The Promotion Effect of Data Factor Allocation Level on Cross-Border E-commerce Development: Evidence from China

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Abstract. This study examines how data factor allocation promotes cross-border e-commerce development in China. Based on provincial panel data (2012–2022), we employ a two-way fixed effects model to analyze this relationship. Results show that enhancing data factor allocation significantly boosts cross-border e-commerce, a finding robust to alternative measures, lagged variables, and winsorization. The promotion operates through two indirect channels: industrial structure upgrading and increased R&D intensity. Heterogeneity analyses reveal stronger effects in regions with higher data allocation levels and a regional gradient (Eastern > Western > Northeastern > Central). The findings underscore data factors as a key driver for high-quality e-commerce growth and offer targeted policy implications.

Keywords: Data Factor Allocation, Cross-Border E-Commerce Development, Industrial Structure Upgrading, R&D Intensity, Fixed Effects Model

1 Introduction

With the rapid development of the global digital economy, data has gradually become a key production factor driving economic growth and industrial transformation [1]. Zheng and Zhou point out that data holds irreplaceable strategic value in promoting resource integration, optimizing production processes, and supporting economic restructuring [2]. In the context of China's ongoing market-oriented reform of data factors, the capabilities for collecting, transmitting, integrating, and applying data resources have continuously improved, leading to enhanced efficiency in data factor allocation. This process not only profoundly changes the organizational models of traditional industries but also reshapes the operational logic of trade activities, providing new momentum for the development of digital trade and cross-border e-commerce (CBE) [3].

As an important carrier of the digital transformation of foreign trade, CBE has experienced sustained high growth in recent years, playing a key role in optimizing foreign trade structures, enhancing international competitiveness, and fostering new drivers of

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foreign trade. According to customs statistics, China's cross-border e-commerce import and export scale reached 2.75 trillion yuan in 2025, representing an increase of 69.7% compared to 2020. Guo et al. argue that the industrial chain, supply chain, and value chain of CBE are highly reliant on a data-driven development model, with core processes such as precise matching, digital logistics, cross-border payments, and intelligent customer service all primarily relying on data as a critical production resource [4]. Efficient allocation and circulation of data resources therefore play an increasingly important role in improving transaction efficiency, optimizing supply chain coordination, and enhancing the overall competitiveness of cross-border e-commerce.

Existing studies primarily explore the impact of digitalization on CBE from perspectives such as digital infrastructure, internet technology, and the overall development level of the digital economy [5]. While these studies provide valuable insights, they often focus on the technological environment rather than the allocation efficiency of data as an independent production factor. In the emerging stage of the data-driven economy, the market-oriented allocation of data factors has become a crucial institutional arrangement for promoting digital economic development. However, systematic empirical evidence on how the level of data factor allocation influences the development of cross-border e-commerce remains relatively limited.

Against this background, this study aims to answer the following research question: How and through what mechanisms does the level of data factor allocation promote the development of cross-border e-commerce? By constructing a provincial-level panel dataset for China and employing a two-way fixed effects model combined with mediation effect analysis, this study systematically examines both the direct impact and the underlying mechanisms of data factor allocation on cross-border e-commerce development.

2 Theoretical Mechanism and Research Hypotheses

2.1 Data Factor Allocation and CBE Development

As a key production factor in the digital economy, the allocation level of data factors can directly promote CBE development from multiple dimensions. First, at the transaction level, the full circulation of data factors reduces information asymmetry in cross-border transactions, helping buyers and sellers achieve precise matching and reducing search costs [4]. Second, at the logistics level, data sharing optimizes supply chain coordination, improving cross-border logistics efficiency through real-time tracking and intelligent scheduling [6]. Third, in payment and after-sales services, data analysis supports credit assessment and risk control, reducing barriers to cross-border payments. Finally, the penetration of data factors promotes the intelligent upgrading of CBE platforms, enhancing user experience and operational efficiency. Therefore, the improvement of data factor allocation constitutes the basic support for CBE development. Accordingly, we propose:

H1: The improvement of data factor allocation level has a significant direct promoting effect on CBE development.

