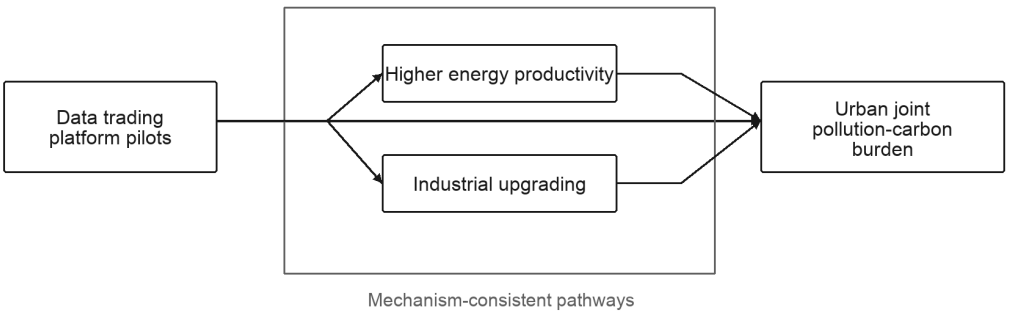


Figure 2. Conceptual framework: data marketization and joint pollution–carbon burden.

3. Materials and Methods

3.1. Outcome Construction and Interpretation

The dependent variable is denoted JB_{it}, the joint pollution–carbon burden for city i in year t. It is an outcome-oriented measure of coordinated environmental performance, rather

than a frontier-based efficiency index or a structural measure of governance coordination. JB_{it} combines the pollution index $POLL_{it}$ with total carbon emissions CO_{2it}; lower values indicate a lower joint pollution–carbon burden.

The pollution component uses three undesirable-output indicators: total wastewater discharge, sulfur dioxide emissions, and smoke/dust emissions. The construction follows three steps. First, each pollutant is transformed into a comparable, direction-adjusted burden measure so that a higher normalized value represents a larger pollution burden. Second, entropy weights are calculated over the city-year panel. Third, the weighted indicators are aggregated using an improved entropy-weighted TOPSIS procedure. Pollutant P_{jit} denotes the direction-adjusted burden measure for pollutant j in city i and year t, and w_j denotes its entropy weight. The resulting pollution index, $POLL_{it}$, is represented by

$$POLL_{it} = TOPSIS(P_{1it}, P_{2it}, P_{3it}; w_1, w_2, w_3) \quad (1)$$

The carbon component, denoted CO_{2it}, aggregates four sources. Following the data documentation and IPCC accounting logic [24], city-level carbon emissions include direct energy-related emissions, electricity-related emissions, transportation emissions, and heat-related emissions. Direct emissions are calculated from reported energy use and standard conversion factors; electricity emissions combine city electricity consumption with the applicable regional grid factor; transport emissions use passenger and freight turnover with the corresponding energy-use intensities; and heat emissions use heating statistics, thermal-efficiency parameters, standard-coal conversion coefficients, and carbon-emission factors. The components are summed before the logarithmic transformation:

$$CO_{2_{it}} = CO_{2_{it}}^{direct} + CO_{2_{it}}^{electricity} + CO_{2_{it}}^{transport} + CO_{2_{it}}^{heat} \quad (2)$$

The final outcome, JB_{it}, is the natural logarithm of the product of the pollution index and total carbon emissions:

$$JB_{it} = ln(POLL_{it} \times CO_{2it}) \quad (3)$$

The index combines the pollution and carbon components multiplicatively, which is equivalent to summing their logarithms. This formulation captures their joint burden without imposing an additional weighting parameter between the two dimensions. Because lower values of JB_{it} denote a lighter combined pollution–carbon burden, a negative treatment coefficient indicates that pilot adoption is associated with a larger reduction in this burden in treated cities than in comparison cities.

Accordingly, JB_{it} is an outcome-based measure of the joint pollution–carbon burden rather than a measure of governance efficiency. Holding the other component constant, the index increases when either the pollution burden or the carbon burden rises. The estimated effects therefore refer specifically to this joint-burden measure.

3.2. Treatment Definition and Sample Construction

The analysis uses a balanced panel of 164 cities observed continuously from 2009 to 2023, yielding 2460 city-year observations. The analysis uses a balanced panel in which all included cities are observed throughout the study period. The unit of observation is the city-year.

Treatment begins in the first documented year in which a city established a data trading platform or formally entered an institutionalized platform-mediated data trading arrangement. The treatment indicator equals one from that year onward and zero otherwise. Adoption dates were compiled and cross-validated using platform-establishment records, local-government and public-agency announcements, official data-exchange websites, and published compilations of Chinese data exchanges.

$$DID_{it} = Treated_i \times Post_{it} \quad (4)$$

where $Treated_i$ equals one if city i ever becomes treated and $Post_{it}$ equals one in years at or after the first effective pilot year. Never-treated cities remain zero throughout the sample.

The final balanced panel includes 164 cities observed continuously from 2009 to 2023. Among these cities, 29 enter treatment during the sample period, whereas 135 remain never treated. The treated-city counts by first treatment year are 1 in 2014, 7 in 2015, 4 in 2016, 3 in 2017, 1 in 2018, 4 in 2020, 3 in 2021, 2 in 2022, and 4 in 2023. Because the pilot programs are adopted in different years across treated cities, the treatment structure is staggered.

