

Article

The Mystery of the High-Carbon Bias in Technology Trade?—An Empirical Examination at the Provincial Level in China Under the Influence of the Digital Economy

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Abstract

Addressing climate change and advancing the “dual-carbon” goals are core tasks for the high-quality sustainable development of the Chinese economy. As a key vehicle for the market-based allocation of technological factors, the direction of the carbon effects and transmission mechanisms of technology transactions remain highly contested. This paper addresses the mystery of the high-carbon bias in technology transactions under the mediation of the digital economy, conducting an empirical analysis based on provincial panel data from China covering the period 2011–2023. The findings reveal that the net outcome of provincial-level technology transactions exhibits a high-carbon bias, significantly increasing carbon emission intensity; the energy consumption structure exerts a significant masking effect, with its emission-reduction effects being entirely overshadowed by the direct carbon-increasing effect; the digital economy exerts a positive moderating effect on this carbon-increasing effect and exhibits a dual-threshold characteristic; the carbon effect evolves in stages and is significant only in provinces with high levels of digital economy and innovation. This paper reveals the intrinsic logic of the carbon effect of technology transactions and provides policy recommendations for guiding the decarbonization of technology transactions and promoting the synergy between the digital economy and green transition, thereby contributing to regional and global sustainability goals.

Keywords: technology transaction activity; carbon emission intensity; digital economy; moderating effect; sustainable development

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1. Introduction

Under the global consensus on low-carbon development, the control of carbon emission intensity has become a key lever for achieving high-quality economic development [1]. As the market-based allocation of technological factors continues to deepen, technology transactions—as its core vehicle—are profoundly reshaping the internal logic of regional low-carbon transition through their deep integration with the digital economy. However, the direction of the carbon effect and the transmission mechanisms resulting from their synergistic interaction remain subject to significant controversy and research gaps.

The drivers of carbon emissions are notably diverse and heterogeneous; a coal-dominated energy structure is the core driver of carbon growth, while emerging economic

forms such as the digital economy may also generate environmental costs through increased consumption. At the policy level, carbon trading pilot schemes have driven emissions reductions through technological spillovers and structural adjustments [2], but the lack of green-oriented financial inclusion may conversely stimulate high-carbon activities [3]. In emissions reduction practice, the “technology + planning” dual-drive model has been validated in areas such as production and logistics optimization [4] and urban spatial planning [5].

The carbon impact of technology trade exhibits a dichotomy between carbon-intensive and carbon-reducing effects, with the diffusion of high-carbon technologies coexisting alongside that of low-carbon technologies; however, no systematic conclusions have yet been drawn at the provincial level. The relationship between the digital economy and carbon emission intensity exhibits an inverted U-shaped relationship or a threshold effect [6,7] primarily transmitted through industrial structure upgrading and technological innovation [8], and exhibit significant regional heterogeneity [9] while factors such as environmental regulations and fiscal decentralization constitute important moderating mechanisms [10,11].

In the long term, digital technologies can facilitate the diffusion of green technologies by reducing information costs and optimizing matching to enable technology flows [12,13]. However, they may also amplify the capacity expansion effects of high-carbon technologies, and the specific forms and boundary conditions of their moderating role remain unclear.

Existing research suffers from three shortcomings: it fails to construct an analytical framework from the holistic perspective of the market-based allocation of technological factors, and does not distinguish between the structural biases of high-carbon and low-carbon technologies; there is insufficient exploration of the moderating mechanisms when incorporating the carbon effects of the digital economy and technology transactions into a unified analytical framework; and there is a lack of identification of the underlying mechanisms of the masking effect on energy consumption structures.

This study selects Chinese provinces as the unit of analysis for two reasons: firstly, provinces are the basic units for the decomposition and assessment of China’s “dual-carbon” targets, as well as the key level for the development of technology markets and the implementation of policies; secondly, there are significant differences among Chinese provinces in terms of industrial structure, energy endowments and the level of digital economic development, providing a favorable natural experimental setting for identifying the heterogeneity of the carbon effects of technology transactions. Compared with existing studies that focus on the city or enterprise level, provincial-level analysis is better able to reveal the overall net effect of the market-based allocation of technological factors, thereby addressing the lack of systematic evidence at the macro level in the existing literature. Based on this, this paper utilizes provincial panel data from China covering the period 2011–2023. Grounded in the provincial level—a critical unit for the implementation of the dual-carbon goals and the development of technology markets—the study focuses on the enigma of the high-carbon bias in technology transactions, addressing three core questions: whether the carbon-increasing effect of provincial technology transactions is dominated by a bias towards high-carbon technologies; the moderating role of the digital economy on this effect and its boundary conditions; and the underlying mechanisms of the masking effect of energy consumption structure. The study aims to provide empirical evidence to guide the decarbonization of technology transactions.

2. Literature Review and Research Hypotheses

2.1. *The Dual Nature of the Carbon Effects of Technology Transactions and Baseline Assumptions*

The impact of technology transactions on carbon emissions follows two opposing theoretical pathways. The first is the emission-reduction pathway: as the core vehicle for the market-based allocation of technological factors, technology transactions can promote the cross-entity diffusion of green and low-carbon technologies. Through knowledge spillovers and optimized matching, they enhance the efficiency of clean production, thereby reducing carbon emission intensity. The second is the carbon-increasing pathway: if the technology trading market is structurally biased towards efficiency-enhancing technologies for energy-intensive industries, it may lead to a “rebound effect” through expanded production capacity and reduced unit costs, thereby actually driving up carbon emissions. Consequently, the overall carbon effect of technology trading depends on the relative proportions of these two types of technologies within the market and the structure of the transactions.

