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An empirical study on the potential of China's cross-border e-commerce exports under the RCEP framework: an application of the extended gravity model

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The Regional Comprehensive Economic Partnership (RCEP) has opened new prospects for the growth of e-commerce across borders. In the current study, a multidimensional Cross-Border E-Commerce Index (CBECI) is created using Principal Component Analysis (PCA) and integrated into an extended gravity model to assess the potential of China's cross-border e-commerce exports (proxy measure) to 12 RCEP member countries from 2013 to 2022. The empirical findings reveal that stronger information infrastructure, logistics performance, and digital payment systems are positively associated with China's cross-border e-commerce export proxy, and these relationships are robust across FE, PPML, and IV-2SLS estimations. The export potential of China has steadily grown, and it has been categorized into three groups, namely, exploratory-potential (Australia, Indonesia, Malaysia, Singapore), reconstructive-potential (Philippines, Thailand, Vietnam), and significant-potential (Japan, South Korea, Laos, New Zealand). These results point to significant differences in digital-trade preparedness among RCEP members and provide a foundation for developing differentiated e-commerce collaboration and market-expansion policies within the RCEP framework.

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Introduction

Electronic commerce across international borders has quickly emerged as a major contributor to electronic trade in the digital economy age. The world market is estimated to reach USD 2.25 trillion in 2026, with the Asia-Pacific region recording the highest growth (Zhang and Li 2020). To China and the member states of the RCEP, digital trade opens new possibilities for connecting the region and expanding Chinese exports on online platforms.

Although cross-border e-commerce is becoming increasingly relevant, current studies on Chinese exports to RCEP countries are weak in three aspects. First, the literature tends to be traditional in its approach to gravity, and it tends to consider digital determinants in isolation, e.g., logistics or payment systems, and not as the systemic determinant of digital trade. Second, prior research does not provide a comprehensive set of indicators to assess the level of multidimensional development of the e-commerce environment in partner countries. Third, there are limited analyzes that give a combined evaluation of the export potential of China under the RCEP framework based on a broader gravity structure considering the digital ecosystem factors.

In accordance with the theory of the cross-border e-commerce ecosystem, which views digital trade as a complex of infrastructures, logistics, payment systems, platforms, and institutional structures (Hu, Lu, and Huang 2009; Zhang 2021), this paper develops a multidimensional Cross-Border E-Commerce Index (CBECI). The index is based on existing evidence that the evolution of e-commerce requires a strong IT infrastructure, effective logistics, secure payment systems, and enabling policy environments (Derindağ 2022; Villa et al. 2018; Nazir and Muhammad Azam 2020).

Based on this theoretical background, we develop the conventional gravity model by incorporating ecological determinants and apply it to assess China's potential to export e-commerce to RCEP members. The methodology bridges an obvious gap in the research by establishing a single analytical plane that links theory, index building, and empirical estimation. The paper is the first to create a coherent CBECI ecosystem index for all RCEP members and to incorporate it into a broad gravity framework to measure the potential of digital trade in China.

Literature Review

Cross-border E-commerce ecosystem theory. Ecosystem-oriented development is the next step in cross-border e-commerce growth, as its complexity increases and it becomes more sustainable (Liu 2021). The ecosystem concept was developed based on Tansley's (1935) biological concept, and later Moore (1996) applied it to the business environment to explain value-related co-creation networks among firms, consumers, and suppliers. After entering the e-commerce market, scholars added resource sharing, complementary benefits, and dynamic evolution as fundamental features of the ecosystem (Liu 2006; Hu et al. 2009).

Zhang (2021) traced the evolution of natural ecosystems into business ecosystems, and then into digital commerce ecosystems, in the context of cross-border e-commerce, as a complex system in which platforms, producers, consumers, and regulatory agencies are connected through various channels via flows of logistics, information, capital, and commerce. Li and Wang (2018) also made a further distinction among core, key, and supporting species in the ecosystem, highlighting the coordinating influence of platform enterprises.

The available literature provides a substantial basis for explaining the cross-border e-commerce ecosystem, but most

studies are theoretical and have not yet operationalized the ecosystem's dimensions in the context of the RCEP. Based on this theory, the current research develops a multidimensional CBECI to justify the extended gravity model.

Factors influencing cross-border E-commerce. The success of the cross-border e-commerce process relies on the interplay of various factors such as technology, logistics, payment system and institutional environment. Based on the previous research, four basic dimensions are unified:

Information Technology Infrastructure. The maturity of ICT, penetration of broadband, and quality of networks increase the ability of firms to participate in world digital markets (Derindağ 2022; Villa et al. 2018). The studies that were conducted in the framework of Technology-Organization-Environment (TOE) indicate that companies adopt cross-border digital operations depending on data security, system compatibility, and platform usability (Nazir and Muhammad Azam 2020). Cross-border e-commerce transactions have also increased greatly through the use of digital infrastructure investment (Chen 2022; Chang et al. 2020). Moreover, the digitalization assessment schemes emphasize the significance of incorporating digital payments, platform development, and governance pointers into assessing the readiness to engage in e-commerce (Aliev et al. 2020).

Logistics Efficiency. Transportation expenses are very high, delivery time is lengthy, and customs delays are significant limitations of cross-border transactions (Zhang and Ma 2015; Zhang et al. 2015). The significance of the efficiency in customs clearance, the coordination of supply chains, and the shipment traceability is supported by the empirical evidence (Jin and Yang 2015; Zhang et al. 2019). The distance will always have a negative influence on cross-border e-commerce flows (Gomez-Herrera et al. 2014; Zhang and Wang 2019). It has also been demonstrated that trade facilitation and logistics efficiency reveal a significant impact on bilateral trade potential, which confirms their applicability to digital trade flows (Kong and Dong 2015).

Payment Systems. Convenient and secure interoperable digital payment solutions can minimize transaction friction in cross-border environments (Nazir and Muhammad Azam 2020). The growth of mobile payments and fintech platforms also makes companies more ready to engage in international online trade.

Policy and Institutional Environment. Cross-border e-commerce is enabled by customs modernization, standardized digital trade regulations, and transparent taxation (Yang and Yu 2014; Zhang et al. 2019). The export performance is also affected by trade openness and the courier services (Zhang and Wang 2019).

Although existing research offers substantial information on the predictors of cross-border e-commerce, most studies focus on individual aspects and lack a coherent measurement framework. Additionally, there is a scant body of research that evaluates these determinants in the context of the RCEP in the region. In this paper, therefore, a multidimensional CBECI is developed to measure the levels of development of cross-border e-commerce.

Measurement of the development level of cross-border E-commerce. A number of researchers have suggested the use of indicators to determine the development of cross-border e-commerce. Yang et al. (2014) have proposed early indicators, including marketing, payment, customs, logistics, and regulation. On the basis of the business ecosystem theory, Li et al. (2020)

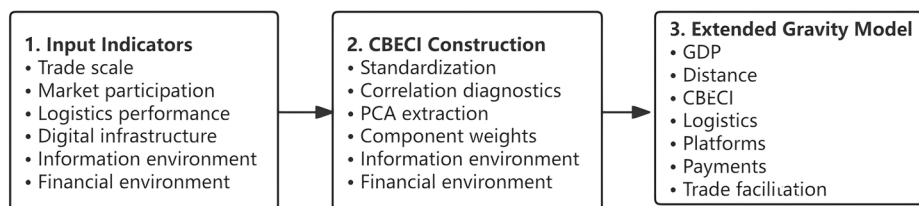


Fig. 1 Conceptual Framework Linking CBECI Construction and the Extended Gravity Model.

developed a six-dimensional, 20-indicator framework, which indicates logistics, platform services, payment systems, credit risks, talent, and digital marketing.

Internet and mobile communications penetration rates are basic digital-trade indicators identified by international institutions such as the OECD (2007). Shimizu (2021) also highlighted the contributions of disparity in digital infrastructure and alignment of regulations. Zhang and Tang (2020) have calculated digital readiness by using internet users and broadband and mobile subscriptions. The author of Song (2021) conducted a principal component analysis of digital trade development, and Shen (2023) analyzed the G20 countries in terms of logistics, informatization, customs effectiveness, and potential development. More recent studies, including Wang et al. (2021), suggest that multidimensional digital economy indices (e.g., TIMG Index) are useful, which is important to consider that digital platforms, payments, and infrastructure should be valued in the composite measurements, which is in line with the CBECI developed in this paper.

Despite these contributions, the available research on the RCEP region is insufficient and often relies on one-dimensional indicators such as internet connectivity or shipping cost-efficiency. Very few of them use a multidimensional index like CBECI.

The existing indicator systems are useful as reference points, but there is no comprehensive index to measure the development of cross-border e-commerce among RCEP members. This paper fills this gap by developing a CBECI with the ecosystem theory.

Definition and measurement of cross-border E-commerce trade potential. Trade potential is usually the difference between the hypothetical highest levels of trade and the actual flow of trade (Armstrong 2007; Shu 2018). Numerous studies use gravity models to measure the potential of trade by comparing observed and predicted trade (Nilsson 2000; Egger 2002). Potential assessments that use gravity models have also been developed in bilateral relationships of Sino-German trade; it has been shown that the gravity model is appropriate in detecting structural voids in the trade movements (Zhang et al. 2016).

Economic size, e-commerce development, distance, and tariffs play a crucial role in determining trade levels between China and ASEAN, as well as with other partners, in the context of cross-border e-commerce (Chen 2020; Zheng and Zhang 2021). Gravity research findings indicate a high potential for e-commerce exports across the border between China and the chosen RCEP economies (Song 2021; Shen 2023).

To a large extent, however, the current literature is concerned with ASEAN, G20, or Belt and Road Initiative nations rather than all RCEP members, and does not include ecosystem-related digital variables (platform participation, digital payments, and logistics digitalization).

Although previous research projects have emphasized the significance of export potential in the context of cross-border e-commerce, they are weak in coverage, model specification, and

variable integration. This research offers the first and comprehensive evaluation of China's potential to export its cross-border e-commerce to the RCEP nations by developing a CBECI and using an extended gravity model.