The pollution and carbon components are constructed from the China City Statistical Yearbook, China Urban Construction Statistical Yearbook, China Energy Statistical Yearbook, and IPCC emission factors and energy-conversion coefficients. The time-varying control variables are compiled primarily from city and provincial statistical yearbooks and prefecture-level statistical bulletins. After monetary units are harmonized, trade openness is measured as total imports and exports divided by city GDP; financial development as outstanding loans divided by GDP; fiscal expenditure intensity as general public-budget expenditure divided by GDP; the science expenditure share as science and technology expenditure divided by general public-budget expenditure; and broadband connectivity as $\ln(\text{broadband users} + 1)$. Energy productivity is defined as the logarithm of economic output per unit of energy consumption, with energy converted into standard-coal equivalents. Industrial upgrading is measured as the ratio of tertiary-sector value added to secondary-sector value added. Pre-treatment energy pressure is measured using standardized energy consumption per capita calculated from the harmonized energy and population series.

3.3. Variables, Data Sources, and Descriptive Statistics

The preferred control vector includes log GDP per capita, log population, trade openness, financial development, fiscal expenditure intensity, science expenditure share, and log broadband users plus one. Broadband users are retained as a broad digital infrastructure control to distinguish platform institutions from general connectivity. Table 1 reports descriptive statistics.

Table 1. Descriptive statistics.

Panel/Variable	N	Mean	SD	Min	Max
Panel A. Outcome and treatment					
JB	2460	12.246	1.634	7.319	17.004
DID	2460	0.067	0.250	0.000	1.000
Panel B. Baseline controls					
ln_pgdp	2460	10.884	0.575	8.863	12.482
ln_pop	2460	6.059	0.729	3.049	8.075
open	2460	0.002	0.003	0.000	0.024
finance	2460	1.209	0.726	0.132	12.822
fiscal	2460	0.169	0.068	0.055	0.535
science	2460	0.022	0.019	0.001	0.178
ln_broadband	2460	8.715	0.220	8.416	9.142

Table 1. *Cont.*

Panel/Variable	N	Mean	SD	Min	Max
Panel C. Mechanism variables					
ind_upgrade	2460	1.108	0.534	0.109	5.690
ln_energy_productivity	2460	2.461	0.652	−1.720	4.743
Panel D. Additional outcomes and heterogeneity variables					
pm25	2460	45.470	16.675	10.315	105.699
ln_carbon	2460	16.342	1.096	12.160	19.036

After unresolved missing observations are excluded and the balanced-panel restriction is imposed, all components are normalized and weighted using the estimation sample. Table 2 documents their units, denominators, transformations, and data sources. Carbon emissions incorporate direct energy use, electricity, transport, and heat-related emissions, without interpolation or moving-average imputation. The resulting index measures the joint pollution–carbon burden rather than technical efficiency.

Table 2. Variable definitions, measurement, and sources.

Variable	Definition	Measurement	Main Source
Panel A. Outcome and treatment			
JB	Joint pollution–carbon burden indicator	JB_it = ln(pollution index × total carbon emissions); lower values denote a lower joint pollution–carbon burden	China City Statistical Yearbook; China Urban Construction Statistical Yearbook; China Energy Statistical Yearbook; IPCC-based carbon accounting
DID	Data trading platform pilot adoption (DID)	Equals one for treated cities in and after the first pilot year	Official platform records, government announcements, data-exchange websites, and published data-exchange compilations
treat	Ever-treated city	Equals one if a city ever becomes treated during 2009–2023	Official platform records, government announcements, data-exchange websites, and published data-exchange compilations
Panel B. Baseline controls			
ln_pgdp	Economic development	Log GDP per capita	China City Statistical Yearbook; provincial and municipal statistical yearbooks; prefecture-level statistical bulletins
ln_pop	Population scale	Log resident population	China City Statistical Yearbook; provincial and municipal statistical yearbooks; prefecture-level statistical bulletins

Table 2. *Cont.*

Variable	Definition	Measurement	Main Source
open	External market exposure	(Imports + exports)/GDP after harmonizing monetary units	China City Statistical Yearbook; provincial and municipal statistical yearbooks; customs and local statistical materials
finance	Financial development	Loan balance relative to GDP	China City Statistical Yearbook; provincial and municipal statistical yearbooks; municipal financial statistics
fiscal	Government fiscal capacity	Fiscal expenditure relative to GDP	China City Statistical Yearbook; provincial and municipal statistical yearbooks; municipal fiscal statistics
science	Public science support	Science and technology expenditure/general public-budget expenditure	China City Statistical Yearbook; provincial and municipal statistical yearbooks; municipal fiscal statistics
ln_broadband	Digital infrastructure	ln(broadband users + 1)	China City Statistical Yearbook; provincial and municipal statistical yearbooks; prefecture-level statistical bulletins
Panel C. Mechanism and heterogeneity variables			
ind_upgrade	Industrial upgrading	Industrial-structure upgrading index constructed from secondary- and tertiary-industry output shares	China City Statistical Yearbook; provincial and municipal statistical yearbooks; prefecture-level statistical bulletins
ln_energy_productivity	Energy productivity	Log economic output per unit of energy consumption	China City Statistical Yearbook; provincial and municipal statistical yearbooks; prefecture-level statistical bulletins; official energy-conversion coefficients
z_pre_energy_per_capita	Baseline energy condition	Standardized pre-treatment city-level energy consumption per capita	China City Statistical Yearbook; provincial and municipal statistical yearbooks; prefecture-level statistical bulletins; population statistics

Notes: All variables were harmonized at the city-year level.

3.4. Empirical Specifications and Identification Diagnostics

The baseline analysis uses a two-way fixed-effects difference-in-differences specification with city and year fixed effects and standard errors clustered at the city level. City fixed effects account for time-invariant differences across cities, whereas year fixed effects absorb shocks common to all cities. Because treatment timing varies across cities and treatment effects may be heterogeneous, the TWFE coefficient is treated as a benchmark rather than the sole estimator. The analysis therefore also applies the Borusyak–Jaravel–Spiess imputation

estimator and the Callaway–Sant'Anna outcome-regression estimator with never-treated cities as the comparison group [25–27].

$$JB_{it} = \alpha + \beta DID_{it} + X'_{it}\gamma + \mu_i + \lambda_t + \varepsilon_{it} \quad (5)$$

where JB_{it} is the joint pollution–carbon burden for city i in year t, DID_{it} is the city-level data trading platform pilot adoption indicator, X_{it} is the baseline control vector, μ_i denotes city fixed effects, λ_t denotes year fixed effects, and ε_{it} is the error term. City fixed effects absorb time-invariant characteristics such as geography, historical industrial base, administrative status, and long-run institutional conditions. Year fixed effects absorb national shocks and macroeconomic changes common to all cities. Standard errors are clustered by city.