Existing research has validated the dual nature of the aforementioned theoretical logic. Regarding carbon-reduction effects, G.Z. found that an enhanced position within the technology trading network can significantly promote knowledge spillovers and strengthen innovation capabilities, providing an efficient channel for the cross-entity flow of low-carbon technologies [14]; the GRA-TOPSIS matching framework proposed by Kong et al. can improve the accuracy of matching low-carbon technologies with emission-reduction needs [15]; Zhenning and Wenjie point out that a high degree of integration within technology trading networks can boost total factor productivity in manufacturing, thereby indirectly supporting emissions reduction [16]. Regarding carbon leakage risks, Song reveals that the tendency for technology intermediary services to operate at the grassroots level leads to a disproportionately high share of high-carbon technology transactions, which can easily exacerbate emissions by expanding energy-intensive production capacity [17]; Liu et al. find that excessive technological disparities can hinder the integration of low-carbon technologies, thereby indirectly increasing carbon emission intensity [18]. Dai et al. confirmed that clean production technologies can systematically improve energy efficiency and reduce carbon emissions through diffusion via trading [19]; meanwhile, Kung pointed out that when trading is concentrated on efficiency technologies in energy-intensive industries, a rebound effect is formed through capacity expansion [20]. Current provincial-level technology trading centers on industrial-scale production technologies, with low-carbon technologies accounting for a relatively small proportion, suggesting an inferred net bias towards high-carbon outcomes. We acknowledge that TTA does not classify individual transactions as high-carbon or low-carbon. However, this paper does not aim to measure the carbon content of each transaction, but to identify the net direction of technology transactions on carbon emissions. The significantly positive coefficient of TTA in the baseline regression, after controlling for confounding factors, empirically demonstrates that the overall effect is carbon-increasing. This net outcome-based approach is widely used in environmental economics when micro-level technology classifications are unavailable. If, after controlling for other factors, higher transaction activity in a technology market leads to higher carbon emission intensity, then that market exhibits high-carbon bias. This definition does not require that every technology traded be high carbon, but rather relies on the net causal effect estimated by a baseline model. Hence, we propose:

H1. *The level of activity in technology transactions has a significant positive driving effect on carbon emission intensity.*

2.2. The Masking Effect of Energy Consumption Structure

In addition to directly influencing carbon emissions, technology transactions may also exert indirect effects by reshaping the regional allocation of factors. Among these, the energy consumption structure represents a key pathway. In theory, the trading of renewable energy technologies can reduce the cost of clean energy and increase the share of non-fossil fuels; the trading of industrial energy-saving technologies can directly reduce the intensity of fossil fuel consumption. Therefore, if the technology trading market can effectively promote the diffusion of clean energy and energy-saving technologies, it should generate emission-reduction effects by optimizing the energy consumption structure. However, when the market as a whole exhibits a high-carbon bias, the direct carbon-increasing effect may offset or even exceed the indirect emission-reduction effect, resulting in a masking effect.

Cao et al. found that technology trading, empowered by the digital economy, influences carbon emissions through technological innovation and industrial restructuring [21]; Su et al. verified the mediating role of heterogeneous technological innovation [22]; Zhang and Saiti point out that the integration of the digital economy with technology transactions can drive carbon reduction by increasing environmental protection investment [23]; Liu and Miao reveal that data as a factor alleviate financing constraints and promote green investment [24]. Chen and Jiang point out that cross-industry flows of technology factors can drive economic structural transformation [25]; Xu et al. confirm that technology transactions can accelerate inter-industry technology diffusion [26]. However, the aforementioned studies pay insufficient attention to the transmission mechanism of the energy consumption structure. In light of the high-carbon bias in China's technology transactions, this paper proposes:

H2. *The energy consumption structure exerts a significant masking effect between the level of technological trading activity and carbon emission intensity.*

2.3. The Moderating Effects and Threshold Characteristics of the Digital Economy

The digital economy may moderate the carbon impact of technology transactions in two opposing directions. On the one hand, it can reduce information asymmetry and accelerate the diffusion of green technologies, potentially weakening the carbon-increasing effect. On the other hand, digitalization can also amplify the capacity expansion effects of high-carbon technologies through smart manufacturing, industrial internet, and AI-driven process optimization, thereby strengthening the positive relationship between TTA and CEI. Given the current dominance of energy-intensive industries in Chinese provinces and the deep integration of digital technologies with these sectors, the amplifying effect is likely to dominate. This suggests that the moderating effect may be non-linear and exhibit threshold characteristics.

Tan and Zhangyong confirmed an inverted U-shaped relationship between the digital economy and carbon emissions [27]; Wang et al. enriched the non-linear implications of carbon emissions in the digital manufacturing sector [28]. Zhang et al. found that the digital economy in China exhibits a gradient decline with higher levels in the east and lower levels in the west [29]; Liu et al. corroborated the spatial spillover effects [30]; Huo and Zhang pointed out that the digital economy's facilitation of technology transactions can reduce local carbon emissions and generate negative spillovers to neighboring areas [31]. Zhang et al. noted that the digital economy can reduce information asymmetry and optimize matching efficiency [32]; Asl et al. demonstrate that digitalization may also amplify the expansion of high-carbon technology production capacity [33]. Yang and Tan confirm that the digital economy's empowerment of the real economy is subject to phased thresholds [34]. Consequently, we propose:

H3. *The level of digital economic development has a significant positive moderating effect on the relationship between the intensity of technology transactions and carbon emissions.*

H4. *The relationship between the level of digital economic development and the relationship between technology transaction activity and carbon emission intensity exhibits a significant non-linear threshold effect.*

2.4. Regional Heterogeneity

Given the significant differences in resource endowments, industrial structures, digital infrastructure, and policy environments across provinces, the carbon effects of technology transactions may exhibit regional divergence. Provinces with a high level of digital economic development tend to have more mature technology markets and more pronounced carbon effects; those with a high level of innovation possess stronger technology absorption capacity, which may amplify environmental impacts.

Jabłoński, A. and Jabłoński, M. point out that disparities in the level of digital economic development lead to divergences in the operational efficiency and technological bias of technology transactions [35]. Yan et al. conducted an empirical analysis of the impact of technology transfer on provincial carbon emissions against the backdrop of the “dual-carbon” goals, finding significant regional heterogeneity [36]. The existing literature still has three shortcomings: insufficient identification of the direct causal relationship of the carbon effect; failure to incorporate the moderating mechanism of the digital economy into a unified framework; and insufficient explanation of the underlying causes of provincial heterogeneity. Consequently, we propose:

H5a. *The impact of technology transaction activity on carbon emission intensity exhibits heterogeneity across levels of digital economic development, with a more pronounced effect in provinces with a high level of digital economic development.*

H5b. *The impact of technological transaction activity on carbon emission intensity exhibits heterogeneity across regional innovation levels, with a more pronounced effect in provinces with high levels of innovation.*

In summary, this paper constructs an analytical framework for the impact of technology transactions on carbon emission intensity, with the digital economy as the core boundary condition, and empirically tests the net effect, transmission mechanisms, and regional heterogeneity, with a view to providing empirical evidence to guide the decarbonization of technology transactions.

