Research on the Impact of Cross-border E-Commerce on Economic Growth in China – An Empirical Test Based on VEC Model

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Abstract. Along with the vigorous development of cross-border e-commerce in China, the research on the cross-border e-commerce domain has also attracted great attention from the academic community. The research covers cross-border e-commerce development model, logistics synergy, trade cost and law. However, in terms of empirical research, there are very few studies on the measurement of economic growth driven by cross-border e-commerce. In view of this, a vector error correction model (VEC) is established to analyze the co-integration relationship between cross-border e-commerce and economic growth in China by means of co-integration test, impulse response analysis and variance decomposition method by selecting the data of cross-border e-commerce transactions and GDP from 2000 to 2020, and the empirical method is used to corroborate the significant positive impact of cross-border e-commerce on economic growth in China.

Keywords: Cross-border e-commerce · Economic growth · VEC model · Cointegration test · Impulse response · Variance decomposition

1 Introduction

Although China's cross-border e-commerce started relatively late, it has been developing rapidly along with the rapid development of China's economy and society against the background of the government's strategies of "Internet Plus" and "The Belt and Road." The total turnover of cross-border e-commerce has grown from RMB 50 billion in 2000 to RMB 12.5 trillion in 2020, with an average annual growth rate of over 33%. At present, cross-border e-commerce has become a new momentum for China's economic growth, and it has exerted a series of far-reaching impacts on China.

A retrieval of the literature since 2018 reveals a polarized trend in the attention paid to cross-border e-commerce by Chinese and foreign academics. Foreign scholars have conducted very few studies on cross-border e-commerce, and the few foreign scholars who have published related papers have merely focused on the study of the factors influencing the development of cross-border e-commerce. Valarezo et al. (2018) surveyed 16,209 consumers in Spain to analyze the drivers and barriers of cross-border

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e-commerce. Elia et al. (2021) surveyed 102 Italian companies of different sizes active in three separate sectors, confirming the drivers of cross-border e-commerce development as: digital technologies and digital capabilities.

With the booming development of cross-border e-commerce in China, Chinese scholars have developed a keen interest in the research of cross-border e-commerce. The research covers cross-border e-commerce development model, logistics synergy, trade cost and law. Based on the grey correlation theory and the composite system synergy model, Liu (2016) constructed an evaluation model of the synergy between cross-border e-commerce and modern logistics, and conducted a comprehensive evaluation of the level of synergistic development between cross-border e-commerce and modern logistics in China from 2008 to 2014. Ju et al. (2020) applied the cross-border export data at international, provincial, and industry levels from 2013 to 2016 and related macro data from DHgate, the largest cross-border e-commerce platform for SMEs in China. Moreover, they discerned the scale and structural impact of different types of trade costs on export trade in cross-border e-commerce from the dual perspectives of export destination and production location of exports. Wang et al. (2021) put forward development strategies of integrating virtual network community marketing + VR (Virtual Reality) experience, RFID (Radio Frequency Identification) technology logistics tracking + new Internet technology of blockchain authenticity traceability, and cross-border e-commerce platform ecosystem.

In terms of empirical studies, there are very few studies on the measurement of economic growth driven by cross-border e-commerce. In view of this, based on vector error correction model (VEC), this paper analyzes the relationship between cross-border e-commerce and economic growth by selecting the data of cross-border e-commerce transactions and gross domestic product from 2000 to 2020, and studies the impact of cross-border e-commerce on China's economic growth.

2 Empirical Analysis

2.1 Regression Equation Form

This paper constructs the following regression equation:

Long term equilibrium equation:

$$\mathrm{lnGDP_t} = \partial + \beta \mathrm{lnCEV_t} \tag{1}$$

Short term wave equation:

$$\Delta \mathrm{lnGDP_t} = \partial \mathrm{ce_{t-1}} + \sum \beta_p \Delta \mathrm{lnGDP_{t-p}} + \sum \gamma_p \Delta \mathrm{lnCEV_{t-p}} + c \tag{2}$$

$$\Delta \mathrm{lnCEV_t} = \partial \mathrm{ce_{t-1}} + \sum \beta_p \Delta \mathrm{lnGDP_{t-p}} + \sum \gamma_p \Delta \mathrm{lnCEV_{t-p}} + c \tag{3}$$

Where, Δ represents the difference between lnGDP and lncev, ce represents error correction term, c represents constant, t represents the time, n represents the maximum lag order, P = 1, 2… n.