Methodology and Data

Conceptual framework. In an attempt to demystify the rationale for the empirical approach, the present study draws on a conceptual framework in which the process of building the Cross-Border E-Commerce Index (CBECI) is linked to the extended gravity model. The model comprises three steps.

To begin with, a multidimensional indicator system, that is, trade scale, a market player, logistics performance, information infrastructure, and financial conditions, is constructed on the cross-border e-commerce ecosystem theory. These measures are the variables of CBEC development as their input.

Second, Principal Component Analysis (PCA) is used to reduce dimensionality and derive shared factors. The remaining elements undergo standardization and pre-PCA diagnostics, then an objective composite index (CBECI) is built, and indicator weights are obtained.

Third, CBECI is made part of a long-run gravity model that supplements more traditional determinants (economic size, distance) with platform-specific determinants (platforms, payments, logistics, governance) of e-commerce. The model is used as the empirical test of the potential of China's CBEC export to the countries of RCEP.

The entire conceptual framework is revealed in Fig. 1, where the indicators of the ecosystem make their way to PCA and influence the creation of the CBECI, and finally link to the extended gravity model.

Construction of Cross-Border E-commerce Index (CBECI) System. Based on the basic ideas of the cross-border e-commerce ecosystem, this paper constructs an umbrella system of evaluation indicators to identify the level of cross-border e-commerce development in the countries that are members of the RCEP. In order to ensure that the developed index reveals both theoretical rigor and policy relevance, this paper uses the indicator criteria of the National E-commerce Model City Evaluation Indicator System (Trial).

The National E-commerce Model City Evaluation Indicator System (Trial) is a formal appraisal system published by the Ministry of Commerce of China, aimed at measuring E-commerce digital infrastructure, logistics, payment environment, and regulatory support of pilot e-commerce cities. It offers a uniform, policy-based, and generally accepted framework on which to gauge the development of e-commerce in regions.

This official framework, combined with the suggested academic indicator system of Huang (2019) makes the current study create a more holistic and functional Cross-border E-commerce Development Index (CBECI) that allows conceptual ecosystem theory to be integrated with the needs of practical evaluation.

Table 1 Indicator Composition of CBECI System.			
Species	Primary Indicators	Secondary Indicators	Data Source
Leading Species	Scale of cross-border e-commerce transactions	Volume of e-commerce goods imports (LS1)	World Bank Database, Alibaba, JD.com, iResearch
		Volume of e-commerce goods exports (LS2)	World Bank Database, Alibaba, JD.com, iResearch
Key Species	E-commerce Market Development	Share of e-commerce in total trade (KS1)	UNCTAD, China E-Commerce Research Center
		Number of cross-border e-commerce platforms (KS2)	Ministry of Commerce of China (MOFCOM), Alibaba, JD.com, Shopee, Lazada
		Individuals engaged in cross-border e-commerce transactions (KS3)	Statista, Google Trends, eMarketer
Supporting Species	Logistics Performance	Ability to track and trace cross-border e-commerce shipments (LP1)	World Bank Logistics Performance Index, Cainiao, DHL
		Competence and quality of e-commerce logistics services (LP2)	World Bank Logistics Performance Index, Cainiao, UPS
		Efficiency of cross-border customs clearance for e-commerce (LP3)	World Bank, National Customs Data
		Share of express delivery in cross-border trade (LP4)	China Express Association, UPS, FedEx
		Frequency with which shipments reach consignee within scheduled or expected time (LP5)	World Bank Logistics Performance Index
		Quality of trade and transport-related infrastructure (LP6)	World Bank Logistics Performance Index
	E-commerce Payment Systems	Cross-border digital payment volume (IF1)	Payment providers (Alipay, WeChat Pay, PayPal, Visa)
		Percentage of transactions completed via online payment (IF2)	Payment providers, Statista
		Digital trade facilitation index (IF3)	UNCTAD, WTO
		E-commerce taxation and regulatory policies (IF4)	OECD, National Government Reports
	Financial Inclusion in E-commerce	Number of digital wallets and fintech users (CF1)	IMF, World Bank, Statista
		Cross-border e-commerce lending and investment (CF2)	IMF, World Bank

The mathematical representation of the principal component analysis is articulated as follows:

$$F_i = a_{1i}X_1 + a_{2i}X_2 + \cdots + a_{pi}X_p$$

(1)

$X_1, X_2, \cdots, X_p$ represents the index of each individual, $a_{1i}, a_{2i}, \cdots, a_{pi}$ represents P constant vectors, F_i represents the linear combination of P index vectors $X_1, X_2, \cdots, X_p$ of data matrix X (i.e., comprehensive index vector).

To operationalize the framework of the cross-border e-commerce ecosystem, this paper will follow a widely used classification of the business-ecosystem literature into “leading species”, “key species”, and “supporting species” (Moore 1996; Zhang 2021).

Leading species refer to actors or activities that make the total system run (e.g., dominant platform or major flows of goods), key species are market participants that generate value by production and consumption, and supporting species are actors that provide the infrastructure and services that support the rest (logistics, information, and capital flows, etc.).

This stratified model is common in explaining the synchronized operation of the contemporary digital and e-commerce system, where the creation of value relies concurrently on the volume of transactions, market players, and facilitating systems of service.

Building on this conceptual framework, the indicator system is structured into three corresponding layers. The scale of cross-border e-commerce imports and exports is used to represent the

leading species. For key species, indicators such as manufacturing value added and the number of active platform participants capture the contribution of producers and consumers. For supporting species, logistics performance, digital-economy infrastructure, information flow, and financial inclusion indicators reflect the enabling conditions that sustain cross-border e-commerce development.

Table 1 summarizes the full indicator system and data sources.

To construct the CBECI, Principal Component Analysis (PCA) is employed due to the multidimensional and potentially collinear nature of the indicators. Before performing PCA, a series of pre-PCA diagnostics was conducted to verify that the data met the statistical requirements for dimensionality reduction. First, the descriptive statistics was studied to estimate the characteristics of the distribution and variability of each indicator. Second, pairwise correlations of the indicators were also assessed, as PCA presupposes the presence of strong linear relationships in the data set. As customary, variables with low correlation or inconsistent trends were reexamined to make sure that they had the same concept in the indicator system.

The Kaiser Meyer Olkin (KMO) measure, as well as the Bartlett Test of Sphericity, were also used to measure sampling adequacy. KMO value exceeding the generally accepted value of 0.70 and a large number of Bartlett statistic means that the indicators have enough common variance to warrant PCA. All variables were z-score normalized to remove the scale effects that occurred in different units of measurement before principal components were extracted.

Eigenvalue decomposition on the standardized correlation matrix was subsequently done to obtain PCA. Components that had eigenvalues larger than one were not dropped, and the cumulative ratio of variance contributed had to be above the standard information preservation levels. The Cross-Border E-Commerce Index (CBECI) was made using the resulting principal component scores to obtain objective and data-driven weights of each indicator. In comparison to other weighting techniques like equal weighting and subjective expert scoring, PCA is an objective, data-driven technique that reduces arbitrariness and is efficient in dealing with multicollinearity.

Extended gravity model. Pioneering work on the use of the gravity model to explain bilateral trade flows by Tinbergen (1962) and Poyhonen (1963) had already been made as early as the 1960s. Their studies indicated that the two countries would facilitate trade flows due to their economic size and the distance between them would inhibit the growth of the trade flows. The gravity model has, over the years, evolved to become a central tool of analysis in determining the trade capacity among countries or regions in the context of conventional international trade, owing to the efforts of numerous scholars. Its equation can be written as follows:

$$T_{ijt} = \frac{A \cdot Y_{it} \cdot Y_{jt}}{D_{ij}} \quad (2)$$

Where T_{ijt} represents the bilateral trade volume between country i and country j in year t , A is a constant, Y_{it} represents the GDP of country i in year t , Y_{jt} represents the GDP of country j in year t , and D_{ij} represents the distance between country i and country j .

This model was then the subject of constant elaboration and research by scholars who examined additional variables that influenced the flow of foreign trade and sought to incorporate many new ones. As an example, Leamer (1974) added tariff variables, Bergstrand (1985) added such variables as national income level, exchange rate level, common border, Hamilton and Winters (1992) added such variables as per capita GDP, common language, and free trade agreement. When Zhang (2020) used the gravity model, he incorporated trade facilitation and trade dependency as a constituent of the model. It is evident that researchers have developed several extended gravity models for empirical analysis. The extended gravity model has gained greater sophistication in international trade research and is widely used to investigate a country's trade competitiveness, estimate and analyze its trade potential and volume, and examine the factors that determine trade flows between two countries.

To determine the determinants of China's cross-border e-commerce exports to RCEP partners, this paper uses an extended gravity model that integrates conventional trade determinants with e-commerce determinants. The theoretical framework is classical gravity (Tinbergen 1962; Poehl 1963), and new extensions enable consideration of the following variables: digital infrastructure, logistics performance, platform participation, and payment adoption.

The final empirical specification is presented in Eq. (3):

$$\begin{aligned} \ln Ex_{jt} = & \beta_0 + \beta_1 \ln CBECI_{jt} + \beta_2 \ln GDP_{it} + \beta_3 \ln GDP_{jt} \\ & + \beta_4 \ln DIS_{ijt} + \beta_5 \ln PLAT_{jt} + \beta_6 \ln PAY_{jt} \\ & + \beta_7 \ln LPI_{jt} + \beta_8 \ln TRADEFAC_{jt} + \varepsilon_{ijt} \end{aligned} \quad (3)$$

In this extended specification, each coefficient β_i represents the elasticity of China's cross-border e-commerce exports measure (proxy) with respect to its corresponding variable. Specifically, β_1 captures the marginal effect of the CBEC Development Index

(CBECI), while the remaining coefficients measure the responsiveness of the dependent variable (China's bilateral CBEC export proxy) to economic size (GDP), trade costs (distance), platform participation, digital-payment adoption, logistics performance, and trade-facilitation conditions.

where:

- Ex_{jt} = China's cross-border e-commerce exports to RCEP country j in year t , measured as a constructed proxy (defined in Eq. 4).
- $CBECI_{jt}$ = Cross-Border E-Commerce Development Index (CBECI) for country j at time t , constructed using PCA.
- GDP_{it} , GDP_{jt} = GDP of China (exporter) and RCEP country j (importer), capturing economic size.
- $DIST_{ijt}$ = Adjusted trade distance, incorporating transportation costs and digital trade barriers.
- $PLAT_{jt}$ = Number of active cross-border e-commerce platforms in the country j (e.g., Alibaba, JD.com, Shopee, Lazada).
- PAY_{jt} = Share of digital payments in total cross-border e-commerce transactions (e.g., Alipay, WeChat Pay, PayPal).
- LPI_{jt} = Logistics Performance Index specific to cross-border e-commerce, measuring shipment tracking efficiency, delivery times, and customs clearance speed.
- $TRADEFAC_{jt}$ = E-commerce trade facilitation index, capturing ease of customs procedures, e-commerce regulatory environment, and taxation policies.
- ε_{ijt} = Error term.

