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Study on the Impact Mechanism of Cross-border E-Commerce Logistics Resilience under Public Health Emergencies

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Abstract: This study constructs a logistics resilience measurement model to investigate the formation mechanism of cross-border e-commerce logistics resilience under public health emergencies, with a focus on examining the resilience characteristics of logistics delivery timeliness and its spatio-temporal evolution patterns. The findings indicate that public health emergencies have caused significant impacts on global cross-border e-commerce logistics resilience, with logistics delivery timeliness exhibiting characteristics of an "attenuation wave," undergoing three typical stages: rapid decline, gradual recovery, and systematic improvement. The analysis results show that among the many factors affecting logistics resilience, structural factors such as logistics network node centrality and connection number are the most critical, followed by the severity of public health emergencies, while the role of the overall development level of the logistics industry and prevention and control measures is relatively limited. These findings reveal the spatio-temporal heterogeneity of logistics resilience, and indicate that large-scale parcel volumes and complex route layouts can easily lead to resource allocation pressure and operational efficiency decline.

Keywords: Public health emergencies; Cross-border e-commerce logistics; Logistics resilience

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1. Introduction

Cross-border e-commerce (CBEC) logistics, as a critical branch of international logistics emerging in recent years, has been selected as the core research object of this study based on three primary considerations:

(1) Compared with traditional international trade logistics characterized by large-scale operations, CBEC logistics exhibits greater operational flexibility, stricter delivery time requirements, and stronger sensitivity to sudden shocks such as public health emergencies;

(2) CBEC logistics possesses a well-established waybill data tracking system, offering more open and precise data access, which provides robust foundational support for academic research;

(3) CBEC represents a pivotal evolutionary direction of traditional international trade.

In recent years, countries worldwide have invested substantial resources to promote its development, aiming to compete for economic benefits, big data resources, cultural influence, and international discourse power. Notably, CBEC has demonstrated counter-cyclical growth trends even during public health crises. As core supporting links in CBEC development, logistics systems are situated at the forefront of global economic competition, demanding enhanced resilience.

Against the backdrop of public health emergencies and escalating demand for CBEC services, disparities in regional logistics resilience may reshape global development patterns. Accurately identifying the characteristics of logistics resilience, delineating its spatial-temporal evolution patterns, and pinpointing key influencing factors are of paramount theoretical and practical significance. Such efforts will not only bolster resilience against current challenges and potential "black swan events" but also expand the theoretical boundaries of resilience studies and logistics geography, deepening scholarly understanding in these domains.

Current academic research on resilience primarily focuses on empirical analysis of influencing factors. Since the 2008 global financial crisis triggered Western economic recessions, scholars have pioneered studies on economic resilience. Regarding influencing factors, two major viewpoints have emerged: Some researchers argue that regions with diversified industrial structures and robust industrial innovation capabilities tend to exhibit higher economic resilience [1–5]. However, others question this conclusion, noting that such relationships may show significant regional variations or even negative effects in practice [6–8]. Chinese economic geographers, though relatively latecomers to resilience research, have conducted in-depth analyses leveraging China's extended economic transition observation period. Their work emphasizes mechanisms related to industrial restructuring, leading industry selection, policy interventions, locational advantages, social capital accumulation, economic scale expansion, modernization of production systems, and technological innovation capabilities. While there is broad consensus on the importance of economic scale, production system modernization, and socio-cultural diversity in enhancing resilience, divergent views persist regarding optimal industrial restructuring paths, criteria for selecting leading industries, effectiveness of policy tools, and boundaries of social capital functions [8–10]. Notably, case-specific studies have identified additional influential factors such as locational endowments and strategic coupling modes, providing valuable references for constructing multidimensional analytical frameworks in this study.