2.2 Indirect Effect through Industrial Structure Upgrading

Data factor allocation not only directly affects CBE but also generates indirect effects by reshaping regional industrial structures. On one hand, data factors can reduce information barriers, guiding production factors such as labor and capital from low-efficiency traditional sectors to high-efficiency modern service industries and high-tech industries, promoting the advancement of industrial structure [7]. On the other hand, the penetration of data factors gives rise to emerging digital industries, which are naturally coupled with CBE and provide technical support and ancillary services. Industrial structure upgrading means that regions can provide higher-quality goods, more complete supply chain systems, and more professional digital services—precisely the industrial foundation on which CBE development relies. Chang finds that the market-oriented allocation efficiency of data factors significantly improves the efficiency of the commercial and trade circulation industry, a mechanism equally applicable to CBE [8]. Accordingly, we propose:

H2: Data factor allocation indirectly promotes CBE development by driving industrial structure upgrading.

2.3 Indirect Effect through R&D Intensity Enhancement

CBE is characterized by technology intensity and model innovation, and its competitiveness highly depends on R&D investment and technological capabilities. Data factor allocation enhances this capability in several ways. First, enterprises can use big data analytics to accurately capture overseas market demands and reduce R&D trial-and-error costs [8]. Second, data sharing platforms accelerate knowledge spillover and technology diffusion, enabling enterprises to access innovative achievements at lower cost. Third, the increase in R&D intensity directly translates into the technological innovation capability, product iteration speed, and operational efficiency of CBE enterprises. Wu confirms at the macro level that digital economy development promotes high-quality growth of regional foreign trade [7]. Therefore, we propose:

H3: Data factor allocation indirectly promotes CBE development by enhancing R&D intensity.

2.4 Heterogeneity of the Effects

The promoting effect of data factor allocation on CBE may vary due to different regional conditions. On one hand, in regions with better data infrastructure and richer data resources, the marginal output of data factors may be higher, forming a "foundation advantage reinforcement" effect. On the other hand, China's eastern, central, western, and northeastern regions differ significantly in digital economy development level, industrial structure, and openness, which may lead to regional gradient characteristics in the effect of data factor allocation. Zhou and Kong find that the enabling effect of data factor market development on industrial structure upgrading exhibits regional heterogeneity [9]. Thus, we propose:

H4: The promoting effect of data factor allocation on CBE exhibits regional heterogeneity, with stronger effects in regions with higher data allocation levels and in the eastern region.

3 Research Design

3.1 Variable Selection

3.1.1 Explained Variable.

This study adopts the development level of cross-border e-commerce as the explained variable and constructs a comprehensive evaluation indicator system based on existing literature. The overall approach draws on research frameworks related to the measurement and evaluation of cross-border e-commerce development potential proposed by relevant scholars. As shown in Table 1, the indicator system is designed across four primary dimensions: trade scale, entity development, logistics capability, and innovation support, aiming to more comprehensively reflect the overall development level of cross-border e-commerce at the provincial level [9,11].

3.1.2 Core Explanatory Variable.

This study draws on the research approaches of relevant scholars regarding the measurement of data factors and the practice of measuring the marketization level of data factors based on the "input-flow-output" framework. The allocation of data factors is divided into three primary dimensions: supply efficiency, circulation efficiency, and output efficiency. Based on this, a provincial-level data factor allocation index system (Table 2) is constructed to more comprehensively reflect the overall allocation level of data factors across different regions [8,10].

Table 1. Evaluation Indicator System for Cross-Border E-Commerce Development Level.

Dimension	Code	Indicator	Attribute
Trade Scale	Trd1	Total Export Volume	+
	Trd2	Total Import Volume	+
	Trd3	E-commerce Sales	+
	Trd4	E-commerce Purchases	+
Entity Development	Ent1	Number of E-commerce Enterprises	+
	Ent2	Number of Cross-Border E-Commerce Comprehensive Pilot Zones	+
	Ent3	Proportion of Enterprises Engaged in E-commerce Transactions	+
	Ent4	Share of Enterprise E-commerce in GDP	+
Logistics Capability	Log1	Cross-Border Express Delivery Volume	+
	Log2	Cross-Border Express Delivery Revenue	+
	Log3	Number of Express Delivery Outlets	+
	Log4	Internet Penetration Rate	+
Innovation Support	Inn1	R&D Expenditure of Industrial Enterprises Above Designated Size	+
	Inn2	Full-Time Equivalent of R&D Personnel in Industrial Enterprises Above Designated Size	+

	Inn3	Number of Granted Patent Applications	+
	Inn4	Total Value of Technology Contracts	+

Table 2. Evaluation Indicator System for Data Factor Allocation Level.

