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LEVERAGING DIGITAL TRADE GOVERNANCE FOR LOW-CARBON TRANSITION: MECHANISM ANALYSIS AND POLICY OPTIMIZATION UNDER CHINA'S DUAL CARBON TARGETS

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Abstract: The intensifying global climate crisis has necessitated innovative approaches to achieve low-carbon development, with digital trade emerging as a promising pathway due to its energy efficiency and technological advantages. China's Cross-border E-commerce Comprehensive Pilot Zones demonstrate a significant reduction in urban carbon emission intensity, supporting the country's "dual carbon" goals. Empirical analysis of 270 cities (2010-2021) reveals stronger effects in coastal regions, megacities, and service-driven economies. Three key pathways drive this impact: enhanced digital infrastructure, service sector agglomeration, and improved business environments. The findings offer actionable insights for aligning digital trade policies with sustainable urban development.
Keywords: Digital trade; Low-carbon transition; E-commerce; Carbon emissions; Policy evaluation

1 INTRODUCTION

The intensifying global climate crisis has accelerated the search for innovative policy solutions to achieve low-carbon development, with digital trade emerging as a particularly promising avenue due to its inherent energy efficiency and technological advantages. As the world's largest carbon emitter and a rapidly growing digital trade power, China's implementation of its "dual carbon" goals (peaking emissions by 2030 and achieving carbon neutrality by 2060) has created an urgent need to reconcile economic growth with environmental protection through optimized resource allocation and green innovation. Against this backdrop, China established its first Cross-border E-commerce Comprehensive Pilot Zone in 2015 [1], a strategic initiative designed to improve policy frameworks, enhance trade facilitation, and drive industrial upgrading while serving as a crucial testing ground for integrating digital trade expansion with emission reduction objectives. This policy experiment represents a significant effort to harness the potential of digital trade as a dual-force for both economic development and environmental sustainability.

Recent research has highlighted the complex relationship between digital trade and carbon emissions, revealing both promising pathways and potential challenges for environmental sustainability. While Yang et al. identify digital trade as a key driver of emission reduction [2], and Deng et al. demonstrate the significant influence of regional digital development levels on carbon footprints [3], the underlying mechanisms appear multifaceted. Evidence suggests digital trade can yield environmental benefits through optimized supply chains and smart logistics [4], yet may simultaneously increase emissions through expanded logistics volumes, energy-intensive warehousing, and packaging waste [5]. This dual effect appears to follow a nonlinear pattern, with Zhou and Guo documenting an inverted U-shaped relationship where emissions initially rise before declining after reaching a development threshold [6]. Further nuance emerges in the findings of Song et al. [7], who observe that cross-border e-commerce's emission-reduction effects vary significantly by region, city size, and baseline pollution levels, being particularly strong in China's eastern and western regions, large cities, and areas with initially underdeveloped digital infrastructure or lower pollution levels. These findings collectively suggest that the environmental impact of digital trade is contingent on developmental stage, implementation context, and complementary infrastructure.

Regarding transmission mechanisms, Ma et al. assert that digital trade effectively reduces regional carbon emission intensity by promoting scale effects [8], driving technological progress, and optimizing industrial structure. Zhu et al. construct an indicator system to measure regional digital trade development and examine its carbon reduction impact mechanisms and spillover effects from both the enterprise supply side and the resident demand side [9]. Their findings confirm that digital trade effectively promotes regional carbon reduction, with a more substantial effect observed in central and western regions and areas with lower carbon emissions.

Furthermore, regional characteristics, trade openness, and industrial agglomeration also influence the carbon reduction effect of digital trade. Zhou and Guo show that the carbon reduction effect of digital trade is stronger in China's central and western regions than in the eastern region [6], and stronger in inland areas compared to coastal areas. Simultaneously, the carbon reduction effect of digital trade may weaken as trade liberalization increases and carbon emission intensity decreases. Wang et al. further analyze the impact of manufacturing and producer services agglomeration on this effect [10], finding that manufacturing agglomeration may weaken it, whereas producer services agglomeration, the synergistic agglomeration of manufacturing and producer services, and carbon emission trading pilot policies enhance the carbon reduction effect. Additionally, Li et al. [11], using the implementation of the Cross-border E-commerce Comprehensive Pilot Zone policy as a quasi-natural experiment to analyze its impact in Central and Eastern Europe, reveal through mechanism analysis that digital trade holds the potential to indirectly affect urban carbon intensity by influencing green technological innovation, industrial agglomeration, and energy structure optimization.