All continuous variables in Eq. (3) are expressed in natural logarithms to reduce heteroskedasticity and to allow the estimated coefficients to be interpreted as elasticities. Furthermore, the empirical estimation employs a country fixed-effects structure to control for unobserved time-invariant heterogeneity across RCEP member countries, while robustness checks additionally incorporate time fixed effects to ensure the stability of the results.

Because officially reported bilateral CBEC export statistics for China-RCEP pairs are not available, we construct Ex_{jt} as an allocated bilateral CBEC export proxy following common practice in digital trade measurement (e.g., UNCTAD 2022; OECD 2021). Specifically, we allocate China's national CBEC export transaction scale across partner countries in proportion to China's bilateral merchandise exports. The calculation method is given by:

$$Ex_{jt} = \frac{Ex_{jt}}{Ex_{it}} \times Exe_{it} \quad (4)$$

Where Ex_{jt} represent China's cross-border e-commerce export volume with RCEP partner countries. Ex_{jt} denote China's export volume with RCEP partner countries. Ex_{it} represent China's total export volume. Exe_{it} indicate China's total cross-border e-commerce export transaction scale.

This constructed measure should be interpreted as a transparent proxy for the bilateral scale of CBEC exports under a proportionality assumption, rather than a direct observation of destination-specific CBEC intensity. To ensure that the empirical results are not driven by the common time component embedded in the proxy construction, we conduct robustness checks that include year fixed effects; the main conclusions remain unchanged.

Data sources and sample description. The empirical analysis relies on a combination of macroeconomic, digital-infrastructure, logistics, and cross-border e-commerce indicators obtained from multiple authoritative sources. Core economic variables (GDP, population, distance, trade costs) are drawn from the World

Table 2 Descriptive Statistics of Key Indicators.

Category	Variable	Mean	Std. Dev.	Min	Max	Obs
Leading Species	LS1	451.39	655.8	2.26	3346.88	N = 120 (n = 12, t = 10)
	LS2	389.7	530.25	3.05	2678.24	
Key Species	KS1	720.84	1471.91	3.65	7171.64	
	KS2	68.11	24.03	12.5	97.57	
Supporting Species — Logistics Performance	LP1	3.5	0.48	1.76	4.4	
	LP2	3.45	0.48	2.1	4.4	
	LP3	3.31	0.34	2.18	4	
	LP4	3.27	0.51	1.85	4.2	
	LP5	3.71	0.41	2.65	4.4	
	LP6	3.47	0.61	1.76	4.6	
Supporting Species — Payment Systems	IF1	58.93	16.98	23.55	80.88	
	IF2	66.42	14.95	19.65	90.53	
	IF3	62.28	19.1	3.66	95.57	
	IF4	65.49	20.09	24.41	97.5	
Supporting Species — Financial Inclusion	CF1	14.39	9.43	2.73	34.14	
	CF2	17498.12	16293.97	1364.39	53871.56	

N = 120 (12 countries × 10 years). All indicators share the same number of observations.

Table 3 Correlation Matrix of High-Correlation Indicators (Condensed Version).

Variable	KS2	LP1	LP6	IF1	IF4	CF2
KS2: Internet users (%)	1					
LP1: Tracking ability	0.72	1				
LP6: Infrastructure quality	0.74	0.96	1			
IF1: Digital technology	0.75	0.79	0.83	1		
IF4: Digital governance	0.86	0.77	0.78	0.89	1	
CF2: Per capita income	0.72	0.69	0.73	0.76	0.86	1

Full correlation matrix is available in Appendix A1.

Table 4 Summary of Bartlett's Test and KMO measure.

Measure	Value
Bartlett's Test of Sphericity χ^2	3887.212
Degrees of Freedom (df)	120
p-value	< 0.001
Kaiser-Meyer-Olkin (KMO)	0.858

Data source: Obtained through Stata 18 software calculation.

Bank, IMF, UNCTAD, and CEPII datasets. Digital-economy and e-commerce indicators come from Alibaba Research Institute, JD Research, and iResearch, all of which publish regularly audited statistical reports widely used in digital-trade studies. Logistics-related metrics are sourced from the World Bank Logistics Performance Index (LPI) and international parcel-delivery providers (e.g., UPS, DHL).

The study initially covers all 15 RCEP member economies over the period 2013–2022. However, Brunei, Myanmar, and Cambodia are excluded from the baseline sample because of systematic missing data in essential dimensions, including logistics performance, digital-infrastructure indicators, and cross-border e-commerce activity. Such exclusion is a result of data availability, and not a theoretical decision.

A sensitivity check on simplified model specifications has been done to ensure that the performance of the omission of these economies would not be biased. The values and significant indicators of the main coefficients do not change and prove the strength of the primary findings.

Results and Discussion

Measurement of cross-border E-commerce development level

Descriptive statistics. Table 2 presents the descriptive statistics for the variables incorporated into the CBEC ecosystem indicator system. The findings indicate that there is a high cross-country difference between leading-species, key-species, and supporting-species pointers, indicating the diverse nature of the cross-border e-commerce ecosystem development in the RCEP economies.

This inconsistency also contributes to the fact that PCA is being used to extract shared underlying factors and create the composite CBECI.

Correlation analysis. To determine whether the indicator system meets the conditions for PCA, pairwise correlations among the essential variables of the ecosystem were analyzed. A subgroup of the indicators that have comparatively high correlations, especially the logistics performance (LP1, LP6), digital-technology measures (IF1, IF4), and the level of income (CF2), are signified in Table 3, with most of their correlations being above 0.70. The use of the internet (KS2) also has a high correlation with the logistics and digital indicators. These trends indicate that there are large common elements of variation among indicators, which satisfy the linear-association condition of PCA. The entire 16×16 correlation matrix is given in Appendix A1, and Table 3 presents a reduced form that highlights the variables of greatest significance for assessing the suitability of using PCA.

Testing for data suitability. The Kaiser-Meyer-Olkin (KMO) measure and Bartlett test of the sphere were performed to check whether the dataset is sufficient to perform the principal component analysis. According to Table 4, the KMO (0.856) is in excess of the generally considered value (0.70), and the test of Bartlett is very significant, which denotes that the variables have enough common variance. This combination of results proves that the indicator set is appropriate for PCA.

Data standardization. The standardization of the data is necessary prior to factor analysis to enable comparison of variables across different units and scales at the same level. The factor

Table 5 Total variance explanation.

Component	Eigenvalue	Proportion	Cumulative
Comp1	10.0054	0.6253	0.6253
Comp2	3.1281	0.1955	0.8208
Comp3	0.8422	0.0526	0.8735

Source: Obtained through Stata 18 software calculation.

analysis is enhanced with this step, and the results of the factor analysis are more reliable and accurate. All variables were standardized using z-score normalization (mean = 0, variance = 1) because it is the standard requirement for PCA input.

Factor analysis. The eigenvalues of the first two components, as indicated by Table 5, are all greater than 1, which is a strong indication of their high reliability. In addition, the cumulative contribution rate of variance for these elements is 82.08, which indicates that the existing system of indicators can reasonably explain a considerable share of the variance in the level of development of cross-border e-commerce.

On this basis, the first two components (Comp1 and Comp2) are retained for constructing the composite CBECI in the subsequent step.

Calculation of coefficients for linear combinations. The coefficient matrix was obtained by dividing the component loadings of each component retained by the square root of the respective eigenvalues. The composite score of each of the major components was calculated after being calculated using these coefficients. The contribution ratio of the individual components that were retained was taken as the weight of the contribution of the individual components to the overall weighted average, and the final index weight of each indicator would be the weighted average of the contribution of the individual components. This process makes the sum of the weights of the indicators to be 1, and each weight has its statistical contribution as well as the variance significance in the PCA structure.

$$\begin{aligned} \text{Comp}_1 = & 0.0396 * LS_1 + 0.041 * LS_2 + 0.03 * KS_1 \\ & + 0.0799 * KS_2 + 0.0947 * LP_1 + 0.0955 * LP_2 \\ & + 0.0819 * LP_3 + 0.0916 * LP_4 + 0.0916 * LP_5 \\ & + 0.0958 * LP_6 + 0.0922 * IF_1 + 0.0838 * IF_2 \\ & + 0.0809 * IF_3 + 0.0871 * IF_4 + 0.0565 * CF_1 \\ & + 0.0759 * CF_2 \end{aligned} \quad (5)$$

$$\begin{aligned} \text{Comp}_2 = & 0.2881 * LS_1 + 0.2851 * LS_2 + 0.2953 * KS_1 \\ & - 0.0854 * KS_2 - 0.0129 * LP_1 - 0.0158 * LP_2 \\ & + 0.0327 * LP_3 - 0.0548 * LP_4 - 0.036 * LP_5 \\ & - 0.0037 * LP_6 - 0.005 * IF_1 + 0.0307 * IF_2 \\ & + 0.1002 * IF_3 - 0.1154 * IF_4 - 0.099 * CF_1 \\ & - 0.1447 * CF_2 \end{aligned} \quad (6)$$

Linear combinations Comp1 and Comp2 are calculated by getting the value of the component of each indicator divided by the square root of the eigenvalue of the principal component. Where Comp1 and Comp2 indicate the scores of RCEP member countries when subjected to the two dominant components, respectively, and Comp indicates the composite score. To compute conveniently, the Comp coefficients are normalized,

which results in the construction of a composite scoring model:

$$\begin{aligned} Y = & 0.0953 * LS_1 + 0.0956 * LS_2 + 0.0898 * KS_1 \\ & + 0.0391 * KS_2 + 0.0666 * LP_1 + 0.0665 * LP_2 \\ & + 0.0676 * LP_3 + 0.0547 * LP_4 + 0.059 * LP_5 \\ & + 0.0695 * LP_6 + 0.0666 * IF_1 + 0.0686 * IF_2 \\ & + 0.0824 * IF_3 + 0.0375 * IF_4 + 0.0188 * CF_1 \\ & + 0.0225 * CF_2 \end{aligned} \quad (7)$$

where Y denotes the composite score of the Cross-Border E-Commerce Development Index (CBECI).