2.2 Sequence Diagram Analysis

To test the stability of data, we first need to draw the time series diagram of data and observe the time series diagram, and analyze the trend term, intercept term and other information contained in the fitting curve depicted by each observation variable in the time series diagram, which is also to prepare for the unit root test in the next step. The sequence diagram of lnGDP and lnCEV is drawn in Figs. 1 and 2.

It can be seen from Figs. 1 and 2 that lnGDP and lnCEV both have an obvious upward trend, which is not a stationary sequence. Although the time data series itself may be unstable, in order to carry out the subsequent cointegration test, we still care about the stationarity of its difference series and determine whether they are first-order or second-order integration series.

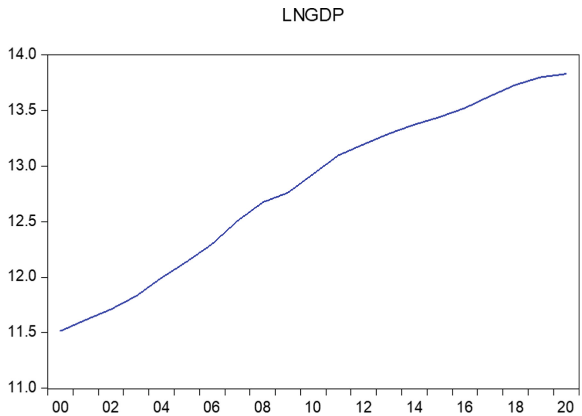

Fig. 1. The sequence diagram of lnGDP

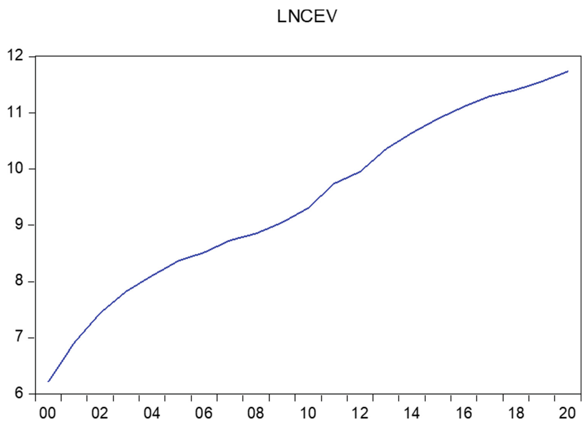

Fig. 2. The sequence diagram of lnCEV

Table 1. China's cross-border e-commerce volume, GDP data and their logarithmic values from 2000 to 2020

Year	GDP (RMB 100 million)	CEV (RMB 100 million)	LNGDP	LNCEV
2000	100280.1	500	11.51572	6.214608
2001	110863.1	1000	11.61605	6.907755
2002	121717.4	1700	11.70946	7.438384
2003	137422	2500	11.83081	7.824046
2004	161840.2	3300	11.99436	8.101678
2005	187318.9	4300	12.14057	8.36637
2006	219438.5	5000	12.29883	8.517193
2007	270092.3	6200	12.50652	8.732305
2008	319244.6	7000	12.67371	8.853665
2009	348517.7	8500	12.76144	9.047821
2010	412119.3	11000	12.92907	9.305651
2011	487940.2	17000	13.09795	9.740969
2012	538580	21000	13.19669	9.952278
2013	592963.2	31500	13.29289	10.35774
2014	643563.1	42000	13.37478	10.64542
2015	688858.2	54000	13.44279	10.89674
2016	746395.1	67000	13.52301	11.11245
2017	832035.9	80600	13.63163	11.29725
2018	919281.1	90000	13.73135	11.40756
2019	986515.2	105000	13.80193	11.56172
2020	1015986.2	125000	13.83137	11.73607

Data source: Cross-border e-commerce volume data comes from the E-commerce Research Center on www.100ec.cn and GDP data comes from China Statistical Yearbook.

2.3 Variables and Data Selection

The purpose of this paper is to study the impact of cross-border e-commerce on economic growth in China, so the annual data of cross-border e-commerce transaction volume (CEV) and gross domestic product (GDP) in China from 2000 to 2020 were selected as the measurement samples, and all data were logarithmically processed. Without changing the original co-integration of the data, the heteroskedasticity prevalent in the time series is eliminated, as shown in Table 1.