Despite the rich findings in existing research exploring the relationship between digital trade and carbon emissions, several questions warrant further investigation. Specifically, the impact and mechanisms of cross-border e-commerce—a specific category of digital trade—on carbon emissions remain unclear. The influence of China's policy of establishing Comprehensive Pilot Zones to foster digital trade on the carbon emissions of host cities, along with its underlying mechanisms, is not well understood. Current research provides limited exploration into how such policies reduce carbon emission intensity through optimizing resource allocation, promoting digital infrastructure construction, and fostering green technological innovation. Moreover, the influence of urban characteristics on the carbon reduction effect of digital trade has not been sufficiently examined.

Therefore, investigating the impact of digital trade development on urban carbon emission intensity and its mechanisms holds significant practical relevance. Can developing digital trade effectively promote low-carbon urban transformation? Through what mechanisms does it operate? Does the impact of digital trade development on carbon emissions vary under different urban characteristics? To address these questions, this paper proposes the following hypotheses:

H1: Developing digital trade reduces urban carbon emission intensity.

H2: Digital infrastructure construction, service industry agglomeration, and business environment optimization mediate the relationship through which through which developing digital trade reduces urban carbon emission intensity.

To explore the impact of digital trade development on carbon emission intensity and analyze its mechanisms, we utilize panel data from 270 Chinese cities spanning 2010-2021. Following Udoka, et al. [12], we employ a Difference-in-Differences (DID) approach, treating the establishment of China's Cross-border E-commerce Comprehensive Pilot Zones as a quasi-natural experiment. We further analyze the mediating effects of digital infrastructure, service industry agglomeration, and business environment optimization on the relationship between the Pilot Zones and carbon emission intensity. The empirical results indicate: First, the establishment of Comprehensive Pilot Zones significantly reduces the level of urban carbon emission intensity, a conclusion that remains robust after multiple rigorous tests. Second, the policy effect exhibits significant heterogeneity related to location, population size, and industrial structure characteristics. The effect is most pronounced in eastern coastal regions, megacities (population >5 million), the Yangtze River Delta and Pearl River Delta urban agglomerations, and cities dominated by the tertiary industry. Third, mechanism tests confirm that the establishment of the Comprehensive Pilot Zone policy promotes low-carbon urban development through three pathways: advancing digital infrastructure construction, promoting service industry agglomeration (especially mid-to-low-end services), and optimizing the business environment.

The marginal contributions of this study are threefold: It focuses specifically on the Comprehensive Pilot Zone policy, systematically evaluating the impact of this digital trade policy on low-carbon transition at the city level. By constructing a city-level panel dataset, it deepens empirical research at the micro-level, clarifying the causal effect of the Pilot Zone policy on urban carbon intensity and providing new directions and references for subsequent research, thereby enhancing the understanding of the mechanisms through which emerging economic models contribute to environmental sustainability. It introduces novel mediating variables—digital infrastructure construction index, service industry agglomeration index, and business environment index—offering fresh perspectives on the pathways through which digital trade policies influence urban low-carbon transformation.

2 THEORETICAL MODEL

2.1 Data Sources

The core dataset consists of panel data for 270 Chinese prefecture-level cities spanning the period 2010–2021. Following Wu et al. [13], primary data was sourced from the China City Statistical Yearbook for the respective years. Supplementary data was obtained from prefecture-level city statistical yearbooks, the China Energy Statistical Yearbook, the China Industrial Statistical Yearbook, the China Agriculture Statistical Yearbook, and the China Environment Statistical Yearbook.

2.2 Research Methods

2.2.1 Model specification

The designation of Cross-border E-commerce Comprehensive Pilot Zones (CBECPZs) was granted in multiple batches across different years. To accurately assess the impact of establishing a CBECPZ on urban carbon emission intensity (CEE), this study employs a multi-period Difference-in-Differences (DID) model, drawing on the methodology of Ding, et al. [14]. The specific model is formulated as follows:

$$CEE_{it}=\alpha+\beta_1 CBEC_{it}+\beta_2 Control_{it}+\lambda_i+\mu_t+\epsilon_{it} \quad (1)$$

In the model, i and t denote city and year, respectively; CEE_{it} is the dependent variable, representing urban carbon emission intensity; $CBEC_{it}$ is the core explanatory variable, indicating the treatment status of a pilot city, specifically defined as the interaction term Time × Treat (where Treat identifies the city and Time identifies the policy implementation period); $Control_{it}$ encompasses a vector of control variables, including urbanization rate, industrial structure, population size, and service sector development level; λ_i and μ_t represent city fixed effects and year fixed effects, respectively; and ϵ_{it} is the stochastic error term.