Dimension	Code	Indicator	Attribute
Supply Efficiency	Sup1	Internet Broadband Access Ports	+
	Sup2	IPv4 Address Count	+
	Sup3	Optical Cable Line Length	+
Circulation Efficiency	Cir1	Enterprise Informatization Level	+
	Cir2	Digital Inclusive Finance Index	+
	Cir3	Software Development and Application Status	+
Output Efficiency	Out1	Digital Technology Market Size	+
	Out2	Number of Innovation and R&D Patents	+
	Out3	Software Service Expenditure	+

3.1.3 Mediating Variables.

Drawing on existing analyses of the economic effects of data factors and their underlying mechanisms, the level of data factor allocation typically influences the development of cross-border e-commerce indirectly through structural upgrading effects and innovation-driven effects [7, 8]. Following this logic, this paper selects industrial structure upgrading (ISU) and research and development intensity (RD) as mediating variables. Specifically, industrial structure upgrading is measured by the ratio of the value-added of the tertiary industry to that of the secondary industry. Research and development intensity is measured by the ratio of R&D expenditure of industrial enterprises above a designated size to GDP. These variables systematically reflect the indirect pathways through which the level of data factor allocation influences cross-border e-commerce development.

3.1.4 Control Variables.

To avoid omitting key influencing factors and enhance the explanatory power of the model, this paper, based on variable specifications in existing studies [1, 7], introduces a series of regional characteristic control variables. These include: industrial agglomeration level (AGG), innovation level (INN), environmental regulation intensity (ENV), transportation infrastructure (TRA), economic development level (ECO), degree of openness to the outside world (OPEN), human capital level (HC), and urbanization level (URB). These variables respectively reflect the industrial foundation, innovation capability, environmental policy pressure, infrastructure conditions, stage of economic development, outward orientation, labor force quality, and population agglomeration characteristics of a region. By incorporating these control variables, we can more accurately identify the net effect of the data factor allocation level on cross-border e-commerce development, thereby mitigating bias arising from regional differences.

3.2 Model Specification

3.2.1 Benchmark Regression Model.

To examine the impact of data factor allocation level on cross-border e-commerce development, the following two-way fixed effects model is constructed:

$$CBE_{it} = \alpha_0 + \alpha_i Data_{it} + \beta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

Where:

- CBE_{it} denotes the cross-border e-commerce development level of province i in year t;
- Data_{it} represents the data factor allocation level, which is the core explanatory variable in this study;
- $\mathbf{X}_{it}$ is a vector of control variables, including economic development level, industrial agglomeration, transportation infrastructure, human capital, among others, to mitigate omitted variable bias;
- μ_i denotes province fixed effects, controlling for time-invariant characteristics of each province, such as geographical location and fundamental economic structure;
- λ_t denotes year fixed effects, controlling for common shocks that vary over time, such as macroeconomic fluctuations and policy impacts;
- ε_{it} is the random error term.

3.2.2 Mediation Effect Model.

To reveal the internal mechanism through which the data factor allocation level influences the development of cross-border e-commerce, this study constructs a unified mediation effect analysis framework based on the benchmark model. Considering that data factor allocation operates through two channels—structural upgrading effect and innovation-driven effect—the mediating variables are collectively denoted as M_{it}. For the sake of unified representation, the following system of mediation effect models is constructed:

(1) The Impact of Data Factor Allocation Level on the Mediating Variables

$$M_{it} = \gamma_0 + \gamma_1 Data_{it} + \delta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

This equation tests whether the data factor allocation level promotes structural upgrading and innovation capability. Different mediating variables (ISU, RD) are estimated separately by substituting them into this model.

(2) The Effect Model After Including the Mediating Variables

$$CBE_{it} = \theta_0 + \theta_1 Data_{it} + \theta_2 M_{it} + \beta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{3}$$

Where:

- θ_1 represents the direct effect after controlling for the mediation.
- θ_2 tests the impact of the mediating variable (industrial structure upgrading or R&D intensity) on cross-border e-commerce development;

3.3 Data Sources

This study uses panel data from 30 Chinese provinces (excluding Tibet, Hong Kong, Macao, and Taiwan) over the period 2012–2022. Data are primarily sourced from the China Statistical Yearbook, China Information Industry Yearbook, China E-commerce Report, the National Bureau of Statistics database, the Ministry of Industry and Information Technology, and the State Post Bureau. The digital inclusive finance index is obtained from the Peking University Digital Financial Inclusion Index of China. Missing values for a few provinces in individual years are interpolated using linear interpolation. All indicators are standardized to ensure consistency.