2.4 Stationarity Test

Testing the stationarity of the variables is the premise of the cointegration test and the establishment of the model, otherwise spurious regression may occur. In this paper, the

Table 2. ADF unit root test results

Variable	1% significant	5% significant	10% significant	ADF	Prob.	Conclusion
LNGDP	−3.8085	−3.0207	−2.6504	−2.6039	0.1086	Non-stationary
D (LNGDP, 1)	−3.8315	−3.0299	−2.6552	−1.5618	0.4817	Non-stationary
D (LNGDP, 2)	−3.8868	−3.0522	−2.6666	−5.1812	0.0008	Stationary
LNCEV	−3.8085	−3.0207	−2.6504	−3.5547	0.0170	Non-stationary at 1% significance level
D (LNCEV, 1)	−3.8315	−3.0299	−2.6552	−3.6252	0.0153	Non-stationary at 1% significance level
D (LNCEV, 2)	−3.8574	−3.0404	−2.6606	−5.8579	0.0002	Stationary

Table 3. Optimal lag order determination

Lag	LogL	LR	FPE	AIC	SC	HQ
0	−13.50921	NA	0.021261	1.824613	1.922638	1.834357
1	56.33906	115.0442	9.25E−06	−5.922242	−5.628166	−5.89301
2	60.21756	5.475533	9.66E−06	−5.907948	−5.417822	−5.859229
3	72.79127	14.79261*	3.77e−06*	−6.916620*	−6.230445*	−6.848413*
4	75.46862	2.51986	5.05E−06	−6.761015	−5.878789	−6.67332

ADF test is used to test the data of LNGDP and LNCEV, and the results are shown in Table 2. The data of LNGDP and LNCEV are both second-order integrated series.

2.5 Optimal Lag Order Determination

The optimal lag order of the VAR model is generally chosen based on AIC (Akaike's Information Criterion) and SC (Schwarz Criterion). In this paper, Eviews was used to observe the five indicators of LR, FPE, AIC, SC and HQ of the model to determine the optimal lag order. As shown in Table 3, the optimal lag order of the VAR model is 3 for all five indicators. Therefore, the VAR (3) model was established first, and the judgment is based on the data marked with * in the table.

2.6 Johansen Cointegration Test

In order to determine whether the VEC model is suitable, Johansen cointegration test was conducted on the variables with a lag period of 3. The results are shown in Table 4.

Table 4. Trace test results

Maximum rank	Eigenvalue	Trace statistic	5% critical value	P-value
None*	0.440638	16.32490	15.49471	0.0374
At most 1*	0.315681	6.448616	3.841466	0.0111

Table 5. Cointegration equation

	D (LNGDP)	T-Statistics
LNCEV (−1)	−0.309484	−3.34384
C	−9.937665	

Table 6. Estimated coefficients of the vector error correction model

	D (LNGDP)	D (LNCEV)
CointEq1	−0.184916	0.119249
D (LNGDP (−1))	0.240371	0.502846
D (LNGDP (−2))	−0.495232	−1.068175
D (LNGDP (−3))	0.500304	1.910192
D (LNCEV (−1))	0.013313	0.136311
D (LNCEV (−2))	−0.01024	0.624447
D (LNCEV (−3))	−0.140402	−0.133899
C	0.128903	−0.094932

At the 5% significance level, the trace test results show that there is a cointegration relationship between lnGDP and lnCEV, and thus a vector error correction model can be established.

2.7 VEC Model Estimation

In order to better examine the impact between variables, a vector error correction model was constructed in this paper to measure the different feedback effects when cross-border e-commerce volume and GDP deviate from the equilibrium state. The results are shown in Tables 5 and 6. R^2 is 0.796801, which indicates that the model fits well.

By observing Fig. 3, we can see that the modulus of the inverse roots of all AR characteristics of the VEC model were within the unit circle, indicating that the model is stationary.