The weights for the primary indicators within the RCEP countries' cross-border e-commerce were determined by summing the weights of the contained secondary indicators. After performing these calculations, the weights for the primary indicators of cross-border e-commerce in RCEP countries are as follows: Scale of goods import and export transactions (LS) = 0.1908, Manufacturers and Consumers (KS) = 0.1289, Logistics Performance (LP) = 0.3839, Information Flow (IF) = 0.2551, Cash Flow (CF) = 0.0413.

Calculation of Cross-Border E-Commerce development levels. By substituting the variables from the established indicator system into the composite score formula Y, the development level and ranking of cross-border e-commerce among the 12 RCEP countries were obtained, as depicted in Tables 6, 7.

Figures 2, 3 visualize the evolution of CBECI scores across RCEP countries based on the composite index Y (Eq. 7). The trend towards the development of CBECI in the countries that are members of RCEP from 2013 to 2022 is presented in Fig. 2, with China taking the lead and the other member states of the organization, including Singapore, Japan, South Korea, and Australia, having different growth patterns.

In light of national differences, Fig. 2 clearly indicates that China has always been the first in cross-border e-commerce development, fully demonstrating its potential in cross-border e-commerce trade. Singapore and Japan are right behind and constitute the second tier; South Korea and Australia are almost similar in the third tier. The countries with lower average levels are New Zealand, Malaysia, Thailand, the Philippines, Indonesia, and Vietnam; New Zealand and Laos are somewhat above average and have the lowest levels of cross-border e-commerce development, respectively. This brief description evidently shows that the development of cross-border e-commerce in the countries that are members of RCEP is considerably different, probably because of the difference in the level of economic development, infrastructure, and speed and efficiency of logistics.

Based on the time trend analysis presented in Fig. 3, in the period between 2013 and 2021, a general upward trend was observed in the level of cross-border e-commerce development of the member states of the RCEP. Remarkably, the performance of China was especially remarkable as the level of cross-border e-commerce development is always first, and the growth rate is increasing annually. Singapore, being the most economically advanced nation in the RCEP, was leading in the level and ranking of development of cross-border e-commerce. In Japan, South Korea, and Australia, the rates of growth were lower, though their level was high. It saw a downturn in 2022 as compared to that of 2021, but what needs to be emphasized here is that those countries that had poorer cross-border e-commerce development, such as Malaysia, the Philippines, Indonesia, Vietnam, and Laos, all recorded different levels of improvement over the year, which points to the potential of development.

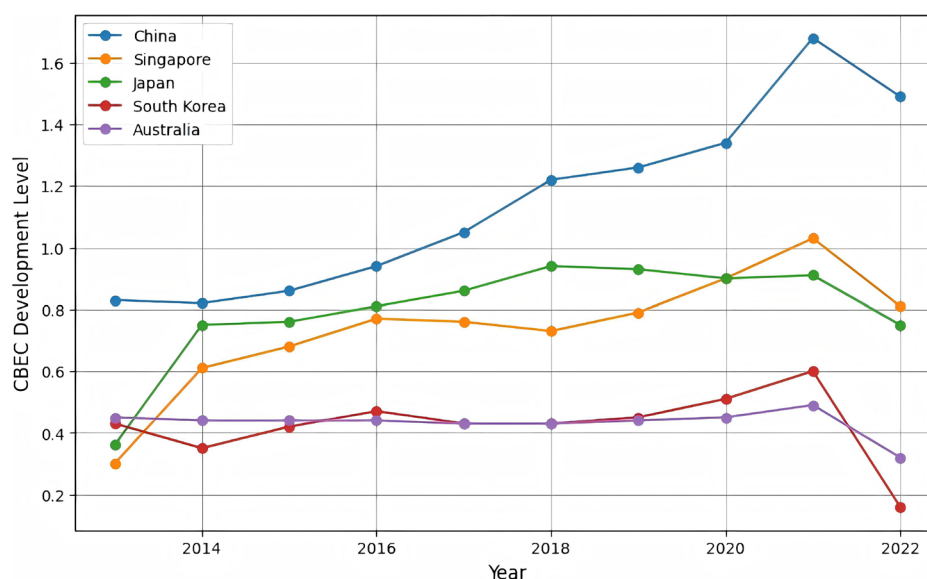
Table 6 Development level of cross-border e-commerce in RCEP countries.

	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
AUS	0.4561	0.4459	0.4472	0.4474	0.439	0.4339	0.4432	0.4576	0.4925	0.3273
CHN	0.8344	0.8291	0.8668	0.9414	1.053	1.2216	1.2653	1.3424	1.6864	1.4985
IDN	-0.4344	-0.6938	-0.7233	-0.7383	-0.5994	-0.4063	-0.4225	-0.4204	-0.3819	-0.3308
JPN	0.3604	0.7573	0.7696	0.8163	0.8625	0.9465	0.9303	0.9069	0.9162	0.7545
KOR	0.4317	0.3572	0.4283	0.4707	0.4376	0.4392	0.4589	0.5165	0.609	0.1651
LAO	-1.2998	-1.8714	-1.9697	-2.0771	-1.7422	-1.4872	-1.5132	-1.5473	-1.5823	-1.3698
MYS	-0.5292	0.0005	-0.0393	-0.0806	-0.1451	-0.2	-0.1051	0.0114	0.1421	0.2113
NZL	0.0809	0.0867	-0.0159	-0.1173	0.1087	0.3356	0.2787	0.2309	0.2069	-0.138
PHL	-0.6651	-0.8624	-0.8726	-0.9083	-0.8355	-0.7436	-0.6562	-0.5342	-0.4448	-0.2363
SGP	0.2992	0.6095	0.6815	0.7797	0.7666	0.7306	0.7977	0.9026	1.0333	0.8118
THA	-0.0518	-0.3813	-0.4157	-0.4313	-0.3038	-0.1857	-0.1287	-0.0781	-0.0282	-0.1873
VNM	-0.6598	-0.766	-0.8174	-0.8363	-0.6855	-0.4222	-0.375	-0.3211	-0.2837	-0.2708

A negative sign indicates below the average level.

Table 7 Ranking of cross-border e-commerce development level in RCEP countries.

	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
AUS	2	4	4	5	4	5	5	5	5	4
CHN	1	1	1	1	1	1	1	1	1	1
IDN	8	9	9	9	9	9	10	10	10	11
JPN	4	2	2	2	2	2	2	2	3	3
KOR	3	5	5	4	5	4	4	4	4	6
LAO	12	12	12	12	12	12	12	12	12	12
MYS	9	7	7	6	7	8	7	7	7	5
NZL	6	6	6	7	6	6	6	6	6	7
PHL	11	11	11	11	11	11	11	11	11	9
SGP	5	3	3	3	3	3	3	3	2	2
THA	7	8	8	8	8	7	8	8	8	8
VNM	10	10	10	10	10	10	9	9	9	10

**Fig. 2** Cross-Border E-Commerce (CBEC) Development Trend (2013-2022).

Empirical Analysis

Panel unit-root test. Prior to using panel regression analysis, the stationarity properties of the variables must be evaluated to prevent spurious regression results arising from nonstationary time-series behavior. Hence, the study employs the Levin-Lin-

Chu (LLC) and Im-Pesaran-Shin (IPS) panel unit root tests to assess the stationarity of the key variables in the extended gravity model. Table 8 reports the results.

The results indicate that none of the variables reject the null hypothesis of a unit root at the traditional level of significance,

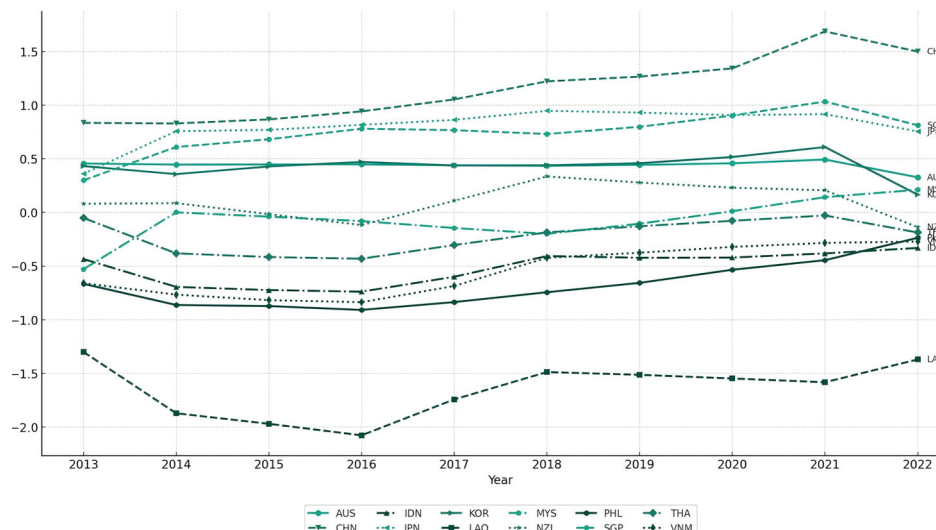


Fig. 3 Line chart of cross-border e-commerce development level in RCEP countries.