3. Research Design

3.1. Variable Selection

Following the analytical paradigms of environmental economics and innovation economics, this paper constructs an empirical framework comprising the dependent variable, core explanatory variables, mediating variables, moderating variables, and control variables. The variables are presented in Table 1. The dependent variable is carbon emission intensity (CEI), which, by controlling for differences in economic scale, accurately reflects the carbon cost per unit of output. This is consistent with the approaches adopted by Li and Zhou [37], Shao et al. [38], and Lin and Jiang [39]; per capita carbon emissions (PCCE) are used as a robustness test indicator. The core explanatory variable, technology transaction activity (TTA), better reflects the commercialization of technological achievements and the efficiency of factor allocation than patent-based indicators; its measurement draws on the research logic of Ding et al. [40] and Sun et al. [41]. The mediating variable selected

is the energy consumption structure (EneLow), which, respectively, characterizes the coordination of factor allocation, the trend towards industrial service transformation, and the level of energy decarbonization, thereby revealing the transmission pathway through which technology transactions influence carbon emissions via resource reallocation and the application of low-carbon technologies. The moderating variable is the level of digital economic development (DED). We adopt the provincial digital economic development index synthesized by Zhao et al. [42] using the entropy-weighted TOPSIS method across five dimensions—internet penetration, workforce, related output, number of mobile users, and digital financial inclusion—to examine its marginal moderating effect on the carbon impact of technology transactions. Control variables include per capita GDP (GDPPER), degree of openness to foreign investment (FDIIdx), intensity of environmental regulation (EnvReg), level of industrialization (IndLv), and regional innovation level (InnoLv), to mitigate endogeneity bias and ensure estimation robustness.

Table 1. Variable definitions and measurement framework.

Variable Type	Variable Symbol	Variable Name	Measurement Method
Dependent Variable	CEI	Carbon Emission Intensity (Main Variable)	Provincial total carbon emissions/actual regional GDP (10,000 tons/100 million yuan)
	PCCE	Per capita carbon emissions (robustness variable)	Total provincial carbon emissions/Permanent resident population at year-end (10,000 tonnes/10,000 people)
Core explanatory variables	TTA	Technology transaction activity	Value of contracts concluded in the technology market/regional gross domestic product (%)
Intermediary variable	EneLow	Energy Consumption Structure	Share of non-fossil energy consumption in total primary energy consumption (%)
Moderating variable	DED	Level of digital economic development	Index derived from the entropy-weighted TOPSIS method (%)
	GDPPER	Per capita GDP	Regional Gross Domestic Product/Permanent Resident Population at Year-End (yuan per capita)
	FDIIdx	Degree of openness	Actual Utilized Foreign Direct Investment/Regional Gross Domestic Product (%)
	EnvReg	Intensity of environmental regulation	Investment in industrial pollution control/Regional Gross Domestic Product (%)
Control variables	IndLv	Level of industrialization	Value added of the secondary sector/Regional GDP (%)
	InnoLv	Regional Innovation Level	Natural logarithm of the number of patent applications and grants in the province

Note: All price-related variables are deflated using 2011 as the base year to eliminate the influence of price fluctuations.

3.2. Specification of the Econometric Model

3.2.1. Baseline Regression Model

To examine the baseline effect of technological transaction activity on carbon emission intensity, this study constructs a two-way fixed-effects panel model. This model effectively controls for provincial-level individual heterogeneity that remains constant over time and for nationwide time shocks that vary across individuals, thereby minimizing endogeneity biases caused by omitted variables. The model specification is as follows:

$$CEI_{it} = \alpha_0 + \alpha_1 TTA_{it} + \sum_{k=1}^5 \alpha_k Controls_{kit} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where i denotes a province, and t denotes a year; the dependent variable is CEI_{it} , representing the carbon emission intensity of the i province in year t , used to measure regional carbon emission levels; the core explanatory variable is TTA_{it} , representing the technical trading activity of the i province in year t , which serves as the core explanatory variable

in the model; $Controls_{kit}$ constitutes the set of control variables; μ_i represents the province-specific fixed effect, λ_t represents the time-specific fixed effect; ε_{it} represents the random disturbance term; α_1 is the core coefficient to be estimated, measuring the net effect of technology trading activity on carbon emission intensity; its sign and significance serve as the basis for testing the core null hypothesis of this paper. The definitions of the above variables and fixed effects will not be repeated in the following text.

3.2.2. Mediation Effect Model

To examine the mediating transmission mechanisms of industrial structure upgrading and the optimization of energy consumption structure, this paper employs the stepwise regression method proposed by Wen and Ye [43] to construct a mediating effects test model. Subsequently, the significance of the mediating effects will be subjected to robustness testing via the Bootstrap method. The model is established in three steps:

Step 1: Test the total effect of technological transaction activity on carbon emission intensity, i.e., the benchmark regression model described above;

Step 2: Test the effect of technological trading activity on the mediating variable; the model is set up as follows:

$$M_{it} = \beta_0 + \beta_1 TTA_{it} + \sum_{k=1}^5 \beta_k Controls_{kit} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

Step 3: Incorporate the mediating variable into the baseline regression model to test the combined effect of technological transaction activity and the mediating variable on carbon emission intensity. The model is set up as follows:

$$CEI_{it} = \gamma_0 + \gamma_1 TTA_{it} + \gamma_2 M_{it} + \sum_{k=1}^5 \gamma_k Controls_{kit} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

In the above models, M_{it} represents the mediating variable, energy consumption structure. If both β_1 and γ_2 pass the statistical significance test, the mediating effect is established; if, on this basis, γ_1 is significant and the absolute value of its coefficient is smaller than that of α_1 in the baseline regression, it constitutes a partial mediating effect; if γ_1 is not significant, it constitutes a full mediating effect.

3.2.3. Moderation Effect Model

Based on the theoretical analysis and research hypotheses outlined above, to test the boundary moderating role of the level of digital economic development in the relationship between technology transaction activity and carbon emission intensity, this study introduces an interaction term between technology transaction activity and the level of digital economic development, constructing a two-way fixed-effects moderation model. The model is specified as follows:

$$CEI_{it} = \beta_0 + \beta_1 TTA_{it} + \beta_2 DED_{it} + \beta_3 (TTA_{it} \times DED_{it}) + \sum_{k=1}^5 \beta_k Controls_{kit} + \mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$

where DED_{it} represents the level of digital economic development; $TTA_{it} \times DED_{it}$ is the core interaction term, and its coefficient β_3 reflects the moderating effect of the digital economy. If β_3 is significantly positive, Hypothesis 3 is supported. The interaction term is constructed after provincial centering of the variables to mitigate multicollinearity, and two-way cluster standard errors by province and year are employed.

3.2.4. Threshold Effect Model

To test Hypothesis 4, a threshold regression model of technology transaction activity (TTA) on carbon emission intensity (CEI) is constructed, using the level of digital economic development (DED) as the threshold variable. A single-threshold model is first used for preliminary testing, followed by a dual-threshold model for core analysis; the single-threshold model serves to validate the validity of the dual-threshold effect.