Dynamic treatment patterns and pre-treatment trends are examined using an event-study specification. Robustness is further assessed through randomized placebo assignments, alternative sample and treatment-coding definitions, and reweighting procedures [28]. The heterogeneity-robust staggered DID estimators provide separate checks on sensitivity to treatment timing, cohort composition, and the construction of comparison groups.

To examine pre-treatment trends and dynamic effects, the study estimates an event-study specification:

$$JB_{it} = \alpha + \Sigma_{k\neq -1}\beta_k D^k_{it} + X'_{it}\gamma + \mu_i + \lambda_t + \varepsilon_{it} \quad (6)$$

where $D_{it}{}^k$ equals one when $t - G_i = k$ for treated cities, G_i is the first treatment year, and k indexes event time; $k = -1$ is omitted. For never-treated cities, all event-time indicators equal zero.

The pathway analysis estimates whether platform adoption changes two prespecified intermediate outcomes: energy productivity and industrial upgrading. The following fixed-effects model is estimated separately for each intermediate outcome,

$$M_{it} = \alpha + \Delta DID_{it} + X'_{it}\gamma + \mu_i + \lambda_t + \nu_{it} \quad (7)$$

where M_{it} denotes either current energy productivity or current industrial upgrading. The coefficient δ captures the within-city change in the intermediate outcome associated with platform adoption, conditional on the preferred controls and fixed effects. To avoid conditioning the outcome equation on variables that may themselves be affected by treatment, the analysis does not include these post-treatment intermediate outcomes in the joint-burden equation or interpret the estimates as a causal mediation decomposition.

Cross-sectional heterogeneity is examined using the predetermined measure of pre-treatment energy use in an interaction specification,

$$JB_{it} = \alpha + \beta_1 DID_{it} + \beta_2 (DID_{it} \times Z_i) + X'_{it}\gamma + \mu_i + \lambda_t + \varepsilon_{it} \quad (8)$$

where Z_i denotes a pre-treatment city characteristic, such as baseline energy use. The coefficient β_2 captures whether the treatment association differs with the moderator.

The BJS imputation estimator and the Callaway–Sant'Anna outcome-regression estimator are used to assess whether the estimated association is sensitive to heterogeneous treatment effects and alternative comparison-group construction. Because these estimators aggregate cohort-time effects differently, differences in magnitude and precision are interpreted as estimator sensitivity rather than as evidence that the estimators identify an identical parameter.

4. Results

*4.1. Baseline Results **Analysis***

Table 3 presents the baseline estimates. The DID coefficient is negative and statistically different from zero across specifications and remains similar as controls are added. Because

lower values indicate a lower joint pollution–carbon burden, the estimate is consistent with improved coordinated environmental performance at the city level.

Table 3. Baseline results.

Variables	(1)	(2)	(3)	(4)
DID	−0.514 ***	−0.488 ***	−0.470 ***	−0.454 ***
Robust SE	(0.148)	(0.145)	(0.146)	(0.142)
Economic and demographic controls	NO	YES	YES	YES
Trade, fiscal, financial, and science controls	NO	YES	YES	YES
Digital infrastructure control	NO	NO	YES	YES
Lagged controls	NO	NO	NO	YES
City fixed effect	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES
Observation	2460	2460	2460	2296
Cities	164	164	164	164
Within R2	0.400	0.432	0.434	0.449

Notes: City-clustered robust standard errors are reported in parentheses. Controls include log GDP per capita, log population, trade openness, fiscal expenditure intensity, financial development, science expenditure share, and log broadband users. Column (4) uses one-year-lagged controls; the first sample year is therefore excluded. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

The baseline coefficient is −0.470, indicating that pilot adoption is associated with a 0.470-log-point larger decline in the composite joint pollution–carbon burden in treated cities than in comparison cities.

The comparison with the low-carbon city pilot literature further clarifies the contribution. Li et al. [5] show that an explicitly low-carbon policy can improve carbon–smog synergistic governance through energy-use and industrial-structure channels. The present result suggests that a data market policy may be associated with a related environmental outcome through a different institutional route. Instead of setting low-carbon targets directly, the policy changes the market environment in which information is exchanged and reused.

4.2. Dynamic Treatment Effect Analysis

Table 4 and Figure 3 present the short-window TWFE event-study estimates, with the year immediately preceding treatment ($t = -1$) omitted as the reference period. The coefficients at $t = -3$ and $t = -2$ are not statistically different from zero, and the joint test does not reject that the two pre-treatment coefficients are jointly zero ($p = 0.123$). The post-treatment point estimates become progressively more negative, a pattern consistent with gradual adjustment following platform establishment. Because conventional event-study estimates can be sensitive to staggered treatment timing, the dynamic evidence is considered together with the heterogeneity-robust estimates reported in Table 5.

Table 4. Dynamic treatment patterns.

Variables	JB	Robust SE	*p*-Value
pre3	−0.105	(0.105)	0.319
pre2	−0.155	(0.094)	0.102
current	−0.280 **	(0.125)	0.027
post1	−0.328 **	(0.161)	0.043
post2	−0.487 **	(0.190)	0.011
post3	−0.628 ***	(0.200)	0.002
post4	−0.730 ***	(0.205)	<0.001
post5	−0.776 ***	(0.217)	<0.001
Control variables	YES		
City fixed effect	YES		
Time fixed effect	YES		
Observation	2460		

Notes: The "**" and "***" indicate statistical significance at the 5% and 1% levels, respectively.