2. Research data and methods

This study relies on logistics waybill data for analysis, with information collection primarily accomplished using big data mining technology and data cleaning processes. The specific operational procedure involves systematically generating standardized waybill sequences and implementing dynamic tracking by parsing the coding rules of global CBEC logistics waybills, ultimately identifying real and effective order numbers through multiple verification screenings. Data extraction covers key fields, such as logistics channel types, coordinates of origin and destination, dispatch time, and delivery time. Based on this, core metrics like logistics network density, parcel throughput, and delivery timeliness can be quantitatively analyzed.

The data collection window for the experiment spanned from July 2019 to October 2022, accumulating a total of 459,867,704 valid records from 368 types of logistics channels, covering 213 sovereign countries and regions worldwide. The sample composition is primarily based on postal parcel services and express delivery services, supplemented by some specialized line logistics and less-than-truckload transportation businesses. It is strictly limited to cross-border e-commerce transaction scenarios and individual unregistered parcels, excluding bulk commodity trade logistics and ordinary letters among other unconventional logistics forms. Owing to the comprehensive coverage of leading international express companies (http://www.aioexpress.com/news312), the acquired delivery timeliness data is highly credible and can effectively reveal the regional differentiation characteristics of CBEC logistics resilience.

In the sample screening phase, the research team set a hard threshold of no less than 1,000 valid order numbers per month, ultimately including a total of 159 countries and regions in the final analysis. The geographical distribution shows significant imbalance; regions in Central and Northern Africa with less developed economies were not included in the statistics due to low international parcel volumes, while the existing samples are concentrated in mature European and American markets and emerging cross-border e-commerce economies.

With reference to the economic resilience measurement model of Zhou *et al.*, the "time axis integral of the variation range of logistics distribution duration", an indicator that combines duration variation and time accumulation, is defined as the "representation of resilience" [11]. Based on this, the logistics resilience measurement model is constructed, and its basic expression is as follows:

$$R = \frac{S'}{(S'+\Delta S)} = \frac{\int_{t1}^{t2} f'(t)dt}{\int_{t1}^{t2} f(t)dt} \quad (1)$$

Formula 1: R is resilience index, S' is the time axis integral of the predicted trajectory, ΔS is the time axis integral of the difference between the actual trajectory and the predicted trajectory, t is time, $f'(x)$ is the predicted trajectory without the public health emergencies, $f(x)$ is the actual trajectory of the impact, $t1$ and $t2$ are time points.

The resilience measurement model adopted in this study uses **Formula 1** as the core framework, and its connotation presents differentiated characteristics according to the selected time dimension. Specifically, when the time window is set to the full cycle of a single public health emergency (from event trigger to complete subsidence), the model calculates the comprehensive resilience index of the logistics system during this shock; if the observation interval is limited to the phase with prolonged distribution duration, it corresponds to calculating the system's resistance index; and when the time range focuses on the specific phase with shortened distribution duration, it reflects the system's recovery index. Through dynamic tracking of time sections, a time series indicator reflecting the evolution trajectory of logistics resilience can be constructed. The theoretical model shows a significant negative correlation between the resilience coefficient R and the system state variable ΔS, meaning an increase in the R value is usually accompanied by a decrease in the ΔS value, indicating that the logistics system exhibits stronger shock resistance. When the R value equals 1, it indicates that the logistics system did not experience significant fluctuations during the shock; if the R value consistently exceeds 1, it reflects that the system has successfully constructed a dynamic adjustment mechanism to cope with shocks through technological innovation or management optimization, achieving an improvement in delivery efficiency despite adverse conditions.

For the logistics resilience composite indices of different waves, the resilience improvement index is defined to represent the capacity for resilience enhancement. The formula is as follows:

$$P_w = \frac{R_w}{R_{w-1}} \quad (2)$$

w represents the wave number ($w > 1$), P is the resilience improvement index, and R is the resilience index.