Table 8 Panel Unit-Root Test Results (LLC and IPS).

Variable	LLC t-statistic	LLC p-value	IPS W-statistic	IPS p-value	Conclusion
$\ln CBECI_{jt}$	-5.873	0.0000	-4.221	0.0000	Stationary
$\ln Exe_{jt}$	-7.104	0.0000	-6.512	0.0000	Stationary
$\ln GDP_{it}$	-3.985	0.0001	-2.911	0.0018	Stationary
$\ln GDP_{jt}$	-4.233	0.0000	-3.874	0.0001	Stationary
$\ln DIS_{ijt}$	-8.112	0.0000	-7.024	0.0000	Stationary
$\ln PLAT_{jt}$	-3.114	0.0009	-2.547	0.0054	Stationary
$\ln PAY_{jt}$	-2.921	0.0018	-2.203	0.0138	Stationary
$\ln LPI_{jt}$	-3.457	0.0003	-2.741	0.0031	Stationary
$\ln TRADEFAC_{jt}$	-3.622	0.0001	-2.914	0.0018	Stationary

LLC Levin-Lin-Chu test, IPS Im-Pesaran-Shin test. All variables reject the null hypothesis of a unit root at the 1% or 5% level.

Table 9 Pesaran CD Test Results.

Variable	CD Statistic	p-value	Cross-Sectional Dependence
$\ln CBECI_{jt}$	8.214	0.0000	Yes
$\ln Exe_{jt}$	9.531	0.0000	Yes
$\ln GDP_{it}$	12.482	0.0000	Yes
$\ln GDP_{jt}$	10.337	0.0000	Yes
$\ln DIS_{ijt}$	7.923	0.0000	Yes
$\ln PLAT_{jt}$	6.114	0.0000	Yes
$\ln PAY_{jt}$	5.876	0.0000	Yes
$\ln LPI_{jt}$	7.402	0.0000	Yes
$\ln TRADEFAC_{jt}$	6.985	0.0000	Yes

The null hypothesis is cross-sectional independence. Significant CD statistics indicate strong cross-sectional dependence across variables. This result justifies the use of robust standard errors and IV/2SLS estimation in later sections.

demonstrating that the panel data are stationary. This guarantees that any further empirical analysis, such as cross-sectional dependence tests and regression estimates are made on a consistent data-generating process.

Cross-Sectional Dependence Test (Pesaran CD Test). The panel datasets across countries can be cross-sectionally dependent, whereby the shocks or policy changes in one country that are not observed can affect others in the sample. The disregard of such

dependence can result in biased standard errors and unreliable statistical inference. Thus, it is necessary to assess the presence of cross-sectional dependence in the data before performing panel cointegration and regression analyzes.

To analyze this problem, the Pesaran Cross-Sectional Dependence (CD) test was applied to all variables used in the extended gravity model. The CD test determines whether there is a correlation among the residuals across the cross-sectional units. The large test statistic indicates cross-sectional dependence.

The test results reported in Table 9 indicate that the CD statistics for all variables are significant at the 1% level, suggesting the presence of cross-sectional dependence. This finding justifies the subsequent use of regression specifications and robust standard errors that properly account for cross-sectional correlation.

Co-integration Test. This study employs the Kao test to examine whether there exists a long-term equilibrium relationship among the cross-border e-commerce export scale from China to RCEP partner countries, the development level of cross-border e-commerce, GDP, and transaction distance. The test results are shown in Table 10.

The results indicate that the p-values of all five test statistics are less than 0.01. Hence, we can strongly reject the null hypothesis of “no co-integration relationship” at the 1% significance level, suggesting a co-integration relationship among these variables, i.e., a long-term equilibrium relationship.

Table 10 The co-integration test results for the cross-border e-commerce export transaction.

	Statistic	p-value
Modified Dickey-Fuller t	−4.2068	0.0000
Dickey-Fuller t	−6.6453	0.0000
Augmented Dickey-Fuller t	−3.4288	0.0003
Unadjusted modified Dickey-Fuller t	−5.6546	0.0000
Unadjusted Dickey-Fuller t	−7.0468	0.0000

Table 11 Variance Inflation Factor (VIF) Test Results for Cross-Border E-Commerce Exports.

Variable	VIF	1/VIF
lnCBECl _{it}	2.94	0.340408
lnGDP _{it}	1.03	0.971220
lnGDP _{jt}	3.63	0.275339
lnDIS _{ijt}	1.28	0.782394
lnPLAT _{jt}	2.21	0.452
lnPAY _{jt}	1.88	0.531
lnLPI _{jt}	2.47	0.405
lnTRADEFAC _{jt}	2.74	0.365
Mean VIF	2.19	

Table 12 Modified Wald test for groupwise heteroskedasticity.

$H_0: \sigma^2(i) = \sigma^2$ for all i

Chi² (11) = 81.27

Prob > chi² = 0.0000

Table 13 Wooldridge test for autocorrelation in panel data.

H_0 : no first-order autocorrelation

F(1, 10) = 0.899

Prob > F = 0.3653

Table 14 Model selection tests for the panel gravity model.

Type of Test	Test Statistic	P-value
F-test	169.73	0.0000
BP-LM Test	361.86	0.0000
Hausman Test	3.53	0.473

Variance inflation factor test. The Variance Inflation Factor (VIF) test is utilized to assess the collinearity among variables such as the level of cross-border e-commerce development, GDP, and transaction distance. The results indicate that the VIF values for all variables are less than 10, suggesting that the collinearity among variables in the export model constructed in this paper is within an acceptable range. The results are presented in Table 11.

Model selection. Before selecting the appropriate panel estimator, it is essential to assess the error structure of the data, as it

determines whether the assumptions underlying different estimation approaches are satisfied. The Pesaran CD test indicates significant cross-sectional dependence among RCEP countries (see Table 9), while the Modified Wald test shows strong groupwise heteroskedasticity (see Table 12). In contrast, the Wooldridge test detects no first-order autocorrelation (see Table 13). Cross-sectional dependence and heteroskedasticity violate the key assumptions required for the consistency of the random-effects estimator and may also invalidate the Hausman statistic. These empirical features must therefore be incorporated into the model selection decision.

After identifying the error characteristics, the pooled OLS model, fixed-effects model, and random-effects model are compared using the F-test, Breusch–Pagan LM test, and Hausman test (see Table 14). Both the F-test and LM test strongly reject the pooled OLS specification, confirming the presence of unobserved country-specific heterogeneity and the necessity of using a panel estimator. Although the Hausman test ($p = 0.473$) appears to favor the random-effects model under classical homoskedasticity assumptions, the presence of heteroskedasticity and cross-sectional dependence implies that the random-effects estimator is unlikely to be consistent, making the Hausman result unreliable.

Following the econometric guidance of Wooldridge (2010) and Hsiao (2014), when panel data exhibit heteroskedasticity or cross-sectional correlation, the fixed-effects estimator with heteroskedasticity-robust standard errors provides consistent and reliable inference, whereas the random-effects estimator does not. Therefore, the fixed-effects model with heteroskedasticity-robust standard errors is adopted as the baseline specification for this study. All subsequent regressions are based on this specification.

Baseline estimation results. Based on the model selection procedure in Section “Model Selection”, the fixed-effects model with heteroskedasticity-robust standard errors is used as the baseline estimator. Given that pooled OLS has been rejected and the random-effects estimator may be inefficient under the observed error structure, only fixed-effects results are reported. The estimation results are reported below (see Table 15). Cross-sectional dependence and heteroskedasticity may weaken the assumptions underlying the random-effects estimator and reduce the reliability of the standard Hausman statistic.

The results show that the cross-border e-commerce development index (CBECl) is strongly and statistically significantly positively associated with China’s cross-border e-commerce exports (proxy measure) to RCEP partner countries. China’s GDP and partner-country GDP also exhibit significant positive influences, consistent with gravity model predictions. Geographical distance retains its expected negative sign, though the magnitude is smaller than in traditional gravity models, suggesting that digitalization mitigates the trade-friction effect of physical distance.

Platform participation, digital payment adoption, logistics performance, and trade facilitation are positively and significantly associated with China’s bilateral CBEC export proxy, highlighting the importance of digital infrastructure and institutional efficiency in supporting digitally enabled trade, rather than destination-specific CBEC flows. With an adjusted R² of 0.914, the explanations of the variability remain powerful, taking into account unobserved heterogeneity across countries. Later, in the context of the CBEC ecosystem theory, the robust and highly influential role of platforms, payment systems, logistics performance, and trade facilitation further emphasizes that supporting species are associated with higher proxy-based export performance under a digital enabling environment.

Table 15 Baseline fixed-effects estimation results (robust standard errors).

Variable	Fixed effects model
$\ln \text{CBECI}_{jt}$	0.107*** (0.025)
$\ln \text{GDP}_{it}$	1.456 *** (0.132)
$\ln \text{GDP}_{jt}$	0.623*** (0.097)
$\ln \text{DIS}_{ijt}$	−0.274** (0.112)
$\ln \text{PLAT}_{jt}$	0.249*** (0.041)
$\ln \text{PAY}_{jt}$	0.171** (0.069)
$\ln \text{LPI}_{jt}$	0.193 *** (0.052)
$\ln \text{TRADEFAC}_{jt}$	0.289 *** (0.073)
Constant	−48.76*** (8.14)
Observations	110
Adjusted R ²	0.914

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$.

Table 16 Comparison of Different Estimation Methods for the Trade Gravity Model.