Table 5. Robustness checks and additional diagnostics.

Test	Coefficient/Statistic	Robust SE	*p*-Value	N
Panel A. Control, trend, and sample specifications				
Baseline preferred controls	−0.470 ***	(0.146)	0.002	2460
No controls	−0.514 ***	(0.148)	0.001	2460
Core controls only	−0.488 ***	(0.145)	0.001	2460
One-year lagged controls	−0.454 ***	(0.142)	0.002	2296
2011–2023 sample	−0.402 ***	(0.135)	0.003	2132
Unbalanced complete-case panel	−0.506 ***	(0.140)	<0.001	3249
Region-specific linear trends	−0.475 ***	(0.145)	0.001	2460
Panel B. Policy, cohort, and coding checks				
Exclude 2023	−0.477 ***	(0.158)	0.003	2296
Exclude 2014/2023 cohorts	−0.432 ***	(0.152)	0.005	2385
Donut window	−0.668 ***	(0.191)	0.001	2377
Control low-carbon city DID	−0.470 ***	(0.146)	0.002	2460
Control new energy demonstration city DID	−0.460 ***	(0.148)	0.002	2460
Control cross-border e-commerce pilot DID	−0.433 ***	(0.143)	0.003	2460
Control all overlapping policies	−0.425 ***	(0.145)	0.004	2460
Source-audited timing/location	−0.508 ***	(0.150)	0.001	2460
Panel C. Placebo and pre-treatment timing				
Randomization placebo	—	—	0.001	1000
Joint test: pre3 and pre2	F = 2.122	—	0.123	2460

Table 5. *Cont.*

Test	Coefficient/Statistic	Robust SE	*p*-Value	N
Panel D. Alternative outcomes and heterogeneity-robust staggered DID estimates				
Equal-weight standardized joint outcome	−0.201 ***	(0.061)	0.001	2460
Equal-weight rank-based joint outcome	−0.073 ***	(0.020)	<0.001	2460
BJS imputation ATT	−0.533 ***	(0.167)	0.001	2460
Callaway–Sant'Anna outcome regression	−0.412 *	(0.218)	0.058	2445
1% winsorized finance control	−0.468 ***	(0.147)	0.002	2460

Notes: Entries report the coefficient on the DID indicator unless otherwise indicated. The unbalanced complete-case specification includes 241 cities and 3249 city-year observations. The source-audited specification applies conservative timing and exclusion rules to records with ambiguous public documentation. The randomization placebo uses 1000 reassignments of treated-city identities while preserving the observed number of cities in each treatment cohort; the reported *p*-value includes a finite-sample correction. The alternative joint outcomes are constructed as the equal-weight mean of the standardized log pollution and carbon components and the equal-weight mean of their within-sample percentile ranks. Panel D reports alternative outcomes and heterogeneity-robust staggered DID estimates. Standard errors are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

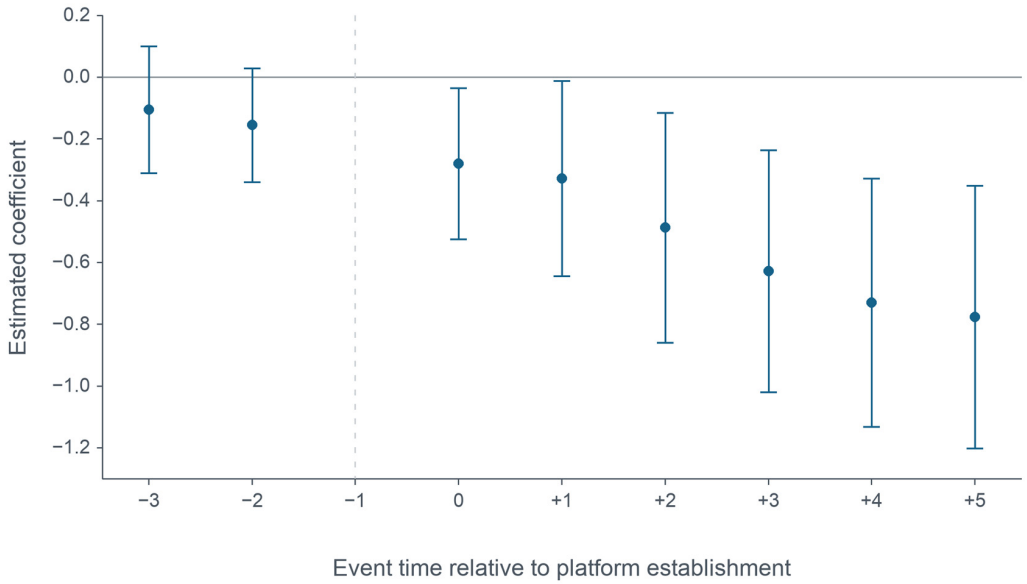


Figure 3. Dynamic estimates for joint pollution-carbon burden. Dots indicate event-time coefficients, and vertical bars indicate 95% confidence intervals based on city-clustered standard errors. The horizontal line marks zero; the dashed vertical line marks event time −1, the omitted reference year.

4.3. Robustness Checks

Table 5 presents robustness checks based on alternative control sets, sample windows, overlapping-policy controls, alternative outcomes, an unbalanced complete-case panel, region-specific trends, source-audited treatment coding, and heterogeneity-robust staggered DID estimators. The BJS imputation estimate is negative and statistically significant. The Callaway–Sant'Anna outcome-regression estimate is also negative and comparable in magnitude to the benchmark estimate, although it is statistically significant only at the 10% level. Together, these estimates support the negative direction of the benchmark association. At the same time, the variation observed in weighting-based specifications indicates that the estimates remain sensitive to comparison-group construction. In the random-assignment placebo exercise, the simulated coefficients are centered near zero, whereas the baseline estimate lies in the lower tail of the distribution.