4 Empirical Results and Analysis

4.1 Benchmark Regression

This study employs a two-way fixed effects model to examine the impact of data factor allocation level (Data) on the development level of cross-border e-commerce (CBE). Table 3 presents the benchmark regression results of the effect of data factor allocation level (Data) on cross-border e-commerce development. Column (1) shows the regression results without control variables, Column (2) adds province and year fixed effects to the model, and Column (3) further introduces control variables, including industrial agglomeration, innovation level, environmental regulation, transportation infrastructure level, economic development level, openness to the outside world, human capital, and urbanization level.

Table 3. Baseline Regression Results.

Variables	(1)	(2)	(3)
Data	0.835** (29.868)	0.884** (25.712)	0.905** (17.092)
AGG			0.323** (5.233)
INN			0.022* (2.330)
ENV			0.003 (1.353)
TRA			-0.060* (-2.203)
ECO			-0.055** (-4.457)
OPEN			0.004 (0.385)
HC			-0.000 (-0.034)
URB			0.008 (0.454)
Cons	-0.003 (-0.629)	-0.011 (-1.729)	-0.012 (-1.652)
Province FE	No	Yes	Yes

Variables	(1)	(2)	(3)
Year FE	No	Yes	Yes
Observations	300	300	300
R 2(within)	0.768	0.765	0.781

Notes: Dependent variable = CBE; * $p < 0.05$, ** $p < 0.01$; parentheses show t-values.

Regarding the regression results of the core explanatory variable, the coefficient of Data is significantly positive in all three models and remains significant at the 1% level. Specifically, the coefficient of Data in Column (3) is 0.905, indicating that, after controlling for other factors, an improvement in the level of data factor allocation significantly promotes the development of cross-border e-commerce, which aligns with theoretical expectations. As control variables are gradually added to the model, the coefficient of Data slightly increases but remains generally stable, demonstrating strong robustness in the results. From the perspective of the control variables, the coefficient of industrial agglomeration (AGG) is significantly positive, suggesting that industrial concentration helps foster economies of scale and supply chain synergy, thereby enhancing the development level of cross-border e-commerce. In terms of model goodness-of-fit, the R^2(within) values for all three models reach relatively high levels (0.765–0.781), indicating that the model has strong explanatory power for cross-province variations over time. Column (3), as the most complete model, achieves an R^2(within) of 0.781, further validating the robustness of the model.

In summary, the benchmark regression demonstrates that the level of data factor allocation is a key factor driving the development of cross-border e-commerce, with its effect being both significant and stable, laying a solid foundation for subsequent tests. Thus, H1 is supported, data factor allocation has a significant direct promoting effect on CBE development.

4.2 Robustness Tests

To test the robustness of the benchmark regression results, this study employed three methods: alternative explanatory variables, one-period lagging of variables, and winsorization (results shown in Table 4).

Table 4. Robustness Test Results.

Variables	Alternative Explanatory Variables	Lagging One Period	Winsorization
Data	15.406** (15.839)		0.624** (15.814)
L.Data		3.316** (4.971)	
Cons	-2.158** (-15.542)	-0.447** (-4.415)	0.024** (4.324)
Controls	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	300	299	300
R 2(within)	0.790	0.538	0.184

Notes: Dependent variable = CBE; * $p < 0.05$, ** $p < 0.01$; parentheses show t-values.

Specifically, the original data factor allocation index was first replaced by an alternative indicator constructed via Principal Component Analysis (PCA) to mitigate measurement bias. Next, the explanatory variable was lagged by one period to alleviate potential reverse causality. Finally, a 5 % winsorization was applied to key variables to exclude the influence of outliers. The results show that the coefficient of the alternative variable remains significantly positive (15.406, $t = 15.839$); the coefficient of the lagged explanatory variable is also significant (3.316, $t = 4.971$); and after winsorization, the coefficient of the core variable retains a significant positive value (0.624, $t = 15.814$). Across all tests, the sign and significance of the coefficients are consistent with the benchmark regression, indicating that the promoting effect of data factor allocation on cross-border e-commerce development is robust to variable construction methods, reverse causality, and extreme values.