The single-threshold model is set as follows:

$$CEI_{it} = \alpha + \beta_1 TTA_{it} I(DED_{it} \leq \gamma_1) + \beta_2 TTA_{it} I(DED_{it} > \gamma_1) + \sum_{k=1}^5 \gamma_k X_{kit} + \mu_i + \varepsilon_{it} \quad (5)$$

The dual-threshold model is set as follows:

$$CEI_{it} = \alpha + \beta_1 TTA_{it} I(DED_{it} \leq \gamma_1) + \beta_2 TTA_{it} I(\gamma_1 < DED_{it} \leq \gamma_2) + \beta_3 TTA_{it} I(DED_{it} > \gamma_2) + \sum_{k=1}^5 \gamma_k X_{kit} + \mu_i + \varepsilon_{it} \quad (6)$$

The meanings of the variables and coefficients in the model strictly correspond to the empirical data to ensure there is no bias. Specific details are as follows: the threshold variable is DED_{it} , representing the level of digital economic development in province i in year t , used to delineate different digital economic intervals; the threshold values γ_1 and γ_2 are the first and second threshold values for the level of digital economic development, respectively, obtained through a panel threshold model exhaustive search method; β_1, β_2 and β_3 represent the coefficients of the impact of technology transaction activity on carbon intensity within the low, medium, and high digital economy intervals, respectively. The focus is on their magnitude, significance, and trends to reveal the phased heterogeneity of the carbon effect of technology transactions. Furthermore, $I(\cdot)$ is an indicator function that takes the value 1 when the condition in brackets is satisfied, and 0 otherwise.

3.2.5. Heterogeneity Test Model

We employ a grouped regression method to test for heterogeneity, using the level of digital economic development and regional innovation levels as grouping variables. The entire sample is divided into high and low groups based on the sample median, and estimates are obtained separately from the baseline regression model to test hypotheses H5a and H5b. The model is specified as follows:

$$CEI_{it} = \alpha + \beta_1 TTA_{it} + \sum_{k=1}^5 \gamma_k X_{kit} + \mu_i + \varepsilon_{it} \quad (7)$$

3.3. Data Sources and Processing

This study utilizes panel data from 2011 to 2023 for 31 provinces in China (excluding Hong Kong, Macao, and Taiwan), comprising a total of 403 valid observations. Carbon emission data are based on final energy consumption figures from the *China Energy Statistical Yearbook*, calculated using IPCC methodologies; technology transaction data are sourced from the *China Science and Technology Statistical Yearbook* and the *National Technology Market Statistical Annual Report*; the digital economy index utilizes the Peking University Digital Inclusive Finance Index, while the remaining indicators are derived from official statistical sources such as the *China Statistical Yearbook*, the *China Industrial Statistical Yearbook* and the *China Environmental Statistical Yearbook*. All continuous variables were trimmed at the 1% level, and missing data were imputed using linear interpolation. To test for cross-sectional correlation in the panel data, this study conducted the Pesaran CD test. The results show that the p -values for all variables are 0.000, significantly rejecting the null hypothesis of cross-sectional independence at the 1% level, indicating the presence of significant cross-sectional correlation. Consequently, all regression models in this study are estimated using Driscoll-Kraay robust standard errors to simultaneously address cross-

sectional correlation, heteroscedasticity, and serial correlation, thereby ensuring the reliability of statistical inferences.

4. Data Characteristics and Visualization Analysis

4.1. Three-Dimensional Coupling Characteristics of Mediating Variables

Figure 1 illustrates the three-variable coupling relationship between technology trade activity, carbon emission intensity, and energy consumption structure. Overall, provinces with higher technology trade activity (right end of the X-axis) are typically located in regions with lower carbon emission intensity (lower end of the Y-axis) and have larger bubbles (indicating a cleaner energy structure). This preliminary correlation suggests that technology trade may indirectly reduce carbon emission intensity by optimizing the energy consumption structure, providing visual evidence for the mediation effect tests discussed later. It should be noted that the above correlation is a bivariate relationship and does not control for confounding factors such as industrial structure and economic development levels; the true net effect will be further revealed in the regression analysis in Chapter 5.

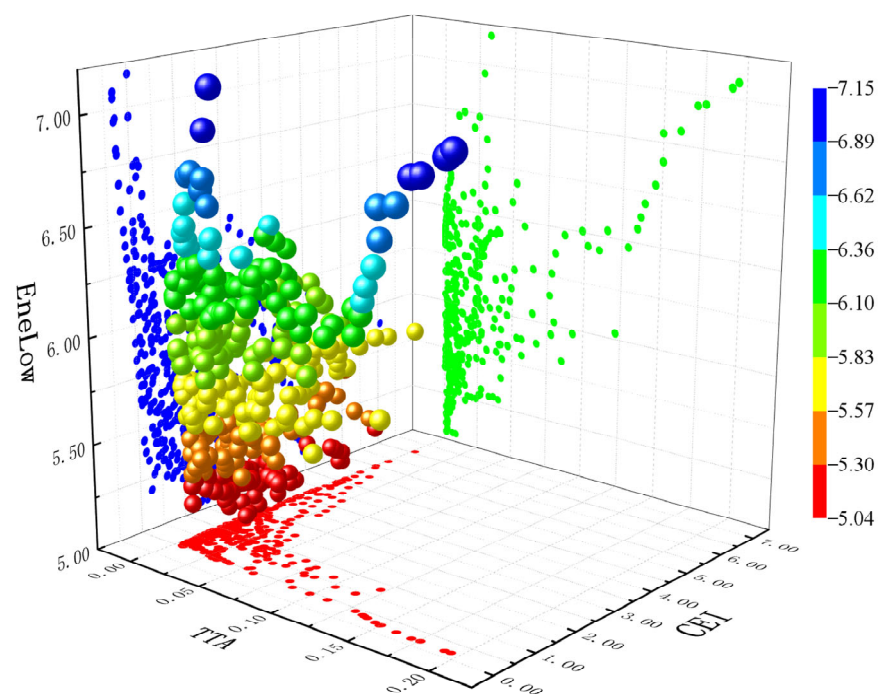


Figure 1. Three-variable coupling of TTA, CEI, and EneLow.

4.2. Three-Variable Coupling Characteristics of Moderating Variables

Figure 2 illustrates the three-variable coupling relationship between the intensity of technology trade, carbon emission intensity, and the level of digital economic development. Overall, provinces with a high intensity of technology trade (on the right-hand side of the X-axis) are typically located in regions with lower carbon emission intensity (at the bottom of the Y-axis), and provinces with a higher level of digital economic development (larger bubbles) are predominantly clustered in this area. This initial correlation suggests

that the digital economy may exert a moderating effect on the relationship between technology transfer activity and carbon emission intensity, providing visual evidence for the subsequent moderation effect test.