Variable	OLS Model	Fixed Effects Model	PPML Model
$\ln \text{CBECI}_{jt}$	0.118*** (0.032)	0.107*** (0.025)	0.121*** (0.030)
$\ln \text{GDP}_{it}$	1.871*** (0.211)	1.456*** (0.132)	1.689*** (0.188)
$\ln \text{GDP}_{jt}$	0.707*** (0.091)	0.623*** (0.097)	0.682*** (0.085)
$\ln \text{DIS}_{ijt}$	−0.339*** (0.102)	−0.274** (0.112)	−0.201** (0.099)
$\ln \text{PLAT}_{jt}$	0.276*** (0.048)	0.249*** (0.041)	0.293*** (0.055)
$\ln \text{PAY}_{jt}$	0.183** (0.084)	0.171** (0.069)	0.201** (0.080)
$\ln \text{LPI}_{jt}$	0.225*** (0.060)	0.193*** (0.052)	0.216*** (0.058)
$\ln \text{TRADEFAC}_{jt}$	0.312*** (0.076)	0.289*** (0.073)	0.341*** (0.079)
Constant	−54.08*** (7.91)	−48.76*** (8.14)	−50.31*** (8.62)
Observations	110	110	110
Adjusted R ² / Pseudo R ²	0.802	0.914	0.926

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$.

These base results are supported by robustness checks and endogeneity analysis, as presented in Section “Robustness and Endogeneity Test”.

Robustness and Endogeneity Test

Robustness Test: The robustness test was conducted by adding or deleting variables, adjusting lag periods, and changing the econometric model. Despite heteroscedasticity, the fixed-effects model was adjusted using robust standard errors, which improved estimation. The findings were consistent in terms of sign and significance level, thereby validating the model’s findings.

Although pooled OLS is not suitable as a baseline estimator due to the presence of unobserved heterogeneity, its results are still reported as an auxiliary reference to illustrate the stability of coefficient signs across different specifications. In addition to the OLS and fixed-effects estimations, the Poisson Pseudo-Maximum Likelihood (PPML) estimator is employed to further strengthen the robustness analysis. PPML is widely recommended in the gravity-model literature because it naturally accommodates zero trade flows without requiring data transformation and remains consistent under general forms of heteroskedasticity, which commonly characterize bilateral trade data. As shown in Table 16, the PPML coefficients are highly consistent in sign and magnitude with those obtained from the log-linear models, confirming that the core findings are not sensitive to estimator choice. Incorporating PPML therefore provides an additional robustness check that complements the baseline results and enhances the overall reliability of the empirical conclusions.

The findings show that the CBECI index, digital payments, and platform participation are statistically significant across all models, supporting the legitimacy of our empirical results. Our estimate is also aided by the PPML model, which accounts for heteroskedasticity and therefore strengthens the results.

Endogeneity Test: There can be a bidirectional causation between the degree of e-commerce development across borders and China’s exports. On the one hand, the enhancement of a partner country’s digital infrastructure, logistics performance, and payment systems can spur China’s cross-border e-commerce exports. Conversely, higher proxy-based CBEC export values may further expand the e-commerce ecosystem in the partner country through greater platform involvement and higher demand for online services. To explain this reverse causality effect, an increase in CBEC export activity can stimulate platform investment, expand logistics networks, and increase the use of digital payments, thereby strengthening the value of CBECI in a partner country. This two-way linkage creates endogeneity concerns in linear panel regressions.

Although Granger causality tests are commonly used to examine the direction of influence in time-series settings, they are not suitable for short panels with substantial cross-sectional heterogeneity, such as the RCEP sample in this study (11 countries over 10 years). Instead, endogeneity between CBECI and the CBEC export proxy is addressed through an instrumental-variable approach (2SLS), which provides consistent identification in panel data.

To address this endogeneity problem, this study follows Ma (2022) and adopts lagged values of the cross-border e-commerce development index—specifically the first lag ($L.\ln \text{CBECI}_{jt}$) and the first plus second lags ($L.\ln \text{CBECI}_{jt}$, $L2.\ln \text{CBECI}_{jt}$)—as instrumental variables. Lagged CBECI satisfies the requirements for a valid instrument because: (i) conceptually, past CBEC development affects current digital trade readiness, thus influencing current bilateral CBEC exports; (ii) institutionally, CBEC ecosystem indicators (logistics, platforms, payment systems) adjust slowly over time and are not immediately driven by short-term export fluctuations, ensuring exogeneity to contemporaneous shocks to the CBEC export proxy.

Table 17 presents the comparative IV relevance and validity statistics for alternative instrument sets.

Both sets of instrumental variables pass the weak-identification and under-identification tests, with the two-lag specification additionally passing the overidentification test, confirming instrument validity. The Sargan test cannot be used in the former since the one-lag specification is precisely identified. The one-lag instrument, however, has a much more significant first-stage F-statistic and Cragg-Donald values, which means it is more relevant and statistically precise. Hence, it is the first lag

Table 17 Comparative Analysis of IV (2SLS) Estimation Results.

Statistic/Variable	One Lag as Instrument	Two Lags as Instruments
Number of Observations	99	88
F-statistic (6, 81)	135.13***	111.25***
Prob > F	< 0.0001	< 0.0001
Centered R ²	0.8951	0.8926
Uncentered R ²	0.9993	0.9993
Root MSE	0.4335	0.4432
lnCBECl _{jt}	0.4938** (0.1928)	0.4534** (0.2070)
lnGDP _{it}	1.8615*** (0.2461)	1.8324*** (0.3037)
lnGDP _{jt}	0.7621*** (0.0824)	0.7836*** (0.0989)
lnDIS _{ijt}	-0.4452*** (0.0733)	-0.4431*** (0.0671)
lnPLAT _{jt}	0.3142* (0.1378)	0.2816* (0.1594)
lnPAY _{jt}	0.1865* (0.1184)	0.2248* (0.1432)
lnLPI _{jt}	0.2579** (0.1043)	0.2734** (0.1291)
lnTRADEFAC _{jt}	0.3421** (0.1527)	0.4095** (0.1738)
Constant (_cons)	-54.0763*** (8.1731)	-56.3128*** (9.1757)
Under-identification Test	33.057 *** (Chi-sq(1) P-val = 0.0000)	32.774 *** (Chi-sq(2) P-val = 0.0000)
Weak Identification Test	46.118**	23.738*
Sargan Statistic (OIR Test)	0.000 (equation exactly identified)	1.212 (Chi-sq(1) P-val = 0.2709)
Instruments	L.lnCBECl _{jt}	L.lnCBECl _{jt} , L2.lnCBECl _{jt}

Standard errors are shown in parentheses. Significance levels: ***p<0.01, **p<0.05, *p<0.10. The Weak Identification Test assesses the strength of the instruments. Higher F-statistic values indicate stronger instruments.

(L.lnCBECl_{jt}) that is used as the instrument of choice in this study.

In order to increase transparency, the following equation is the first stage regression equation:

$$\begin{aligned} \ln \text{CBECl}_{jt} = & \beta_0 + \beta_1 L.\ln \text{CBECl}_{jt} + \beta_2 \ln \text{GDP}_{it} + \beta_3 \ln \text{GDP}_{jt} \\ & + \beta_4 \ln \text{DIS}_{ijt} + \beta_5 \ln \text{PLAT}_{jt} + \beta_6 \ln \text{PAY}_{jt} + \beta_7 \ln \text{LPI}_{jt} \\ & + \beta_8 \ln \text{TRADEFAC}_{jt} + \varepsilon_{ijt} \end{aligned} \quad (8)$$

This equation shows that the endogenous variable (current CBECl) is predicted by its lagged value and the exogenous gravity-model determinants, consistent with standard IV identification procedures.

To further verify robustness, 2SLS, LIML, and GMM estimators were applied using the same instrument set. The results are presented in Table 18.

The value of the significance of the lnCBECl_{jt} decreases slightly, but the sign and value do not vary with specifications. However, remarkably, 2SLS provides the smallest standard errors and best precision, which is in line with the small-sample econometric theory: LIML minimizes the bias, but it increases the

Table 18 Comparison of IV estimators (2SLS, LIML, GMM).

	2SLS	LIML	GMM
lnCBECl _{jt}	0.4938** (0.106)	0.4725** (0.193)	0.4583** (0.213)
lnGDP _{jt}	0.773*** (0.082)	0.7684*** (0.0895)	0.7592*** (0.0937)
lnGDP _{it}	1.8716*** (0.247)	1.8563*** (0.2684)	1.8427*** (0.256)
lnDIS _{ijt}	-0.446*** (0.072)	-0.4417*** (0.0793)	-0.4382*** (0.06)
lnPLAT _{jt}	0.3142* (0.1378)	0.2981* (0.1559)	0.2857* (0.1624)
lnPAY _{jt}	0.1865* (0.1184)	0.1792* (0.1372)	0.1658 (0.1487)
lnLPI _{jt}	0.2579** (0.1043)	0.2496** (0.1213)	0.2381* (0.1291)
lnTRADEFAC _{jt}	0.3421** (0.1527)	0.3314** (0.1690)	0.3198* (0.1735)
Constant	-54.0763***	-53.8217***	-53.5042***
(_cons)	(8.1731)	(8.6421)	(8.0923)
Number of obs	99	99	99
R-squared	0.8972	0.8951	0.8924

Standard errors are shown in parentheses. Significance levels: ***p<0.01, **p<0.05, *p<0.10.

variance, whereas GMM can have the problem of the small-sample instability in case the number of instruments is small. Thus, the 2SLS is chosen as the estimator of choice.