2.3 Variable Definitions

2.3.1 Dependent variable

The dependent variable is Carbon Emission Intensity (CEE). Following Li, K. et al. [15], carbon emission intensity is calculated by dividing total carbon emissions by real GDP (2010 constant prices). This indicator incorporates both economic output and carbon emissions, effectively reflecting the synergy between regional economic growth and environmental protection. Compared to the single metric of total carbon emissions, CEE better reveals the structural emission reduction effects driven by the CBECPZ policy and its role in enhancing the quality of low-carbon economic transformation. This aligns with the policy evaluation needs of balancing development and emission reduction under China's "dual carbon" goals. Total city-level carbon emissions are derived by summing emissions generated from electricity, gas and liquefied petroleum gas consumption, transportation, and thermal energy consumption. The specific calculation method follows the approach of Wu et al. [16].

2.3.2 Core explanatory variable

The core explanatory variable is the CBECPZ establishment interaction term (CBEC). It is constructed as the product of a spatial dummy variable (Treat) indicating the CBECPZ policy implementation and a time dummy variable (Time). Treat identifies cities designated as CBECPZs. It is assigned a value of 1 if the prefecture-level city established a CBECPZ, and 0 otherwise. Time identifies the timing of the CBECPZ establishment. Following the multi-period DID approach, Time is assigned a value of 1 for city i in year t and all subsequent years after the city is designated as a CBECPZ, and 0 otherwise.

2.3.3 Control variable

Control variables are introduced to enhance the accuracy and reliability of the analysis by isolating the effect of the CBECPZ policy from other potential confounding factors that might simultaneously influence carbon emission intensity. This study selects the following control variables:①Economic Development Level (GDP): Measured by real GDP per capita (real GDP divided by the city's year-end population), taken as the natural logarithm. ②Urbanization Level (Urban): Measured by the proportion of the urban population to the total population. ③Government Intervention (Gov): Measured by the proportion of local government fiscal expenditure to GDP. ④Internet Development Level (Inter): Reflecting the state of digital infrastructure, measured by the natural logarithm of the number of internet users in each city. ⑤Infrastructure Level (Infra): Measured by road area per capita.

3 EMPIRICAL ANALYSIS

3.1 Baseline Regression

Table 1 presents the regression results assessing the impact of the Cross-Border E-commerce (CBEC) Pilot Zone policy on urban carbon intensity, with city and year fixed effects controlled. Column (1) reports the estimation results without control variables, while Column (2) incorporates them. The results consistently indicate that the implementation of the CBEC Pilot Zone policy significantly reduces carbon intensity in designated cities.

Table 1 Baseline Regression Result

	(1)	(2)
CBEC	-0.0846*	-0.0475*
	(-3.12)	(-3.80)
GDP		-0.923***
		(-18.93)
Urban		0.157
		(1.11)
Gov		0.350*
		(2.13)
Inter		-0.00232
		(-0.17)
Infra		0.00155
		(1.58)
Cons	0.992*	1.636*
	(83.28)	(5.27)
N	3 240	3218

R-squared	0.225 5	0.7088

Note: *, **,*** indicate significance at the level of 0.1%,1% and 5%, respectively, and the numbers in parentheses are standard errors.

3.2 Robustness Checks

3.2.1 Parallel trend test

The validity of the difference-in-differences (DID) model hinges on the parallel trends assumption. Following Ryan et al. [17], we confirm that the treatment and control groups exhibit similar trends in carbon intensity before the policy implementation. Employing an event-study framework inspired by Derindağ [18], we construct the following specification:

$$CEE_{it} = \theta + \sum_{k\geq-8(+)}^{k\leq6(+)} k_{Dum}^{it}\beta_k + \mu_i + v_t + \xi_{it} \tag{2}$$

Where, Dum represents a set of dummy variables indicating the event window periods relative to policy implementation, with k = -8(+), -7, -6, ..., 5, 6(+). Using the period immediately preceding the policy implementation as the reference period for the parallel trends test, the results demonstrate that the coefficients for all pre-policy periods are statistically insignificant at the 10% level. This confirms that the parallel trends assumption holds.