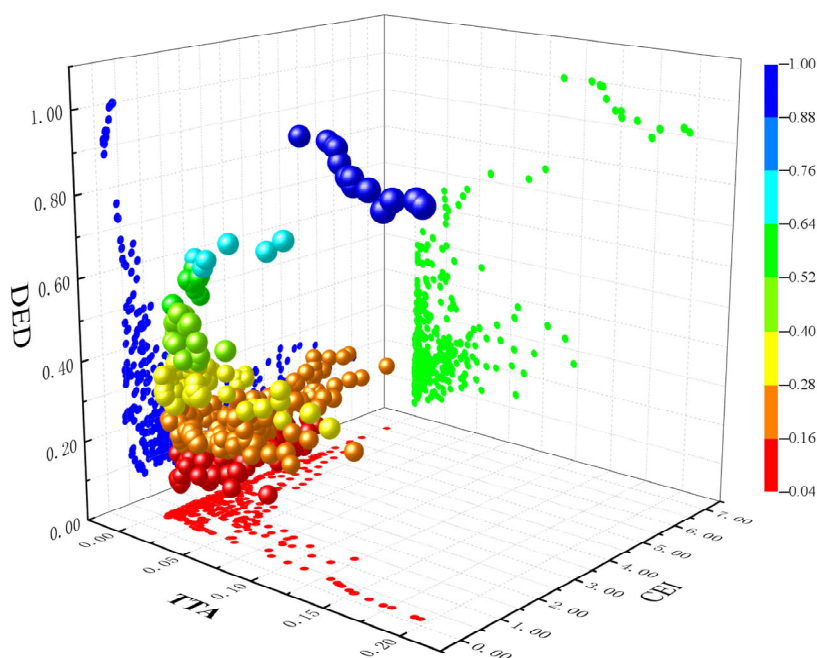


Figure 2. Three-variable coupling of TTA, CEI, and DED.

5. Empirical Results and Analysis

5.1. Descriptive Statistics

This paper conducts descriptive statistics for the entire sample on the core variables, mediating variables, moderating variables, and control variables to examine the distribution characteristics and outliers in the sample data. The results are shown in Table 2.

Table 2. Descriptive statistics for the full sample.

Variable Symbol	Observation	Mean	Standard Deviation	Minimum	Maximum
CEI	403	1.748	1.157	0.186	6.566
PCCE	403	8.667	5.152	2.978	34.974
TTA	403	0.019	0.031	0.000	0.195
EneLow	403	50.754	0.417	50.041	70.145
GDPPer	403	60,350.526	32,039.827	16,024	200,278
FDIIdx	403	0.264	0.275	0.008	10.464
EnvReg	403	0.003	0.004	0	0.031
IndLv	403	0.312	0.09	0.072	0.556
InnoLv	403	9.556	1.559	4.394	12.399

The mean CEI was 17,480 tons per 100 million yuan, with a standard deviation of 1.157; there were significant inter-provincial differences, consistent with the characteristics of regional development imbalances. The mean TTA was 0.019%, with a standard deviation of 0.031, and there was a marked divergence across provinces. The values of the

remaining variables all fell within a reasonable range; the data quality met the requirements for empirical analysis, providing a reliable basis for hypothesis testing.

5.2. Correlation Analysis

This study employs a Pearson correlation matrix to examine linear relationships between variables, while using the variance inflation factor (VIF) to assess multicollinearity. The results are presented in Tables 3 and 4.

Table 3. Matrix of correlation coefficients.

Variables	(1) CEI	(2) TTA	(3) EneLow	(4) DED	(5) GDPPER	(6) FDIIdx	(7) EnvReg	(8) IndLv	(9) InnoLv
(1) CEI	1.000								
(2) TTA	−0.369 *** (0.000)	1.000							
(3) EneLow	−0.362 *** (0.000)	0.446 *** (0.000)	1.000						
(4) DED	−0.412 *** (0.000)	0.689 *** (0.000)	0.604 *** (0.000)	1.000					
(5) GDPPER	−0.505 *** (0.000)	0.655 *** (0.000)	0.664 *** (0.000)	0.771 *** (0.000)	1.000				
(6) FDIIdx	−0.472 *** (0.000)	0.464 *** (0.000)	0.491 *** (0.000)	0.838 *** (0.000)	0.633 *** (0.000)	1.000			
(7) EnvReg	0.598 *** (0.000)	−0.214 *** (0.000)	−0.165 *** (0.001)	−0.162 *** (0.001)	−0.305 *** (0.000)	−0.203 *** (0.000)	1.000		
(8) IndLv	0.074 (0.136)	−0.267 *** (0.000)	−0.384 *** (0.000)	−0.143 *** (0.004)	−0.086 * (0.085)	−0.006 (0.901)	−0.162 *** (0.001)	1.000	
(9) InnoLv	−0.643 *** (0.000)	0.411 *** (0.000)	0.213 *** (0.000)	0.475 *** (0.000)	0.594 *** (0.000)	0.516 *** (0.000)	−0.469 *** (0.000)	0.365 *** (0.000)	1.000

*** $p < 0.01$, * $p < 0.1$.

Table 4. Results of the variance inflation factor test.

Variable Symbol	VIF	1/VIF
DED	6.87	0.145664
GDPPER	4.12	0.242692
FDIIdx	4.07	0.245907
InnoLv	2.68	0.372571
TTA	2.59	0.385899
EneLow	2.42	0.413925
IndLv	1.81	0.551817
EnvReg	1.34	0.747434
Mean VIF		3.24

Table 3 presents the Pearson correlation matrix for the main variables. The results show that TTA is significantly negatively correlated with CEI at the 1% level. While this appears to contradict the significantly positive coefficient direction observed between the two variables in the baseline regression, it actually reflects the limitations of the correlation analysis, which did not control for other variables. When control variables are not included, TTA exhibits strong correlations with other economic and environmental variables, which may mask its net effect on CEI; however, subsequent regression models, after controlling for individual and time fixed effects as well as other variables, eliminate the influence of confounding factors and reveal the true positive relationship between the two. In the model presented in Table 4, the VIF values for all variables are well below the multicollinearity threshold, indicating no serious multicollinearity issues, and thus, panel regression analysis can be conducted.

5.3. Results of the Baseline Regression

The results are shown in Table 5. This paper first determines the model specification via the Hausman test, selecting the individual fixed-effects model as the baseline regression model to control for provincial heterogeneity that does not vary over time. The baseline regression is conducted in two steps: first, only control variables are included; then, TTA is added to test its net effect. The results are shown in Table 6.