Table 6 reports component-specific estimates for the joint pollution–carbon burden. The coefficients for the pollution index and log carbon emissions are both negative and statistically significant, whereas the PM2.5 point estimate is negative but statistically imprecise. These results indicate that the composite finding is supported by changes in both the aggregate pollution and carbon components, but they do not imply equally precise effects across individual pollutants.

Table 6. Outcome decomposition.

Test	Coefficient/Statistic	Robust SE	*p*-Value	N
Pollution index	−0.025 **	(0.011)	0.021	2460
Log carbon emissions	−0.251 ***	(0.088)	0.005	2460
PM2.5 concentration	−2.298	(1.415)	0.106	2460

Note: The "**" and "***" indicate statistical significance at the 5% and 1% levels, respectively.

Taken together, Tables 5 and 6 and Figure 4 assess sensitivity to model specification, sample construction, treatment coding, outcome definition, component outcomes, random treatment reassignment, and staggered treatment estimation. The conventional robustness specifications, the BJS estimator, and the Callaway–Sant'Anna outcome-regression estimate retain a negative coefficient, although the latter is significant only at the 10% level. The evidence therefore supports the negative direction of the benchmark association while also indicating sensitivity to how cohort-time comparisons are constructed and weighted.

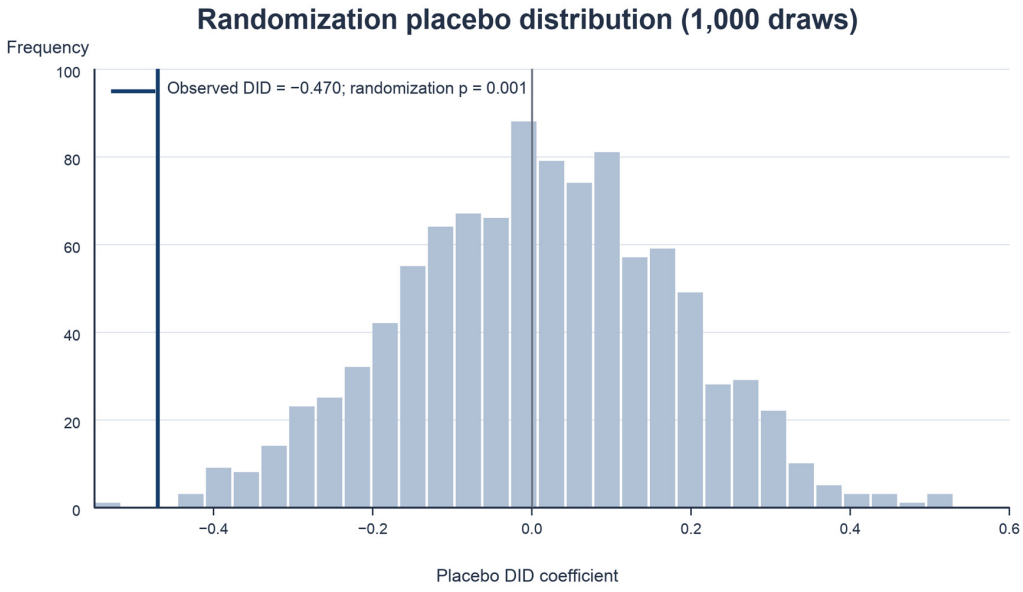


Figure 4. Randomization placebo distribution. Notes: The figure shows the distribution of placebo coefficients from 1000 random treatment assignments that preserve the observed number of treated cities and the treatment-year distribution. The vertical line marks the baseline estimate. The finite-sample-adjusted randomization *p*-value, calculated from the absolute t-statistics, is 0.001.

4.4. Evidence on Proposed Pathways

4.4.1. Intermediate-Outcome Responses

Table 7 reports the estimated policy response of each prespecified intermediate outcome. Platform adoption is positively associated with energy productivity (coefficient = 0.229) and industrial upgrading (coefficient = 0.161), and both estimates are statistically significant at the 1% level. These results indicate that changes in both intermediate

outcomes are consistent with the directions predicted by H2a and H2b. They are interpreted as evidence consistent with the proposed production-side pathways, not as estimates of mediated effects on the joint pollution–carbon burden.

Table 7. Policy effects on proposed intermediate outcomes.

Variable	Energy Productivity	Industrial Upgrading
DID	0.229 ***	0.161 ***
Robust SE	(0.083)	(0.058)
Control variables	YES	YES
City fixed effects	YES	YES
Year fixed effects	YES	YES
Observations	2460	2460
Cities	164	164
Within R^2	0.417	0.657

Notes: Each column estimates Equation (7) for one prespecified intermediate outcome. No joint-burden regression conditions on the post-treatment intermediate variables. All models include the preferred controls, city fixed effects, year fixed effects, and city-clustered robust standard errors. Robust standard errors are reported in parentheses. *** denotes significance at the 1%.

4.4.2. Heterogeneity Results Analysis

Table 8 examines heterogeneity by baseline energy pressure and adoption cohort. Because baseline energy pressure is standardized, the coefficient of −0.376 represents the estimated treatment association at the sample mean of the moderator. The interaction coefficient is −0.744 and statistically significant, indicating that a one-standard-deviation increase in pre-treatment energy pressure is associated with a 0.744-log-point more negative estimate. The jointly estimated coefficients are −0.561 for early adopters and −0.376 for late adopters. Although the early-cohort estimate is numerically larger, the formal equality test does not reject equal coefficients across the two cohorts. The evidence therefore indicates heterogeneity by baseline energy pressure, but no statistically detectable heterogeneity by adoption timing.