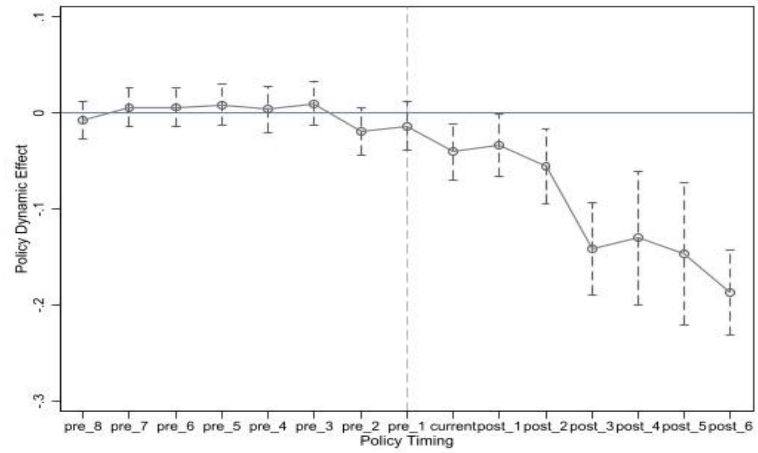


Figure 1 Parallel Trend Test Results

3.2.2 Robustness checks

The benchmark regression results in this paper may be affected by other policy shocks and other conditions, so in order to verify the reliability of the benchmark regression results, robustness tests are carried out from the following aspects:

(1) Placebo Test

To address potential omitted variable bias, we conduct placebo tests by randomly assigning treatment status across 270 cities for 500 iterations. The resulting coefficients form a normal distribution centered around zero, with no statistically significant outliers, confirming the robustness of our baseline estimates. This approach effectively rules out confounding from unobserved time-varying factors.

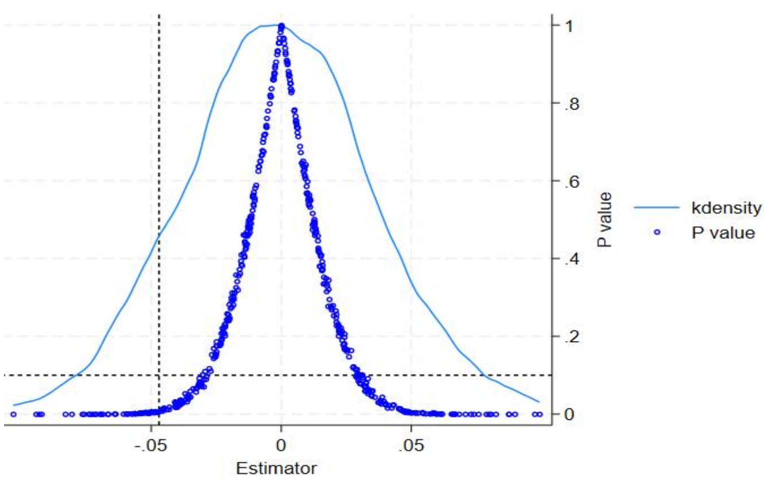


Figure 2 Placebo Test Results

(2) Controlling for Concurrent Policies
To address potential policy confounding during our study period (including “Broadband China,” “Low-Carbon City”, “Smart City”, and “Key Air Control” initiatives), we incorporated these as additional controls in our multi-period DiD specification. The results (Table 2) demonstrate that the CBEC pilot zones maintain statistically significant carbon-reduction effects after accounting for concurrent policies, confirming the robustness of our causal identification. This suggests that while these complementary policies may influence carbon intensity through various channels, their presence does not substantially alter our primary findings regarding the CBEC zones’ environmental impact.