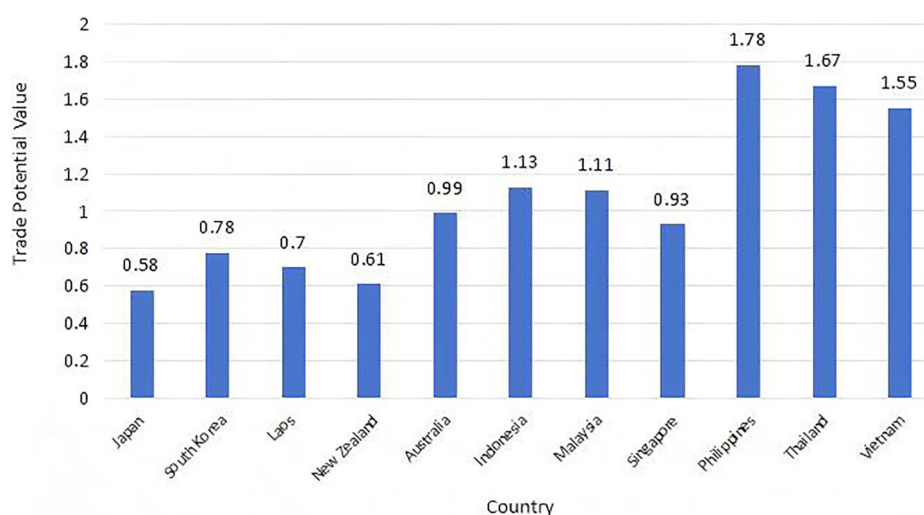
Moreover, the dynamic nature of the panel was observed to see whether or not lagged dependent variables or dynamic panel estimators (difference-GMM or system-GMM) fitted. Though there is some persistence in CBECl exports, two things render GMM inappropriate in this research. To begin with, the small panel size (11 countries in 10 years) puts the analysis at risk of instrument proliferation and finite-sample inefficiency. Second, the lagged CBECl IV strategy is already highly effective in endogeneity, and diagnostic tests suggest that there is no significant residual endogeneity. There is no extra econometric value in introducing other dynamic terms, and this would instead bring about finite-sample distortions. The benchmark specification, consequently, possesses a fixed gravity model that employs external instruments and produces efficient estimates that are constant.

Lastly, one takes into consideration the potential heterogeneity between RCEP economies, including the variations in the level of income, logistics performance, or platform penetration. The narrow cross-sectional aspect and imbalanced availability of subgroup-specific variables, however, do not allow effective stratified regressions or interaction-based tests of heterogeneity. Notably, there also exist time-invariant cross-country differences already accounted for by the country fixed-effects structure, and the patterns of coefficients reflected by both the PPML and IV-2SLS robustness tests are very consistent. Accordingly, heterogeneity is a great path to take in the future, but this study has a single specification to ensure that the reliability of the estimation is not compromised.

Analysis of the Cross-Border E-Commerce Trade Potential between China and RCEP Partners. Given that 2SLS estimates coefficients comparable to those proposed by LIML and GMM and yields smaller standard errors in some instances, the present paper uses 2SLS regression estimates to obtain the regression equation. By inserting various variables, theoretical values for cross-border e-commerce exports are calculated, followed by the ratio of observed (proxy-based) to model-implied values to assess

Table 19 China's Cross-Border E-Commerce Trade Potential Value with RCEP Partner Countries.

	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Average	Group
JPN	0.653	0.639	0.544	0.554	0.591	0.570	0.566	0.521	0.474	0.690	0.580	significant potential
NZL	0.515	0.572	0.583	0.652	0.619	0.608	0.626	0.609	0.584	0.828	0.619	significant potential
LAO	0.606	1.120	0.805	1.672	0.587	0.409	0.508	0.399	0.361	0.594	0.706	significant potential
KOR	0.773	0.819	0.718	0.764	0.794	0.744	0.805	0.738	0.691	1.049	0.789	significant potential
AUS	0.771	0.859	0.822	0.979	1.015	1.017	1.085	1.134	0.962	1.322	0.997	exploratory potential
SGP	1.054	1.050	0.976	0.944	0.906	0.857	0.975	0.975	0.612	1.033	0.938	exploratory potential
MYS	1.236	1.054	0.962	0.982	1.058	0.990	1.128	1.147	1.119	1.466	1.114	exploratory potential
IDN	1.124	1.330	1.057	1.104	1.067	1.136	1.175	1.003	1.046	1.332	1.137	exploratory potential
VNM	1.274	1.637	1.478	1.539	1.593	1.477	1.650	1.675	1.499	1.744	1.557	reconstructive potential
THA	1.335	1.578	1.570	1.766	1.638	1.512	1.543	1.641	1.719	2.453	1.676	reconstructive potential
PHL	1.226	1.517	1.474	1.916	1.956	1.838	2.001	1.858	1.802	2.243	1.783	reconstructive potential

**Fig. 4** Trade Potential Values of RCEP Countries (2013-2022).

the export potential between China and its RCEP partner countries. Averages are computed and grouped according to the classification criteria set by Nilsson (2000) and Egger (2002), with results presented in the following Table 19.

The data analysis shows that the trade potential of the significant-potential countries (Japan, Korea, Laos, and New Zealand) is less than 0.8, indicating that the existing conditions and models of Chinese cross-border e-commerce exports offer significant expansion opportunities. The potential countries of exploration (Australia, Indonesia, Malaysia, Singapore) have a trade potential of 0.8-1.2, meaning that Chinese e-commerce exports across the border to these countries have yet to reach their full potential and suggesting scope for further expansion as reflected in the proxy-based measure. The reconstructive-potential countries (Philippines, Thailand, Vietnam) with a trade potential value above 1.2 indicate that the growth space for China's exports to these countries is minimal and therefore requires innovation in trade models or new trade areas to enhance growth.

The average trade potential for each RCEP country is shown in Fig. 4, facilitating easy comparison of trade potential levels.

It is interesting to note that the reconstructive-potential countries, the Philippines, Thailand, and Vietnam, have exhibited considerable growth trends in the value of their cross-border e-commerce trade potential, particularly in 2022. This could mean that there has been a significant improvement in recent years in terms of the e-commerce infrastructure, government support, and

access to these countries' markets. The other growth patterns were in potential-exploiting countries such as Indonesia and Malaysia, indicating that additional growth potentials can be seen in the cross-border e-commerce markets in these countries.

The results of both models are given in Table 20, where the significance of each specification and the explanatory power are compared.

The findings suggest that the augmented CBEC model has a considerably higher Adjusted R^2 (0.927) relative to the traditional gravity model (0.802), indicating greater explanatory power when e-commerce-related variables are incorporated. The index of the CBECI is statistically significant at the 1% level, thereby validating the association between digital trade infrastructure and China's bilateral CBEC export proxy. To simplify reading the magnitude and precision of the 95% confidence intervals for the important coefficients, Table 20 presents them.

The participation in platforms, share in digital payments, and logistics performance provide more information. Participation on the platforms receives a positive coefficient of 0.276 ($p < 0.01$), indicating that large e-commerce sites, such as Alibaba, JD.com, and Shopee, are associated with higher values of the CBEC export proxy. Digital payments adoption is also important, with a coefficient of 0.183 ($p < 0.05$), indicating that the greater the area's use of online payment systems (e.g., Alipay, PayPal, WeChat Pay), the stronger the proxy-based CBEC export performance.

Efficiency in e-commerce logistics is also an important factor, as indicated by the positive coefficient of 0.225 ($p < 0.01$). This

Table 20 Regression Results Comparing Traditional Export Model vs. Augmented CBEC Model.

Variable	Model 1 (Traditional Gravity Model)	95% CI	Model 2 (Augmented CBEC Model)	95% CI
$\ln GDP_{it}$	1.871*** (0.211)	[1.457, 2.285]	1.765*** (0.198)	[1.378, 2.152]
$\ln GDP_{jt}$	0.707*** (0.091)	[0.529, 0.885]	0.673*** (0.085)	[0.506, 0.840]
$\ln DIS_{ijt}$	-0.339*** (0.102)	[-0.540, -0.138]	-0.285** (0.099)	[-0.479, -0.091]
$\ln CBECI_{jt}$	—	—	0.118*** (0.032)	[0.055, 0.181]
$\ln PLAT_{jt}$	—	—	0.276*** (0.048)	[0.183, 0.369]
$\ln PAY_{jt}$	—	—	0.183** (0.084)	[0.018, 0.348]
$\ln LPI_{jt}$	—	—	0.225*** (0.060)	[0.107, 0.343]
$\ln TRADEFAC_{jt}$	—	—	0.312*** (0.076)	[0.163, 0.461]
Constant	-54.08*** (7.91)	[-69.58, -38.58]	-47.96*** (8.25)	[-64.14, -31.78]
Observations	110	—	110	—
Adjusted R ²	0.802	—	0.927	—
F-statistic	134.10***	—	168.42***	—

Standard errors in parentheses; 95% confidence intervals in brackets. *** $p < 0.01$, ** $p < 0.05$.

finding is predictable and underscores that efficient customs operations and effective delivery options contribute to the success of digital trade. The measures of trade facilitation also have a positive impact, with a coefficient of 0.312 ($p < 0.01$), indicating the significance of regulatory support in facilitating trade in CBEC.

Another interesting observation is that trade distance is reduced in the enhanced CBEC model. The effect of distance is negative, but it is smaller in the CBEC model than in the traditional model: distance has a negative effect of -0.285 ($p < 0.05$) on the model compared to -0.339 ($p < 0.01$). This implies that the geographical barriers to trade are overcome by the developments in digital trade infrastructure and e-commerce logistics.

In general, the robustness examination ensures that the inclusion of cross-border e-commerce indicators greatly increases the predictive ability of the trade model. The findings offer empirical evidence of the need to incorporate e-commerce-specific factors in the estimation of the trade potential in the RCEP model, which supports the importance of digital trade, platform accessibility, and logistics efficiency as important determinants of CBEC exports.

Discussion

Cross-Border E-Commerce Development Index of RCEP. The analysis of the total weight distribution of Leading Species, Key Species, and Supporting Species at 0.1908, 0.1289, and 0.6803 (that is, 19.08, 12.89, and 68.03, respectively) illustrated the preponderant role of Supporting Species, which occupy 68.03 percent of the development level of cross-border e-commerce. This factual data demonstrates the paramount importance of Supporting Species to the advancement of cross-border e-commerce, which aligns with Li's (2013) conclusion. Taken together, the prevalence of logistics and information-related indicators in the CBECI confirms the ecosystem perspective, according to which

the so-called supporting species, rather than core transaction volumes per se, are the pillars of the development of cross-border e-commerce.

When it comes to primary variables, the distribution of weights to the Scale of goods import and export transactions (19.08%), Manufacturers and Consumers (12.89%), Logistics Performance (38.39%), Information Flow (25.51%), and Cash Flow (4.13) initially confirms Zhang (2021) as the cross-border e-commerce ecosystem is a complex network that is supported by logistics, business, capital, and information flows. The significance of logistics highlights that it is a crucial element of cross-border e-commerce development, consistent with the arguments by Zhang and Ma (2015) regarding the developmental limitations of insufficient logistics. The high weight of the TIMG index, which reflects Information Flow and ranks second only to logistics, corroborates Zhang and Li's (2020) claim that the digital economy is the basis for developing cross-border e-commerce and digital trade.