Table 8. Heterogeneity analysis. Notes: The "***", "**" and "*" indicate statistical significance at the 1%, 5%, and 10% levels.

Variables	Pre-Energy Use	Early Pilot	Late Pilot
DID	−0.376 ***	−0.531 **	−0.329 *
Robust SE	(0.132)	(0.204)	(0.180)
Interaction term	−0.744 ***	—	—
Robust SE	(0.215)	—	—
Control variables	YES	YES	YES
City fixed effect	YES	YES	YES
Time fixed effect	YES	YES	YES
Observation	2460	2460	2460
Equality test: early = late	—	F = 0.46; p = 0.500	—

5. Discussion

The findings extend the environmental-policy literature in two respects. First, research on China's low-carbon city pilots has established that city-level institutions can alter energy use, industrial composition, and carbon-pollution outcomes [4–6,29]. These studies provide an important benchmark because they show that environmental performance can respond to coordinated local policy packages rather than only to national emission standards. The present evidence concerns a different intervention: a market institution designed to organize data circulation rather than directly regulate emissions. The negative association between pilot adoption and the joint pollution–carbon burden is therefore consistent with a possible information-allocation and production-coordination route, while not implying that data marketization substitutes for direct environmental regulation.

Second, the results speak to the ambiguous relationship between digitalization and energy use. The data-economics literature emphasizes the non-rival and reusable character of information, while also showing that institutional rules determine whether data can be priced, shared, verified, and applied across organizational boundaries [8,9,11]. A trading platform is consequently more than a digital interface: it is a market-making arrangement that can reduce search, authorization, matching, and verification frictions. This distinction matters for environmental analysis. Digital capacity alone may not change operational decisions when energy, production, and emission information remain fragmented across firms and agencies. By contrast, a functioning data market can make information more usable in production scheduling, equipment management, technology matching, and environmental monitoring. The current results are consistent with this institutional interpretation, but they do not imply that all forms of data circulation have the same environmental value. The environmental relevance of a platform depends on data quality, credible authorization and verification rules, intermediary capacity, and actual use by firms and public agencies.

The results also contribute to the digitalization–energy nexus by highlighting the coexistence of efficiency and scale effects. The ICT-environment literature identifies at least three forces: the direct electricity and material requirements of digital infrastructure; efficiency gains from monitoring, optimization, and dematerialization; and rebound effects that arise when lower effective costs stimulate additional production or digital activity [13–16]. A data trading platform can therefore be environmentally beneficial only if the information-enabled efficiency margin is large enough to offset the additional energy demand associated with digital expansion. The present outcome pattern is consistent with a net reduction in city-level joint pollution–carbon burden, and the outcome decomposition shows reductions in both the pollution index and carbon emissions. This supports an interpretation centered on urban environmental outcomes rather than a claim that platform facilities themselves consume less energy.

The heterogeneity analysis indicates that the negative association is more pronounced in cities with higher pre-treatment energy pressure. The most consistent environmental pattern is the larger estimated association in cities with higher pre-treatment energy pressure, where the potential gains from monitoring, benchmarking, and process optimization are greater. This finding is consistent with a greater-room-for-improvement interpretation: when baseline energy use is high, the information value of identifying waste, coordinating equipment, and targeting cleaner technologies may be larger. Early- and late-cohort estimates are both negative, but their difference is not statistically distinguishable from zero. The evidence therefore supports baseline energy pressure as the more stable cross-city conditioning factor.

The intermediate-outcome estimates provide evidence consistent with the proposed production-side pathways. Platform adoption is associated with higher energy productivity, which accords with the possibility that improved information supports benchmarking,

predictive maintenance, demand forecasting, and production scheduling. Platform adoption is also associated with industrial upgrading, consistent with improved matching among industrial firms, producer-service providers, technology suppliers, and logistics operators. These regressions establish that the policy is associated with changes in the two intermediate outcomes, but they do not identify how much of the joint-burden estimate is mediated through either pathway.

The environmental interpretation is also consistent with the co-benefits literature. Conventional air pollutants and carbon dioxide often originate from common fossil-energy use, so interventions that reduce avoidable energy use or shift production structure can produce simultaneous climate and air-quality benefits [30–33]. The composite outcome is therefore useful for evaluating whether a market institution is associated with coordinated environmental performance rather than with an isolated change in one pollutant. At the same time, the component estimates show why composite indicators should not replace pollutant-specific analysis: the carbon and pollution index results are more clearly estimated than the PM2.5 result. One possible explanation is that PM2.5 reflects a broader source mix, including residential combustion, vehicle exhaust, secondary aerosol formation, and regional transport, that may be less directly affected by industrial data circulation than the aggregate pollution and carbon components.

From an environmental-engineering perspective, the findings point to a design problem as much as to a policy-evaluation result. A platform can become environmentally relevant when it connects heterogeneous data to measurable operating decisions, but that connection requires standards for data quality, temporal frequency, spatial matching, authorization, and verification. Energy-consumption records are useful for benchmarking only when boundaries and reporting units are compatible; emission data are useful for diagnosis only when they can be linked to production activity; and green-technology matching requires information on both technology performance and firm-specific operating conditions. These requirements place data governance alongside monitoring and optimization as part of a city's environmental information infrastructure. They also imply that platform performance should be evaluated using verified environmental applications and operational outcomes, not only the number of listed data products or completed transactions.

One plausible interpretation of the findings is that the environmental consequences of data marketization depend not simply on digital expansion, but on whether data market institutions improve the usability of information for production and energy management decisions. The negative city-level association represents a net environmental outcome and does not rule out higher electricity use by particular digital facilities or services. The stronger association in cities with greater baseline energy pressure suggests that potential gains may be larger where monitoring and efficiency-improvement needs are greater. Direct examination of the links among platforms, firms, utilities, and public agencies would require transaction-level and facility-level data.