4.3 Mediation Effect Test

To examine the mechanism through which industrial structure upgrading influences the relationship between data factor allocation and cross-border e-commerce development, industrial structure upgrading (ISU) and R&D intensity (RD) were selected as mediating variables and analyzed using a mediation effect model. The results in Table 5 show that data factor allocation not only directly enhances cross-border e-commerce development but also exerts a significant indirect effect through industrial structure upgrading and R&D intensity. Specifically, data factor allocation significantly promotes industrial structure upgrading (coefficient = 1.862, $p < 0.01$), which in turn significantly boosts cross-border e-commerce development (coefficient = 0.031, $p < 0.01$). The impact of data factor allocation remains significant after including ISU, confirming its mediating role. Similarly, data factor allocation significantly increases R&D investment and innovation activity (coefficient = 1.204, $p < 0.01$), and R&D intensity positively affects cross-border e-commerce (coefficient = 0.034, $p < 0.05$). Controlling for RD, the effect of data factor allocation remains robust, indicating that innovation capacity is another transmission channel. Overall, data factor allocation indirectly promotes cross-border e-commerce through structural upgrading and innovation-driven mechanisms, forming an important pathway of influence. Thus, H2 and H3 are supported, industrial structure upgrading and R&D intensity serve as significant mediating channels.

Table 5. Results of Mediation Effect Analysis.

Variables	CBE	ISU	CBE	RD	CBE
Data	0.905** (17.092)	1.862** (5.345)	0.847** (15.456)	1.204** (5.010)	0.864** (15.714)
ISU			0.031** (3.335)		
RD					0.034* (2.509)
Cons	-0.012 (-1.652)	-0.261** (-5.245)	-0.004 (-0.553)	-0.169** (-4.916)	-0.007 (-0.852)
Controls	Yes	Yes	Yes	Yes	Yes

Variables	CBE	ISU	CBE	RD	CBE
Province FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	300	300	300	300	300
R 2(within)	0.781	0.066	0.721	0.563	0.797

Notes: * $p < 0.05$, ** $p < 0.01$; parentheses show t-values.

4.4 Heterogeneity Tests

To examine the heterogeneous effects of data factor allocation on cross-border e-commerce, we conducted group-wise analyses based on both the level of data factor allocation and geographic regions (results in Table 6).

Table 6. Heterogeneity Tests Results.

Variables	Hight-Data	Low-Data	East	Northeast	Central	West
Data	0.821**	0.533**	0.744**	0.430*	0.315**	0.676**
	(7.868)	(7.097)	(6.027)	(2.448)	(3.190)	(17.972)
Cons	-0.082	0.057**	-0.682**	0.150	0.024	-0.074
	(-1.621)	(2.641)	(-4.697)	(1.167)	(0.852)	(-1.092)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	150	150	100	30	60	110
R 2(within)	0.738	0.768	0.822	0.881	0.016	0.783

Notes: Dependent variable = CBE; * $p < 0.05$, ** $p < 0.01$; parentheses show t-values.

First, the sample was split into high- and low-Data groups according to the median of the data allocation index. The promoting effect is significantly stronger in the high-Data group (coefficient = 0.821, $p < 0.01$) than in the low-Data group (0.533, $p < 0.01$), indicating that regions with better digital infrastructure and richer data resources gain more from data factor allocation, reflecting a "foundation-dependent" pattern. Second, regional heterogeneity tests show a clear gradient: the effect is strongest in the eastern region (0.744, $p < 0.01$), followed by the western (0.676, $p < 0.01$), northeastern (0.430, $p < 0.10$), and central regions (0.315, $p < 0.01$). This east-to-west gradient aligns with disparities in digital industrial foundations, openness, and data resource mobility. Together, the results confirm that the impact of data factor allocation is not uniform but varies systematically with both regional data readiness and broader geographic-economic conditions. These findings provide strong support for H4, confirming the regional heterogeneity of the promoting effect.

5 Conclusion

Using Chinese provincial panel data (2012–2022), this study finds that data factor allocation significantly promotes cross-border e-commerce development, a result robust to various tests. The mechanism analysis shows that data factors not only directly enhance transaction efficiency and supply chain coordination but also indirectly contribute by advancing industrial structure upgrading and boosting R&D intensity. Regional heterogeneity is evident, with effects strongest in high-data regions and following an "Eastern > Western > Northeastern > Central" gradient.

To foster high-quality growth, policymakers should: (1) accelerate the development of a unified, well-regulated data factor market; (2) promote deep integration of data in key industrial and supply chain processes; (3) strengthen policy support for industrial upgrading and innovation; and (4) enhance regional coordination to narrow the digital divide and unlock the full potential of cross-border e-commerce.

This study has several limitations that point to future research directions. First, due to data availability, the measurement of data factor allocation remains at the provincial level; future studies could explore firm-level or city-level analyses. Second, while this study identifies two mediating mechanisms, other potential channels—such as institutional quality or digital infrastructure—deserve further investigation. Third, cross-country comparative studies would help validate the generalizability of the findings beyond the Chinese context.

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