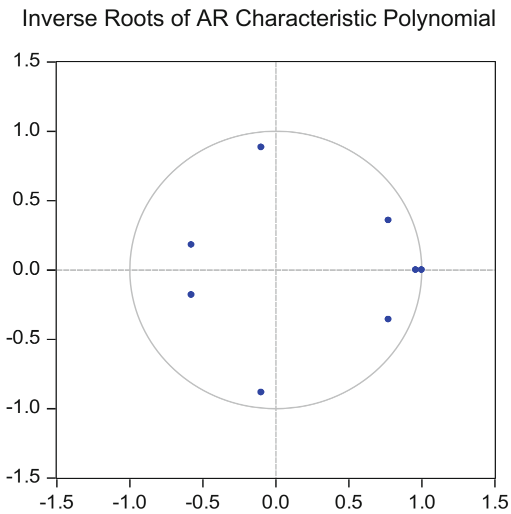

Fig. 3. Unit root test

2.8 Impulse Response Analysis

The impulse responses between the two variables were analyzed with a lag of 10 periods, and the results are shown in Fig. 4. As can be seen from the top left panel, the response of GDP to its own shock fluctuates considerably, generating a positive response of 0.0291 in the current period, increasing incrementally to 0.0303 in the second period, and decaying rapidly to 0.0116 in the third period. The shock responses follow an oscillating and overall downward trend. The shock response of gross domestic product (LNGDP) to cross-border e-commerce volume (LNCEV) was 0 in the current period, with a positive response of 0.0038 in second period, increasing to 0.007 in the third period, and then decaying to 0.0027 in the fourth period, after which the shock response gradually intensified. The impact of cross-border e-commerce volume (LNCEV) on gross domestic product (LNGDP) showed a negative response in the current period, which turned positive in the second period and then declined rapidly to a negative response of 0.02 in the third period, and then showed an overall increasing trend. The response of cross-border e-commerce volume (LNCEV) to its own shocks tends to increase in general, indicating the existence of a pronounced network scale effect in the cross-border e-commerce industry.

2.9 Variance Decomposition

According to the results in Table 7, economic growth is influenced by both cross-border e-commerce and economic growth itself. In the current period, economic growth is completely influenced by itself, and the contribution of cross-border e-commerce transaction scale gradually increases from the second period. In the 10th period, the contribution of cross-border e-commerce scale to economic growth exceeds 20%, reaching 28.03%, while the contribution of economic growth to itself gradually decays to about 72%. In

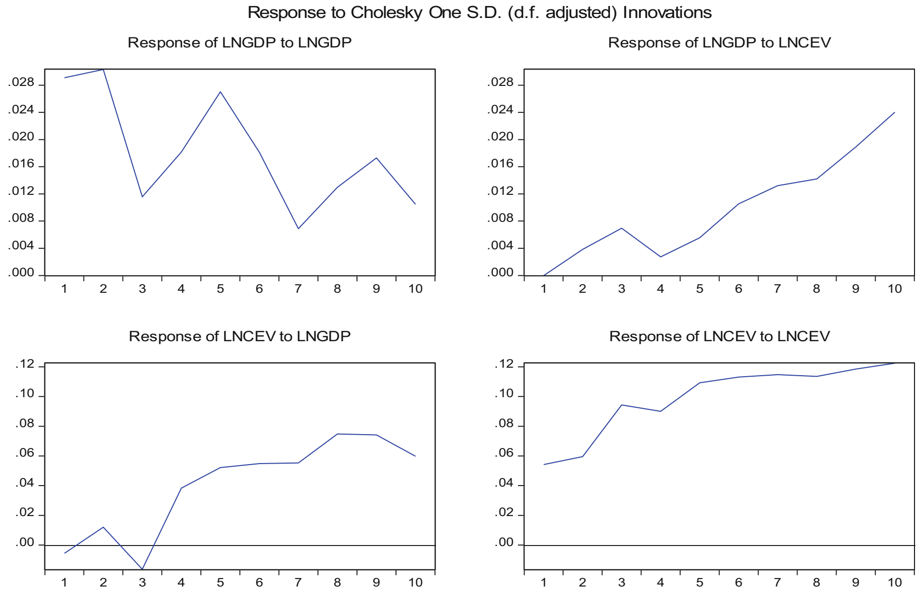

Fig. 4. Impulse response between variables

Table 7. Results of variance decomposition

Period	S.E.	LNGDP	LNCEV	Period
1	0.029102	100	0	1
2	0.042204	99.17851	0.821486	2
3	0.044314	96.78413	3.215871	3
4	0.047972	96.931	3.068996	4
5	0.055345	96.68701	3.312986	5
6	0.059182	93.9276	6.072395	6
7	0.061029	89.60006	10.39994	7
8	0.063989	85.61328	14.38672	8
9	0.068929	80.07234	19.92766	9
10	0.073746	71.97003	28.02997	10

the long run, the development of cross-border e-commerce has a significant impact on economic growth.

3 Conclusions

In this paper, the annual data of China's cross-border e-commerce transactions and GDP from 2000 to 2020 were selected, and a vector error correction model was established by using unit root test and co-integration test. The relationship between cross-border e-commerce and economic growth was empirically analyzed by model stationarity test, impulse response analysis and variance decomposition. In view of the long-term equilibrium relationship between the two and the significant impact of cross-border e-commerce development on economic growth, the following recommendations are made: Preferential policies for cross-border e-commerce should be introduced at an accelerated pace, with greater financial support, tax incentives, financial subsidies and other support. Moreover, it should accelerate the construction of public services, payment, logistics, warehousing and other infrastructure for cross-border e-commerce. At the same time, efforts should be increased to cultivate talents related to cross-border e-commerce to match the actual demand and improve the quality of talent training.

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