6. Conclusions and Environmental Implications

This study asks whether a market institution designed for data circulation is associated with environmental co-benefits. Using a staggered DID design and a balanced panel of 164 Chinese cities from 2009 to 2023, the analysis finds a negative city-level association between platform establishment and the joint pollution–carbon burden. The estimate remains negative under alternative outcome constructions, an unbalanced complete-case panel, regional trends, source-audited treatment coding, random placebo assignments, and the BJS imputation estimator.

The intermediate-outcome regressions show that platform adoption is associated with higher energy productivity and industrial upgrading. These changes are consistent

with the two proposed production-side pathways, but they are not interpreted as a causal decomposition of the total association. The negative association between platform adoption and the joint burden is also stronger in cities with greater pre-treatment energy pressure.

The findings have three environmental implications. First, evaluation of data trading platforms should complement transaction volume and digital-industry output with environmental application indicators, including energy benchmarking, emission diagnosis, green-technology matching, and low-carbon logistics. Second, data exchanges, environmental agencies, energy authorities, utilities, and industrial-service providers need interoperable standards for secure and authorized data use. Third, cities facing high energy pressure can link platform development to energy audits, industrial upgrading, and independently verifiable environmental-performance metrics.

Policy design could link data market development with environmental and energy management while maintaining clear regulatory responsibilities. Environmental and energy authorities could establish interoperable data standards and pilot applications for energy benchmarking, emission diagnosis, cleaner-technology matching, and low-carbon logistics. The environmental performance of these applications should be evaluated using facility-level energy and emission data before wider adoption.

Overall, data trading platform adoption is associated with a lower city-level joint pollution–carbon burden in the benchmark specification. The BJS and Callaway–Sant'Anna outcome-regression estimates support the negative direction of this association, although the latter is less precisely estimated and weighting-based specifications indicate comparison-group sensitivity. Platform adoption is also associated with higher energy productivity and industrial upgrading, two intermediate outcomes predicted by the conceptual framework, and the negative benchmark association is more pronounced in cities with greater pre-treatment energy pressure. These findings suggest that data market institutions can have environmental implications when information circulation supports energy management and production coordination.

Several limitations should be noted. First, the city-level panel does not observe the specific platform transactions, data products, or facility-level applications underlying the aggregate association. Second, the balanced-panel requirement may underrepresent smaller or data-poor cities, although the unbalanced complete-case analysis produces a similar negative estimate. Third, the staggered DID estimates vary in precision across comparison and weighting structures. Fourth, the intermediate-outcome regressions identify policy-related changes in energy productivity and industrial upgrading but do not establish causal mediation. Future research could link platform transaction records with firm- or facility-level energy and emission data and apply designs that identify mediated effects more directly.

Author Contributions: X.S.: conceptualization, supervision, methodology, and writing—review and editing. J.Z.: data curation, formal analysis, visualization, and writing—original draft. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Major Project of Fujian Provincial Social Science Research Base (Grant No. FJ2024JDZ081) and the Natural Science Foundation of Fujian Province (Grant No. 2025J01330) and the Young Project of the Social Science Planning of Fujian Province (No. FJ2023C037).

Institutional Review Board Statement: Not applicable. This study uses aggregated city-level secondary data and does not involve human participants, animals, or individual-level personal data.

Informed Consent Statement: Not applicable.

Data Availability Statement: The processed city-year dataset, treatment-coding file, variable codebook, and Stata replication code are available from the corresponding author upon reasonable request for research verification and replication. Public redistribution of the complete dataset is not currently

possible because several underlying variables were compiled from third-party statistical yearbooks and databases that remain subject to provider-specific access and reuse conditions. The manuscript documents the original sources, variable definitions, and construction procedures to facilitate independent reconstruction of the analysis.

Conflicts of Interest: The authors declare no competing interests.

Abbreviations

BJS, Borusyak–Jaravel–Spiess; DID, difference-in-differences; ICT, information and communication technology; IPCC, Intergovernmental Panel on Climate Change; IPW, inverse-probability weighting; PM2.5, particulate matter with an aerodynamic diameter of 2.5 μm; TOPSIS, Technique for Order Preference by Similarity to Ideal Solution.