Table 2 Controlling for Other Policy Interventions

Variable	(1)	(2)	(3)	(4)	(5)
CBEC	-0.0438***	-0.0478***	-0.0475***	-0.0480***	-0.0445***
	(-3.61)	(-3.84)	(-3.79)	(-4.01)	(-3.90)
Constant	10.3153*	10.2845***	10.2797***	10.2785*	10.3087*
	(20.58)	(19.99)	(20.06)	(20.00)	(20.52)
Broadband China	Control				Control
Low-carbon City		Control			Control
Smart City			Control		Control
Key Atmospheric Control				Control	Control
Controls	Yes	Yes	Yes	Yes	Yes
N	3206	3206	3218	3218	3206
R-squared	0.7100	0.7091	0.7088	0.7089	0.7101

Note: *, **,*** indicate significance at the level of 0.1%,1% and 5%, respectively, and the numbers in parentheses are standard errors.

3.3 PSM-DID Estimation

This paper adopts the following model to estimate the predicted probability *probit* of each sample city becoming a cross-border e-commerce comprehensive pilot zone, that is, propensity score:

$$probit(treat_i=1)=\alpha+\beta X_i+\varepsilon_i \tag{3}$$

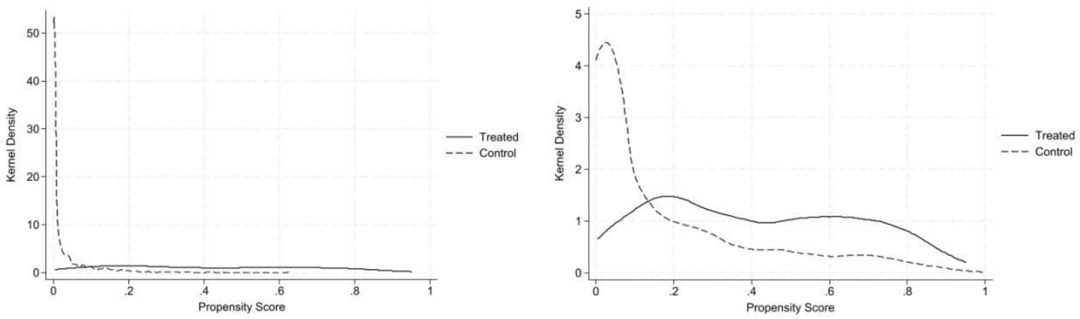
Where, $treat_i$ represents the policy variable for Cross-border E-commerce Comprehensive Pilot Zones: sample cities are assigned a value of 1 if they were designated as Cross-Border E-commerce Comprehensive Pilot Zones during 2010-2021, and 0 otherwise. X_i denotes the matching variables, including real GDP (logarithm), population size (logarithm), urbanization rate, internet user data (logarithm), and infrastructure level.
To ensure robust causal identification, we implement kernel matching (bandwidth=0.20) following established methodologies [19-20]. Balance test results (Table 2) confirm the matching quality: (1) post-matching t-tests reveal no significant mean differences in covariates (all p>0.10); (2) standardized biases decrease for all variables except population size; and (3) the negligible R^2 from the propensity score model indicates successful achievement of conditional randomness in treatment assignment. These diagnostics collectively validate our matching approach and support the conditional independence assumption underlying our analysis.
To satisfy the common support condition critical for propensity score matching [21], we conducted rigorous diagnostic tests. Figure 3 demonstrates that while pre-matching propensity score distributions showed limited overlap between treatment and control groups, post-matching distributions achieved substantial alignment, with only minimal sample loss outside the common support region. This marked improvement in covariate balance ensures our average treatment effect estimates reflect comparable subpopulations, addressing the potential subset effect concern and enhancing the validity of our causal inferences.

Table 3 Covariate Balance Test

Variable	Sample	Mean difference test			Standardization difference test	
		Treated	Untreated	T-test (p-value)	Standardization Differences	Decreasing Amplitude (%)
GDP	Unmatched	10.915	10.238	17.68(0.000)	106.1	99.0
	Matched	10.915	10.922	-0.11(0.909)	-1.1	
Urban	Unmatched	0.7214	0.5363	22.05(0.000)	140.7	99.0

	Matched	0.7214	0.7196	0.1(0.872)	1.4	
Gov	Unmatched	0.1580	0.1998	-7.17 (0.000)	-50.5	74.5
	Matched	0.1580	0.1687	-1.97 (0.049)	-12.8	
Inter	Unmatched	14.791	13.319	28.29(0.000)	190.2	98.9
	Matched	14.791	14.776	0.27 (0.791)	2.0	
Infra	Unmatched	18.909	17.543	3.05 (0.002)	19.0	24.9
	Matched	18.909	17.883	1.60 (0.109)	14.3	
Pseudo R^2	Unmatched				0.423	
	Matched				0.010	

Note: *, **,*** indicate significance at the level of 0.1%,1% and 5%, respectively, and the numbers in parentheses are standard errors.