Table 5. Results of model specification tests.

Test Type	Statistic	p-Value	Test Conclusion
F-test	128.748	0	Reject mixed regression; select fixed effects
Hausman test	27.34	0.001	Reject random effects, choose fixed effects

Table 6. Benchmark regression results.

	CEI	CEI
GDPPer	−0.000 *** (−2.68)	−0.000 *** (−2.57)
FDIIdx	−0.649 ** (−2.62)	−0.538 * (−1.86)
EnvReg	23.414 ** (2.37)	24.105 ** (2.59)
IndLv	−0.719 ** (−0.93)	−0.720 ** (−1.05)
InnoLv	−0.463 *** (−5.00)	−0.403 *** (−4.06)
TTA		2.074 ** (0.98)
Cons	6.933 *** (7.17)	7.434 *** (19.535)
R ²	0.690	0.664
GDPPer	−0.000 ***	−0.000 ***

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6 indicates that technical trading activity exerts a significant positive driving effect on carbon emission intensity, consistent with the findings of Popp (2010) [44] that the environmental impact of technical trading depends on the type of technology. This does not contradict the negative correlation observed between the two in Table 3: the bivariate correlation did not control for confounding factors, and provinces with higher TTA are often characterized by higher per capita GDP and a cleaner industrial structure, factors that in themselves reduce carbon emission intensity. After controlling for these confounding factors in the individual fixed-effects model, the net effect of TTA becomes positive, supporting the inferred net outcome-based high-carbon bias hypothesis; **therefore, Hypothesis H1 is accepted.**

5.4. Testing for Mediation

This study employs stepwise regression combined with Bootstrap testing to conduct a mediation analysis of the mechanism through which technology transaction activity influences carbon emission intensity. The results are shown in Tables 7 and 8.

Table 7. Results of the three-step regression for mediation.

	CEI	EneLow	CEI
TTA	6.488 ** (2.056)	2.909 ** (2.667)	8.214 ** (2.644)
DED	−1.141 (−1.201)	−0.435 (−0.853)	−1.399 * (−1.746)
GDPPer	−0.000 *** (−4.525)	0.000 *** (7.625)	−0.000 ** (−2.585)
EneLow			−0.593 ** (−2.604)
Cons	2.913 *** (11.840)	5.258 *** (39.049)	6.031 *** (5.216)
R ²	0.518	0.652	0.560

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; individual fixed effects only.

Table 8. Results of Bootstrap tests for mediating effects.

Effect Type	Observed Coefficient	Standard Error	Bias-Corrected 95% Confidence Interval	Significance
Indirect effect	−1.725	0.688	[−3.432, −0.656]	Significant ($p < 0.05$)

As shown in Tables 7 and 8, the total effect of TTA on CEI is significantly positive, and its coefficient for the mediating variable EneLow is significantly positive; after including EneLow, the direct effect of TTA on CEI remains significantly positive, while the coefficient for EneLow is significantly negative, and the Bootstrap test indicates that EneLow plays a significant partial mediating role between TTA and CEI. Taken together, the transmission mechanism is as follows: increased technological transaction activity → decarbonization of the energy consumption structure → reduction in carbon emission intensity. As the direct effect of TTA is positive while the mediating effect is negative—the two having opposite signs—this mediating effect is essentially a masking effect, meaning that the optimization of the energy consumption structure masks the positive driving effect of technological transaction activity on carbon emission intensity. **Therefore, Hypothesis H2 is supported.**

This masking effect reflects a typical market failure: while the emission-reduction benefits of low-carbon technologies are shared by society as a whole, the costs of their research, development, and application are borne solely by enterprises. In the absence of effective carbon pricing or green subsidies, there is insufficient demand for low-carbon technologies in the trading market; conversely, high-carbon technologies that enhance production efficiency offer buyers exclusive returns and are thus more attractive to the market. Consequently, although increased technological trading activity can reduce carbon intensity by optimizing the energy consumption structure, this positive indirect effect is overshadowed by its direct high-carbon bias, ultimately resulting in a net high-carbon bias. This confirms the practical dilemma that the market fails to fully internalize the social benefits of low-carbon technologies.

5.5. Moderation Effect Test

5.5.1. Regression Results for the Moderating Effect

To further investigate the moderating effect of the level of digital economic development (DED) on the relationship between technology transaction activity (TTA) and carbon emission intensity (CEI), this paper constructs a centered interaction model.

As shown in Table 9, the coefficient of the $TTA \times DED$ interaction term is 37.177 and is significantly positive at the 1% significance level, indicating that the level of digital economic development significantly moderates the positive effect of technology transaction activity on carbon emission intensity, i.e., as the level of digital economic development increases, the positive driving effect of technology transaction activity on carbon emission intensity is further strengthened. **Therefore, Hypothesis H3 is supported.**

Table 9. Results of the moderation effect test for the digital economy.

Variables	Moderation Effect Model
TTA	1.280 (2.297)
DED	−1.286 * (0.633)
$TTA \times DED$	37.177 *** (8.961)
GDPPer	−0.000 *** (0.000)
FDIIdx	0.108 (0.356)
EnvReg	18.351 ** (7.710)
IndLv	−1.282 ** (0.589)
InnoLv	−0.361 *** (0.088)
Cons	5.979 *** (0.860)
R ²	0.720

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.5.2. Collinearity Test for Moderating Effects

To verify the robustness of the model, this study conducted a variance inflation factor (VIF) test on the centered variables. As shown in Table 10, a multicollinearity test was performed on the centered variables; the results indicate that the average VIF of the model is 4.04, with all variables having VIF values below 10. There are no serious multicollinearity issues, and the results are robust and reliable.

Table 10. Results of the VIF test for multicollinearity.

Variable	VIF Value	1/VIF
TTA	4.46	0.224338
DED	9.17	0.109110
$TTA \times DED$	4.93	0.202756
GDPPer	3.65	0.273825
FDIIdx	4.33	0.231038
EnvReg	1.35	0.742166
IndLv	1.71	0.585268

InnoLv	2.72	0.366992
Mean VIF	4.04	

5.6. Threshold Effect Test

The results of the threshold effect test indicate that the model exhibits a significant double-threshold effect; therefore, a double-threshold model was adopted, with the results shown in Table 11. Using the level of digital economic development as the threshold variable, the sample was divided into three intervals: low, medium, and high.

Table 11. Results of the dual-threshold effect test for the digital economy.