References

1. Central Committee of the Communist Party of China and State Council. Opinions on Building a More Complete Institutional Mechanism for Market-Based Allocation of Factors. 2020. Available online: https://www.beijing.gov.cn/zhengce/zhengcefagui/202004/t20200410_1799120.html (accessed on 12 October 2026).
2. National Development and Reform Commission. Accelerating the Improvement of Market-Oriented Allocation of Data Elements. 2021. Available online: https://www.ndrc.gov.cn/fggz/jyysr/jysrsbxf/202108/t20210818_1293894_ext.html (accessed on 12 October 2026).
3. Central Committee of the Communist Party of China and State Council. Opinions on Building the Data Basic System to Better Leverage the Role of Data as an Element. 2022. Available online: https://app.www.gov.cn/govdata/gov/202212/19/495422/article.html (accessed on 12 October 2026).
4. 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. [CrossRef]
5. Li, Z.; Bai, T.; Tang, C. How does the low-carbon city pilot policy affect the synergistic governance efficiency of carbon and smog? Quasi-experimental evidence from China. *J. Clean. Prod.* **2022**, *373*, 133809. [CrossRef]
6. Zhao, Z.Y.; Gao, L.; Zuo, J. How national policies facilitate low carbon city development: A China study. *J. Clean. Prod.* **2019**, *234*, 743–754. [CrossRef]
7. Cao, X.; Li, X.; Zhou, Y. Greenhouse gas inventory evaluation of low-carbon cities in the context of spatial planning: A case study of Shenzhen, China. *Environ. Eng. Sci.* **2023**, *40*, 153–166. [CrossRef]
8. Jones, C.I.; Tonetti, C. Nonrivalry and the economics of data. *Am. Econ. Rev.* **2020**, *110*, 2819–2858. [CrossRef]
9. Abraham, R.; Schneider, J.; Vom Brocke, J. Data governance: A conceptual framework, structured review, and research agenda. *Int. J. Inf. Manag.* **2019**, *49*, 424–438. [CrossRef]
10. Bergemann, D.; Bonatti, A.; Smolin, A. The design and price of information. *Am. Econ. Rev.* **2018**, *108*, 1–48. [CrossRef]
11. Einav, L.; Levin, J. Economics in the age of big data. *Science* **2014**, *346*, 1243089. [CrossRef]
12. Goldfarb, A.; Tucker, C. Digital economics. *J. Econ. Lit.* **2019**, *57*, 3–43. [CrossRef]
13. Añón Higón, D.; Gholami, R.; Shirazi, F. ICT and environmental sustainability: A global perspective. *Telemat. Inform.* **2017**, *34*, 85–95. [CrossRef]
14. Belkhir, L.; Elmeligi, A. Assessing ICT global emissions footprint: Trends to 2040 & recommendations. *J. Clean. Prod.* **2018**, *177*, 448–463. [CrossRef]
15. Lange, S.; Pohl, J.; Santarius, T. Digitalization and energy consumption. Does ICT Reduce Energy Demand? *Ecol. Econ.* **2020**, *176*, 106760. [CrossRef]
16. Sadorsky, P. Information communication technology and electricity consumption in emerging economies. *Energy Policy* **2012**, *48*, 130–136. [CrossRef]
17. Gupta, A. Transparency under scrutiny: Information disclosure in global environmental governance. *Glob. Environ. Politics* **2008**, *8*, 1–7. [CrossRef]
18. Mason, M. Transparency for whom? Information disclosure and power in global environmental governance. *Glob. Environ. Politics* **2008**, *8*, 8–13. [CrossRef]
19. Sand, P.H. Information disclosure as an instrument of environmental governance. *Heidelb. J. Int. Law* **2003**, *63*, 487–502. Available online: https://zaoerv.de/63_2003/63_2003_2_a_487_502.pdf (accessed on 12 October 2026).
20. Batty, M.; Axhausen, K.W.; Giannotti, F.; Pozdnoukhov, A.; Bazzani, A.; Wachowicz, M.; Ouzounis, G.; Portugali, Y. Smart cities of the future. *Eur. Phys. J. Spec. Top.* **2012**, *214*, 481–518. [CrossRef]
21. Kitchin, R. The real-time city? Big data and smart urbanism. *GeoJournal* **2014**, *79*, 1–14. [CrossRef]

22. Neirotti, P.; De Marco, A.; Cagliano, A.C.; Mangano, G.; Scorrano, F. Current trends in smart city initiatives: Some stylised facts. *Cities* **2014**, *38*, 25–36. [CrossRef]
23. Zheng, J.; Shao, X.; Liu, W.; Kong, J.; Zuo, G. The impact of the pilot program on industrial structure upgrading in low-carbon cities. *J. Clean. Prod.* **2021**, *290*, 125868. [CrossRef]
24. IPCC. 2006 IPCC Guidelines for National Greenhouse Gas Inventories. 2006. Available online: https://www.ipcc-nggip.iges.or.jp/public/2006gl/ (accessed on 12 October 2026).
25. Borusyak, K.; Jaravel, X.; Spiess, J. Revisiting event-study designs: Robust and efficient estimation. *Rev. Econ. Stud.* **2024**, *91*, 3253–3285. [CrossRef]
26. Sun, L.; Abraham, S. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *J. Econom.* **2021**, *225*, 175–199. [CrossRef]
27. Callaway, B.; Sant'Anna, P.H.C. Difference-in-differences with multiple time periods. *J. Econom.* **2021**, *225*, 200–230. [CrossRef]
28. Abadie, A. Semiparametric difference-in-differences estimators. *Rev. Econ. Stud.* **2005**, *72*, 1–19. [CrossRef]
29. Khanna, N.; Fridley, D.; Hong, L. China's pilot low-carbon city initiative: A comparative assessment of national goals and local plans. *Sustain. Cities Soc.* **2014**, *12*, 110–121. [CrossRef]
30. Nemet, G.F.; Holloway, T.; Meier, P. Implications of incorporating air-quality co-benefits into climate change policymaking. *Environ. Res. Lett.* **2010**, *5*, 014007. [CrossRef]
31. West, J.J.; Smith, S.J.; Silva, R.A.; Naik, V.; Zhang, Y.; Adelman, Z.; Fry, M.M.; Anenberg, S.; Horowitz, L.W.; Lamarque, J.F. Co-benefits of mitigating global greenhouse gas emissions for future air quality and human health. *Nat. Clim. Change* **2013**, *3*, 885–889. [CrossRef]
32. Markandya, A.; Sampedro, J.; Smith, S.J.; Van Dingenen, R.; Pizarro-Irizar, C.; Arto, I.; González-Eguino, M. Health co-benefits from air pollution and mitigation costs of the Paris Agreement: A modelling study. *Lancet Planet. Health* **2018**, *2*, e126–e133. [CrossRef]
33. Vandyck, T.; Keramidas, K.; Kitous, A.; Spadaro, J.V.; Van Dingenen, R.; Holland, M.; Saveyn, B. Air quality co-benefits for human health and agriculture counterbalance costs to meet Paris Agreement pledges. *Nat. Commun.* **2018**, *9*, 4939. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.