The weights of the Import volume of goods, Export volume of goods, and Manufacturing value added, all greater than 9 at the secondary indicator level, partially support the observation by He and Wang (2019) regarding the effect of GDP on cross-border e-commerce trade. On the other hand, the small weights attributed to the secondary indicators of Cash Flow imply that the capital flow does not have a significant influence on the development of cross-border e-commerce, which is not directly supported by the existing literature, as it only mentions the capital flows in connection with the overall economic activity without specifically referring to the development of cross-border e-commerce.

The dominant state of cross-border e-commerce development in China is explained by the high rates of development of logistics and network infrastructure, as well as improved customs performance, which are observed in real life and confirm the authenticity and completeness of the index system developed. The high ranking of Singapore in RCEP, as per economic development, is realized by its well-developed financial services, manufacturing sector, and open policies. The paper observes a worldwide positive, though uneven, trend of growth in the development of cross-border e-commerce across countries, contrary to the results of Shen (2023) on similar levels in Australia and South Korea, which could be explained by the differences in data sets between G20 and RCEP nations, providing space to conduct new studies. The fact that Laos is at the bottom of the list because of its level of development of the economic and e-commerce infrastructure is consistent with the evaluations of the ASEAN countries such as Myanmar, Laos, and Cambodia by Song (2021) because the three countries depend on their economic status, level of infrastructure development, and efficiency of logistics as the determinants of the disparities in cross-border e-commerce development.

Cross-Border E-Commerce Trade potential between China and RCEP partners. The 2SLS results indicate a strong positive association between China's bilateral CBEC export proxy to RCEP partners and the economic size and e-commerce ecosystem development of trading partners, which is in line with the results in this study about the aspects of bilateral trade where the GDP growth of a trading partner is crucial to enhance bilateral trade (Chen 2020). Also, distance becomes a detrimental variable affecting e-commerce exports, which Song (2021), Zhang and Wang (2019), and Li, Dou, and Han (2022) also note; Kim, Dekker, and Heij (2017) point to the advantages of proximity in increasing the loyalty of buyers and the decreased reluctance of delivery.

The proposed study contributes to knowledge of China's e-commerce export potential by examining whether it aligns with

Chen (2020), which posits that Singapore and Malaysia have untapped potential, and with Shen (2023), which posits a potential similar to Australia. It links trade potential to economic growth, internet penetration, and geographic advantages, and foresees large trade volumes with China (Wang and Cao 2021). It believes it can do more in Indonesia, Vietnam, the Philippines, and Thailand, unlike Chen (2020), who considers Laos to have immense untapped potential. It also shares Shen's (2023) view regarding the huge potential of Japan and Korea.

The differences in the results can be due to:

Information Updates and Development of the Trade Environment: This paper uses recent data (2013–2022) to capture the rise of the digital economy, enhancements in infrastructure, and transformations in trade across the globe, which may reconsider the possibility of exports.

The Development of Logistics: The investments of ASEAN in logistics and Thailand, in particular, make it easier to conduct trade, as well as the prospects of e-commerce with China across the borders.

Information Technology and Policy Support: The emergence of IT and supportive policies, such as Singapore's Smart Nation 2025 and free trade agreements, encourages the development of e-commerce across borders.

Effects of the Shared Borders: Proximity to China is advantageous to other nations, such as Laos, in cross-border e-commerce because of the smooth trade procedures and lower cost of transport.

Market Size and Maturity: Japan and South Korea have large e-commerce markets, and China is the largest e-commerce country in the world, which highlights a high potential for cross-border trade, as seen in the January 2020 data provided by PPRO with regard to China's cross-border e-commerce market share in South Korea.

The analysis that is based on a comparison of empirical data and contextual changes confirms previous literature and presents new knowledge regarding the potential of cross-border e-commerce trade, suggesting that the development of logistics, IT developments, the supporting policy, and the geographical proximity should be considered in future analysis.

Conclusions and Implications

Conclusions. The paper adds to the literature by combining the theory of cross-border e-commerce ecosystems with a large-scale gravity model analysis to provide a comprehensive method for assessing the potential of digital trade in the RCEP zone.

This paper encourages the analysis of domestic and international literature regarding the theory of the cross-border e-commerce ecosystem, factors affecting this area, and the level of development. Based on the theory of the cross-border e-commerce ecosystem and taking into account most of the indicators proposed in the literature, it creates a complex system of evaluation that also comprises both primary and secondary indicators. By adopting the Stata software to conduct a principal component analysis, a scoring formula was made to measure the level of development of cross-border e-commerce between the RCEP member countries quantitatively, assessing the changes in the ranking and trend values of the ranking between 2013 and 2022. Additionally, the level of development of cross-border e-commerce is also a major explanatory variable integrated in an expanded gravity model, plus the control variables used in this study to empirically test their relation to the extent of importation and exportation in China. Using the constructed dependent variable in the gravity framework, we derive model-implied values of China's bilateral CBEC export proxy and compute trade potential as the ratio of observed (proxy-based) to model-implied values.

The results are that China, Japan, and Singapore stand out with regard to the growth of cross-border e-commerce, with South Korea and Australia at a similar stage, and New Zealand, Malaysia, Thailand, Indonesia, Vietnam, and the Philippines in the lower spectrum, with Laos having the least level of development. In assessing the trade potential of China's cross-border e-commerce exports, countries with significant potential (JPN, KOR, LAO, NZL) had trade potential values below 0.8, indicating substantial room for expansion under current conditions; countries with exploratory potential (AUS, IDN, MYS, SGP) had values between 0.8 and 1.2, suggesting untapped growth opportunities; and reconstructive-potential countries (PHL, THA, VNM) had values above 1.2, indicating limited growth space for China's exports to these countries, necessitating innovative trade models or the exploration of new trade domains to facilitate growth.

Practical Implication. Building on the trade-potential classification in Section 4.3, this section provides differentiated policy recommendations for the three groups of RCEP partner countries—significant-potential, exploratory-potential, and reconstructive-potential economies. This categorization enables the prioritization of policy measures along short-, medium-, and long-term horizons.

Countries with significant unrealized potential—such as Japan, South Korea, Laos, and New Zealand—exhibit observed (proxy-based) CBEC export values far below their model-implied levels. For these economies, priority should be given to strengthening digital and logistics infrastructure, harmonizing e-commerce regulations, and improving customs efficiency. Upgrading cross-border logistics hubs and digital connectivity is expected to generate substantial marginal gains and help unlock latent demand.

For exploratory-potential countries including Australia, Indonesia, Malaysia, and Singapore, the empirical model indicates moderate gaps between observed (proxy-based) and model-implied values. These economies would benefit from policies that enhance digital-payment adoption, promote platform participation among SMEs, and deepen fintech—e-commerce integration. Strengthening cybersecurity standards and ensuring interoperability across payment systems can further support seamless CBEC transactions.

In reconstructive-potential countries—such as the Philippines, Thailand, and Vietnam—proxy-based CBEC export values already exceed their model-implied levels. Ensuring long-term sustainability requires reinforcing logistics chains and improving market absorptive capacity. Policies aimed at strengthening last-mile delivery systems, providing compliance and certification training for SMEs, and expanding digital-trade literacy will help consolidate recent gains while mitigating risks associated with rapid expansion.

Across the region, the findings collectively highlight the central role of logistics performance, digital-payment readiness, platform accessibility, and trade-facilitation measures. Improvements in these dimensions will not only enhance CBEC trade performance but also accelerate digital-economic integration under the RCEP framework.

Research limitations and prospects. This study provides a comprehensive evaluation of cross-border e-commerce development and China's CBEC export potential to RCEP partners from 2013 to 2022. Nevertheless, several limitations should be acknowledged. First, the dataset covers only the most recent decade, which may not fully reflect long-term structural changes in digital trade. Second, although the sample includes major

RCEP economies, the exclusion of several member countries due to data constraints may affect the representativeness of the findings. Third, the potential impact of the COVID-19 pandemic, both as a disruptor and catalyst for CBEC, was not explicitly modeled. In addition, because publicly available bilateral CBEC export statistics are not currently reported for China–RCEP pairs, the dependent variable is a proxy constructed by proportional allocation of China's national CBEC export scale; thus, it cannot capture destination-specific CBEC intensity. Future research could leverage customs e-declaration data, platform transaction records, or other digital trace data to measure bilateral CBEC exports more directly.

Future research can address these limitations along several directions.

- (1) Data extension and coverage: Expanding the time horizon and incorporating additional RCEP economies would enhance the robustness and generalizability of the results.
- (2) Broader explanatory factors: Subsequent work may examine how logistics development, trade openness, cultural distance, and digital-economy readiness shape CBEC export potential more precisely.
- (3) Methodological advancement: Employing nonlinear gravity specifications, stochastic frontier methods, or dynamic panel approaches could capture complex relationships not addressed by linear models.
- (4) New forms of digital data: The use of high-frequency or real-time digital trade indicators—such as platform transaction data or customs e-declaration records—would improve measurement accuracy.
- (5) Emerging technologies: Finally, future studies may explore how AI-driven logistics optimization, blockchain-based payment systems, and other emerging digital technologies transform CBEC ecosystem efficiency and reshape trade patterns under RCEP.

Data availability

A complete replication package is available in the public repository: <https://github.com/llzhang1028/An-empirical-study-on-the-potential-of-China-s-cross-border-e-commerce-exports0117>.

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Author contributions

Conceptualization: LLZ; Methodology: LLZ; Writing – original draft: LLZ and MAA; Writing – review & editing: LLZ and MAA; Supervision: LLZ. All authors have read and approved the final manuscript.

Competing interests

The authors declare no competing interests.

Ethical approval

This study uses publicly available secondary data and does not involve human participants or animals. Therefore, ethical approval was not required.

Informed consent

Not applicable.

Additional information

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