(a) Before Matching (b) After Matching

Figure 3 Distribution of Propensity Scores Before and After Matching

After confirming that the matched sample satisfies both the conditional independence assumption and the common support condition, the average treatment effect on the treated (ATT) is estimated using the matched sample, following the method of Sun et al. [22]. The results are reported in Table 4. The coefficient is significantly negative, indicating that the CBEC pilot policy significantly reduced carbon intensity in treated cities. This finding is consistent with the baseline regression results, further supporting the robustness of the core conclusion.

Table 4 Average Treatment Effect of CBEC Pilot Policy (ATT Estimation Using Kernel Matching)

	ATT Estimate
	Carbon Intensity
Kernel Matching	-0.2524***(-3.61)
Treated Group Size	302
Control Group Size	2916
Total Sample Size	3218

Note: *, **,*** indicate significance at the level of 0.1%,1% and 5%, respectively, and the numbers in parentheses are standard errors.

3.4 Heterogeneity Analysis

3.4.1 Location heterogeneity

Due to disparities in resources, economy, and industrial structure between China's coastal and inland areas, as well as across eastern, central, western, and northeastern regions and city agglomeration, this study examines the heterogeneous effects of cross-border e-commerce pilot zones. Coastal cities exhibit stronger carbon reduction effects from these policies compared to inland cities, attributed to differences in resource endowments and economic foundations [23-24]. Regionally, the eastern region shows significant policy impacts, while central and western regions see negligible effects, and the northeastern region may even experience increased emissions due to industrial structure and economic factors [25-26]. Among major city clusters, the Pearl River Delta demonstrates notable carbon reduction benefits owing to logistics and industrial transformation advantages, whereas the Beijing-Tianjin-Hebei and Yangtze River Delta regions show no significant impact [27].

Table 5 Location Heterogeneity

	Coastal (1)	Inland (2)	Eastern (3)	Central (4)	Western (5)	Northeastern (6)
Coast×CBEC	-0.0821** (-2.84)					
Inland×CBEC		-0.0145 (-1.20)				
East×CBEC			-0.0765*** (-4.02)			
Mid×CBEC				-0.0029 (-0.17)		
West×CBEC					-0.0204 (-0.95)	
Northeast×CBEC						0.0482 (1.87)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	3218	3218	3218	3218	3218	3218
R-squared	0.4006	0.3984	0.4022	0.4413	0.3974	0.3967

Note: *, **,*** indicate significance at the level of 0.1%,1% and 5%, respectively, and the numbers in parentheses are standard errors.

Table 6 Urban Agglomeration Heterogeneity

	Beijing-Tianjin-Hebei Region (1)	Yangtze (2)	Pearl (3)
BTH×CBEC	-0.0220 (-1.11)		
Yangtz×CBEC		-0.109 (-1.15)	
Pearl×CBEC			-0.2556** (-2.96)
Controls	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N	3218	3218	3218
R-squared	0.3973	0.3979	0.4013

Note: *, **,*** indicate significance at the level of 0.1%,1% and 5%, respectively, and the numbers in parentheses are standard errors.

3.4.2 Population size heterogeneity

Cities are classified by population: megacities (permanent population>5 million) and large cities (1-5 million). As shown in Table 7, cross-border e-commerce pilot zones significantly reduce carbon intensity in megacities but not in large cities. Megacities benefit from strong policy coordination, large consumer markets, and efficient logistics integration, which lower energy use and emissions [28]. Their technological innovation capacity and higher consumer environmental awareness also drive low-carbon supply chains [29]. In contrast, large cities lack sufficient scale for optimal resource integration, slowing low-tech adoption and process optimization, leading to weaker policy effects.

Table 7 Population Size Heterogeneity

	Megacities (1)	Large Cities (2)
Large×CBEC	-0.0676*** (-1.09)	
Medium×CBEC		0.00407 (0.27)
Controls	Yes	Yes
City Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
N	3218	3218

R-squared	0.4064	0.3974

Note: *, **,*** indicate significance at the level of 0.1%,1% and 5%, respectively, and the numbers in parentheses are standard errors.