Variables	Low Digital Economy Zone (DED ≤ 0.0904)	Medium Digital Economy Zone (0.0904 < DED ≤ 0.3874)	High Digital Economy Zone (DED > 0.3874)
TTA	21.74 *** −6.6	2.441 ** −1.225	15.51 *** −2.341
GDPPER	−1.30 × 10 ^{−5} *** (1.46 × 10 ^{−6})	−1.30 × 10 ^{−5} *** (1.46 × 10 ^{−6})	−1.30 × 10 ^{−5} *** (1.46 × 10 ^{−6})
FDIIdx	−0.587 *** −0.181	−0.587 *** −0.181	−0.587 *** −0.181
EnvReg	13.36 *** −4.764	13.36 *** −4.764	13.36 *** −4.764
IndLv	−1.075 *** −0.356	−1.075 *** −0.356	−1.075 *** −0.356
InnoLv	−0.434 *** −0.0365	−0.434 *** −0.0365	−0.434 *** −0.0365
Cons	6.976 *** −0.368	6.976 *** −0.368	6.976 *** −0.368
R ²	0.699	0.699	0.699

*** $p < 0.01$, ** $p < 0.05$; the two-threshold estimates for the digital economy are 0.0904 and 0.3874.

The regression results indicate that the impact of technology transaction activity on carbon intensity varies significantly across different intervals, exhibiting an overall U-shaped pattern: the carbon-increasing effect is strongest in regions with a low level of digital economy; as the level of digital economy rises, this effect first weakens and then strengthens again; the digital economy plays a significant moderating role in the environmental effects of technology transactions. This result reveals the phased evolutionary pattern of the carbon effects of technology transactions during the development of the digital economy, **thereby validating Hypothesis H4**.

5.7. Heterogeneity Analysis

Based on disparities in regional digital economic development and innovation levels, the sample was divided into high and low groups according to the median of these two variables. Grouped regression was used to test the heterogeneous impact of technology transaction activity on carbon emission intensity; the results are shown in Table 12.

Table 12. Results of heterogeneity analysis.

	Low Digital Economy Group	High Digital Economy Group	Low Innovation Level Group	High Innovation Level Group
TTA	CEI 1.256 (0.776)	CEI 4.856 *** (1.617)	CEI −0.842 (−0.666)	CEI 3.235 *** (0.815)
GDPPER	−0.000 **	−0.000 ***	−0.000	−0.000 ***

	(−2.272)	(−5.402)	(−1.668)	(−3.781)
FDIIdx	−0.545 **	2.161 **	−0.247 **	0.760
	(−2.277)	(2.242)	(−2.114)	(0.762)
EnvReg	−4.073	1.340	39.829 ***	−3.643
	(−0.364)	(0.161)	(4.914)	(−0.584)
IndLv	−2.536 *	−0.460	1.445 *	−0.116
	(−2.061)	(−0.421)	(1.743)	(−0.096)
InnoLv	−0.556 ***	−0.181 **	−0.175 ***	−0.321 **
	(−3.644)	(−2.265)	(−4.182)	(−2.079)
Cons	8.507 ***	4.799 ***	2.849 ***	6.176 ***
	(4.407)	(5.554)	(4.265)	(4.857)
R ²	0.703	0.804	0.719	0.805

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.7.1. Heterogeneity in the Level of Digital Economic Development

Grouped regression analysis indicates that the level of technological transaction activity in the low-digital economy group has no significant impact on carbon emission intensity, whereas in the high-digital economy group, it is significantly positive at the 1% level. This is because provinces with a high level of digital economy have more mature technology trading markets, with increased transaction volumes and matching efficiency; while promoting the diffusion of low-carbon technologies, this also amplifies the circulation of high-carbon technologies. Furthermore, as energy-intensive industries have undergone a higher degree of digital transformation, the deep integration of digital technologies with these industries has enhanced the production efficiency and capacity utilization of high-carbon technologies, thereby strengthening the carbon-increasing effect of technology transactions. **Therefore, Hypothesis H5a is supported.**

5.7.2. Heterogeneity in Regional Innovation Levels

Grouped regression analysis indicates that technology transactions in the low-innovation group have no significant impact on carbon emission intensity, whereas in the high-innovation group, the effect is significantly positive at the 1% level, with the positive impact concentrated in high-innovation regions. This is because technology transactions are active in high-innovation regions, where the scale of high-carbon technology transactions is large, and their conversion capacity is strong, thereby amplifying the carbon-increasing effect; in contrast, transactions in low-innovation regions are small in scale and dominated by mature technologies, resulting in a limited impact. **Therefore, Hypothesis H5b is supported.**

5.7.3. Summary of Heterogeneity Analysis

Interpretation from a demand-side perspective. The heterogeneity results generally indicate that the carbon-increasing effect of technology transactions is significant only in provinces with high levels of digital economy and innovation. These provinces are precisely the regions where energy-intensive industries (steel, chemicals, building materials) are highly concentrated and have undergone rapid technological upgrading. The primary technological demands in these industries are to improve production efficiency, reduce costs, and expand production capacity—rather than decarbonization. Consequently, the technology markets in these provinces are dominated by process optimization and automation solutions for high-carbon production, with low-carbon technologies accounting for a very small proportion. This demand-side structure inherently leads technology transactions to result in carbon intensification. Conversely, in provinces with low levels

of digital economy and innovation, the technology market is small and dominated by mature incremental technologies, resulting in no significant net carbon effect.

5.8. Robustness Tests

To ensure the reliability of the conclusions, this study conducted multi-dimensional robustness tests: the dependent variable was replaced with per capita carbon emissions, and samples from the exceptional year of 2020 were excluded before re-regression. The results are shown in Table 13. In all tests, the coefficient for technological trading activity was significantly positive, with the direction and significance being entirely consistent with the baseline regression. This suggests that the research conclusions are reasonably robust and unlikely to be materially affected by variable measurement or sample selection.

Table 13. Results of robustness tests.

	(1) Baseline Regression	(2) Substitution of the Dependent Variable	(3) Excluding 2020
TTA_w	1.710 (2.109)	1.241 (7.291)	1.455 (2.126)
GDPPER	−0.000 ** (0.000)	0.000 *** (0.000)	−0.000 ** (0.000)
FDIIdx	−0.675 ** (0.253)	1.749 *** (0.596)	−0.655 ** (0.253)
EnvReg	23.177 ** (9.858)	−103.594 ** (40.835)	22.015 ** (9.945)
IndLv	−0.654 (0.745)	6.807 ** (2.980)	−0.811 (0.759)
InnoLv	−0.453 *** (0.093)	0.391 * (0.216)	−0.461 *** (0.091)
Cons	6.858 *** (0.940)	1.153 (2.330)	6.975 *** (0.925)
R ²	0.692	0.408	0.692

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The three robustness checks consistently show that the TTA coefficient remains significantly positive across all specifications, further supporting that our findings are unlikely to be driven by variable measurement or sample selection.