3.4.3 Industrial structure heterogeneity

Cities are classified as secondary industry-dominant (secondary sector GDP > tertiary sector) or tertiary industry-dominant (tertiary sector GDP > secondary sector). Regression results (Table 8) reveal that cross-border e-commerce pilot zones exert a stronger carbon intensity reduction effect in tertiary industry-dominant cities. This aligns with Ma [30], who highlights the synergy between industrial upgrading and e-commerce pilot policies. Tertiary-driven cities benefit more from institutional and technological innovations in these zones, facilitating structural transformation and emission reductions. Empirical evidence, such as Shanghai pilot zone, further supports this trend, as these initiatives primarily target service-sector optimization.

Table 8 Industrial Structure Heterogeneity

	Secondary industry (1)	Tertiary industry (2)
Second×CBEC	-0.0520 (-1.54)	
Third×CBEC		-0.0356** (-2.91)
Controls	Yes	Yes
City Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
N	3216	3216
R-squared	0.3981	0.4010

Note: *, **,*** indicate significance at the level of 0.1%,1% and 5%, respectively, and the numbers in parentheses are standard errors.

3.5 Mechanism Analysis

Existing studies confirm that cross-border e-commerce pilot zones significantly reduce carbon intensity by facilitating digital transformation, industrial upgrading, and business environment optimization (Government Policy Documents, Year). However, the underlying mechanisms require systematic empirical examination.

Aligned with policy objectives, we hypothesize three key intermediate pathways:

(1) Digital infrastructure development - Enhancing technological penetration in traditional industries; (2) Service industry agglomeration - Promoting structural transformation toward tertiary sectors; (3) Business environment improvement - Increasing operational efficiency and green practices.

To rigorously test these mechanisms, we employ a Sobel-Goodman mediation analysis using the following model:

$$M_{it}=\beta_0+\beta_3 CBEC_{it}+\gamma X_{it}+\lambda_i+\mu_i+\varepsilon_{it} \tag{4}$$

$$\gamma_{it}=\beta_0+\beta_1 CBEC_{it}+\beta_2 M_{it}+\gamma X_{it}+\lambda_i+\mu_i+\varepsilon_{it} \tag{5}$$

The intermediate variable is replaced by digital infrastructure construction index (Diginf), service industry agglomeration index (Spec) and urban business environment index (Envir), and other variables are the same as those mentioned above.

3.5.1 Digital infrastructure construction

As a key indicator of digital economy development, digital infrastructure reflects hardware investment, technology adoption, and application depth. Following Wang et al. [31], we measure it through six indicators including IT investment and internet penetration. Regression results (Table 9) show that cross-border e-commerce pilot zones significantly improve digital infrastructure, which in turn reduces urban carbon intensity. The mediation test confirms digital infrastructure's crucial role in this relationship. Specifically, pilot zones promote digital technology applications in urban energy management, logistics networks, and industrial collaboration, thereby enhancing energy efficiency and green innovation to lower carbon emissions.

Table 9 Mechanism Analysis: Digital Infrastructure

	(1)
CBEC	-0.4771*** (-8.99)
Diginf	-5.4285*** (-12.23)
Controls	Yes
Con	1.2773*** (62.14)
City Fixed Effects	Yes
Year Fixed Effects	Yes
Sobel-Z	-10.69***

N	3240
R-squared	0.0990

Note: *, **,*** indicate significance at the level of 0.1%,1% and 5%, respectively, and the numbers in parentheses are standard errors.

3.5.2 Agglomeration of services

Following the National Bureau of Statistics (2019) classification and Gu's framework [32-33], we define production services as comprising six sectors: (1) transportation/warehousing/postal services, (2) wholesale/retail trade, (3) leasing/business services (medium-low tier), and (4) information technology, (5) finance, (6) scientific research (high-end tier) [34]. Using Han and Yang's methodology, we calculate the specialization agglomeration index (SAI) as:

$$Spec_{it}=\frac{\sum_{j=1}^{J} S_{ijt} / \sum_{i=1}^{N} \sum_{j=1}^{J} S_{ijt}}{S_{it} / \sum_{i=1}^{N} S_{it}} \tag{6}$$

Among these, S_{ijt} represents the total number of employees in each industry in city i in year t, S_{it} represents the total number of employees in each industry in city i in year t, and N represents the number of cities. The results in Table 6 demonstrate that CBEC pilot zones significantly reduce urban carbon intensity (Spec) by promoting agglomeration of producer services, particularly mid-to-low-end services (Spec_low). This sector's responsiveness stems from e-commerce-driven demand for logistics and warehousing, forcing rapid efficiency gains. In contrast, high-end services (Spec_high) show weaker agglomeration effects due to their dependence on long-term capital and knowledge accumulation. Sobel test confirm this mediating pathway, highlighting service sector agglomeration as a key mechanism linking CBEC policies to emission reductions.

Table 10 Mechanism Analysis: Service Industry Agglomeration

	(1)	(2)	(3)
CBEC	-0.7709*** (-9.53)	-0.7568*** (-9.44)	-0.9015*** (-11.15)
Spec	-0.5780*** (-10.74)		
Spec_low		-0.5540*** (-12.18)	
Spec_high			-0.2702*** (-5.94)
Controls	Yes	Yes	Yes
Con	1.4940*** (34.22)	1.4548*** (40.11)	1.2724*** (32.15)
City Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Sobel-Z	-8.479***	-8.905***	-5.138***
N	2699	2699	2699
R-squared	0.0932	0.1037	0.0666

Note: *, **,*** indicate significance at the level of 0.1%,1% and 5%, respectively, and the numbers in parentheses are standard errors.

3.5.3 Business environment improvement

The development of cross-border e-commerce comprehensive pilot zones has prompted policy innovations targeting reducing operational costs for businesses, enhancing market access, fostering the emergence of new market players, promoting transparent and fair market rules, and creating a favorable business environment. To assess the impact of these pilot zones on the local business environment, this study uses the China City Business Credit Environment Index (Envir) published by the National Information Center as an indicator of urban business conditions. The findings indicate that improvements in the business environment have a significant negative impact on carbon intensity.

Table 11 Mechanism Mechanism Analysis: Business Environment Optimization

	(1)
CBEC	-0.3327*** (-6.67)
Inenvir	-6.3885*** (-22.68)
Controls	Yes
Con	28.2092*** (23.61)
City Fixed Effects	Yes
Year Fixed Effects	Yes

Sobel-Z	-15.06***
N	3231
R-squared	0.1871

Note: *, **,*** indicate significance at the level of 0.1%,1% and 5%, respectively, and the numbers in parentheses are standard errors.

4 CONCLUSIONS AND RECOMMENDATIONS

4.1 Conclusions

This study employs a DID approach with panel data from 270 Chinese cities (2010-2021) to examine the impact of CBEC Pilot Zones on carbon intensity. The results demonstrate that the policy significantly reduces urban carbon emissions, with effects varying by region and city characteristics: the reduction is more pronounced in eastern coastal areas, megacities, the Yangtze/Pearl River Deltas, and service-oriented cities, while being weaker in western regions, smaller cities, and manufacturing-dominated areas. Mechanism analysis reveals three key pathways-digital infrastructure development [35-36], service industry agglomeration (particularly mid-to-low tier services), and business environment optimization-through which the policy achieves its emission reduction effects. These findings provide empirical evidence on how digital trade policies can contribute to environmental sustainability at the urban level.

4.2 Policy Implications

Based on our findings, we propose four targeted policy measures:
First, implement regionally differentiated policies that account for developmental disparities. Coastal regions should establish low-carbon e-commerce benchmarks, while inland areas require fiscal support and technical assistance. Megacities need enhanced ecological regulation, service clusters should develop green finance, and industrial bases must accelerate clean energy adoption.
Second, prioritize digital infrastructure investment to address urban digital divides. Strategic upgrades of network capacity and green computing in underdeveloped regions will amplify the carbon-reduction effects of cross-border e-commerce policies.
Third, accelerate the green transition of mid-to-low-end services through fiscal subsidies, green credit products tied to emission performance, and consumer incentives for low-carbon services. This multi-stakeholder approach can improve sector-wide energy efficiency.
Fourth, optimize the e-commerce business environment by streamlining approvals, enhancing policy transparency, and tailoring local interventions. Innovation hubs should focus on low-carbon R&D support, while less-developed cities need foundational business climate improvements.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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