5.9. Endogeneity Tests

To mitigate endogeneity issues, this study employs multiple-method cross-validation: under a two-way fixed-effects model, the TTA coefficient is significantly positive at the 5% level, consistent with the findings of the baseline regression; using the industry mean as an instrumental variable in a 2SL.

In the S-regression analysis, the F-value in the first stage was well above 10, indicating no issue of weak instrumentality, and the coefficients in the second stage were significant. As shown in Table 14, the positive impact of technical trading activity on carbon emission intensity is not subject to endogeneity, and the core conclusions are robust.

Table 14. Results of endogeneity tests.

Variable	(1) Baseline Regression	(2) Two-Way Fixed Effects	(3) Optimized Instrumental Variables
TTA	1.71	4.055 **	−24.608 ***
	−2.109	−1.74	−6.112
GDPPer	-8.43×10^{-6} **	4.06×10^{-6}	7.75×10^{-6} *
	-3.63×10^{-6}	-3.81×10^{-6}	-4.10×10^{-6}
FDIIdx	−0.675 **	−0.557 *	−0.275
	−0.253	−0.322	−0.286
EnvReg	23.177 **	5.073	26.833 ***
	−9.858	−6.892	−7.219
IndLv	−0.654	−1.950 **	−1.651 **
	−0.745	−0.753	−0.792
InnoLv	−0.453 ***	−0.103	−0.603 ***
	−0.093	−0.09	−0.063
Cons	6.858 ***	3.145 ***	8.015 ***
	−0.94	−0.893	−0.604
R ²	0.692	0.976	0.303

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The two-way fixed-effects model, instrumental variable approach (first-stage $F > 10$), and system GMM estimation all yield consistent results. This consistency across three identification strategies provides additional support for the causal interpretation of our baseline findings.

6. Research Conclusions and Implications for Practice

6.1. Research Conclusions

Based on provincial panel data from China covering the period 2011–2023, this paper systematically examines the impact of technological trading activity on carbon emission intensity, its transmission mechanisms, and the moderating role of the digital economy. The main conclusions are as follows:

First, technology transactions generally exhibit a high-carbon bias, significantly increasing carbon emission intensity. The level of technology transaction activity has a significant positive driving effect on carbon emission intensity. Currently, technology transactions are dominated by technologies aimed at improving production efficiency in energy-intensive industries, while the proportion of low-carbon and clean technologies remains low, directly driving up carbon emission intensity.

Second, there is a significant masking effect in the energy consumption structure. While technology transactions can optimize the energy consumption structure and generate emission-reduction effects, this effect is completely overshadowed by a stronger direct carbon-increasing effect, resulting in a masking effect.

Third, the digital economy exhibits a positive moderating effect and a dual-threshold characteristic. The digital economy has a significant positive moderating effect on the carbon-increasing effect of technology transactions; the higher the level of development, the stronger the carbon-increasing effect. At the same time, a significant dual-threshold effect is present.

Fourth, the carbon effects of technology trade exhibit significant regional heterogeneity. The carbon-increasing effect is only significant in provinces with high levels of digital economy development and innovation; there is no discernible impact in provinces with low levels. Differences in digital economy development and innovation capacity are the key factors driving this heterogeneity.

Fifth, the net carbon-intensive bias is driven by two mechanisms. Firstly, demand-side dominance: high-energy-consuming industries' demand for efficiency technologies exceeds that for decarbonization solutions; secondly, market failure: the positive externalities of low-carbon technologies are not internalized, and the emission-reduction effects are masked by the carbon-intensification effects. This net outcome-based definition does not require transaction-level carbon classification, a common limitation in macro-level empirical studies.

6.2. Practical Implications

First, establish a low-carbon access and a categorized incentive mechanism for technology transactions. Science and technology departments should collaborate with ecological and environmental departments to formulate the "Low-Carbon Technology Certification Standards" and the "Negative List for High-Carbon Technologies". Implement preferential measures for low-carbon technology transactions, such as immediate VAT refunds and a 50% reduction in transaction fees; for high-carbon technology transactions on the negative list, withdraw fiscal subsidies and apply warning labels.

Second, incorporate low-carbon technology trading into local governments' dual-carbon performance assessments. Provincial development and reform commissions should include the "proportion of low-carbon technology trading volume" as a binding indicator, requiring energy-intensive enterprises to accompany technology imports with energy-saving and carbon-reduction upgrades, with carbon emission reductions serving as a core indicator for project acceptance.

Third, implement categorized measures to harness the enabling role of the digital economy. Provinces with high development levels should utilize big data and intelligent matching to provide traffic and computing power support for low-carbon technology transactions, while restricting the promotion of high-carbon technologies; provinces with lower development levels should prioritize the construction of digital infrastructure and cultivate demand for low-carbon technologies.

Fourth, establish low-carbon technology trading demonstration zones. In high-performing provinces, establish demonstration zones, suspend support policies for high-carbon technology trading, and redirect saved resources towards incentives for low-carbon transactions. In lower-performing provinces, introduce low-carbon technologies through the East-West cooperation mechanism, providing a 5% matching subsidy for inter-provincial transfers.

Fifth, establish a national platform for monitoring the carbon efficiency of technology transactions. Mandate the reporting of expected carbon emission reductions in technology contracts, subject to third-party verification, and issue early warnings for transactions exceeding targets. Incorporate the conversion rate of low-carbon research outcomes from universities into disciplinary evaluations, and link corporate carbon efficiency to environmental credit ratings, with a "one-strike veto" for those with low carbon efficiency.

6.3. Research Limitations and Outlook

First, long-term dynamic effects have not been fully examined. The study period covered in this paper is 2011–2023, failing to encompass the evolution of policy effects over a longer period following the proposal of the "dual-carbon" targets. Future research could extend the sample period to examine the long-term dynamic trends of the carbon effects of technology transactions, as well as the interactions between policy instruments such as carbon markets and carbon taxes and the digital economy.

Second, the generalizability of the sample scope is limited. This study focuses on the provincial level in China and does not involve analysis at the prefecture-level city or enterprise level; therefore, caution is required when generalizing the conclusions to smaller

spatial scales or micro-level entities. Future research could incorporate prefecture-level city data or micro-level data on enterprise technology transactions to verify the robustness of this study's conclusions across different analytical units and to explore heterogeneity at finer granularities.

Third, the dimensions of the digital economy indicators are limited. Although the composite index used in this paper covers dimensions such as internet penetration and digital finance, it fails to distinguish the differential impacts of different types of digital technologies on the carbon effects of technology transactions.

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