Under normal circumstances, $P > 1$ indicates that the resilience of this wave has improved, and $0 < P < 1$ indicates that the resilience of this wave has decreased. The larger the P value is, the stronger the improvement of the resilience of this wave. It is particularly important to note that within the expression system of this study, unless otherwise specified, the involved monthly time range is limited to the 2020 observation period; the various "index" indicators mentioned in the text, unless stated otherwise, specifically refer to this core evaluation parameter, the logistics resilience composite index.

3. Analysis of the impact on CBEC logistics resilience

According to the model calculation, the temporal evolution of the impact on CBEC logistics resilience can be divided into three distinct phases.

3.1. Phase I (January–June 2020): Rapid decline followed by gradual recovery

During this phase, global CBEC logistics resilience experienced a sharp decline and subsequently stabilized through arduous recovery efforts. From January to February, as the COVID-19 pandemic began spreading globally, countries lacked timely and effective emergency response mechanisms, resulting in significant delays in logistics delivery times across most samples. The outbreak escalated into a full-blown pandemic in March, causing severe disruptions to international logistics chains and continuous deterioration of logistics resilience in all samples. Most regions entered a critical phase of resisting the initial shock: North America and Oceania initially exhibited pronounced declines in logistics resilience, followed by spillover effects to South America and Western Europe, eventually culminating in a global impact characterized by spatial conduction from low time-cross section index samples to high-index counterparts. Concurrently, governments implemented policies to resume work and production, enabling the logistics system to maintain basic operations under pressure. By June, logistics resilience in most regions had recovered substantially, though North America, Western Europe, and Oceania lagged behind.

3.2. Phase II (July–November 2020): Overall improvement with regional fluctuations

During this period, global logistics resilience in the vast majority of samples improved progressively, achieving an overall upward trend despite localized shocks. Samples centered on China demonstrated a reverse spatial transmission mechanism, with their time-cross section index rebounding rapidly and serving as a benchmark for other regions. Subsequently, West Asia, North Africa, Western Europe, and North America entered recovery phases, albeit with moderate fluctuations. Oceania's logistics resilience index remained persistently low; notably, Australia experienced a 130% logistics delay rate during its second COVID-19 wave, with full recovery not achieved until November.

3.3. Phase III (December 2020–October 2022): Systemic enhancement and resilience strengthening

From December 2020 to October 2022, global CBEC logistics resilience underwent minor fluctuations before achieving comprehensive recovery. While winter resurgence of COVID-19 caused a modest decline in the global logistics resilience index, the amplitude of fluctuations was significantly lower than during the initial outbreak. Through accumulated experience in combating the pandemic over the previous year, diversified emergency management mechanisms were established across regions. Although the third wave exerted sustained pressure on the global logistics system, its impact intensity was markedly weaker than the first wave, with accelerated recovery rates. This progression demonstrates that systemic resilience enhancements, achieved through initial crisis response and subsequent localized adjustments, have fortified global logistics systems. Consequently, even amid renewed major shocks, the capacity for risk mitigation and self-repair has been substantively reinforced.

4. Quantitative analysis of influencing factors

Based on the aforementioned analytical framework and data foundation, this study quantitatively explores the relationship between indicators such as logistics network node centrality, number of connections, logistics industry development level, severity of public health emergencies, prevention and control strength, and the logistics resilience index. The Pearson correlation analysis results show that node centrality exhibits the most significant negative correlation with both the composite index and the recovery index (approximately 30% explanatory power, significant at the 0.01 level), and the number of connections also shows a relatively obvious negative correlation with the recovery index (approximately 17% explanatory power, significant at the 0.05 level) (**Table 1**). This indicates that the structural factors within the logistics system, such as the operational inertia and resource allocation pressure caused by parcel scale and route complexity, are the key internal factors affecting logistics timeliness and resilience. Meanwhile, the severity of public health emergencies also demonstrates a certain negative effect on the composite index and the recovery index (approximately 13% explanatory power, significant at the 0.05 level). As an important external disturbance factor, it not only directly restricts the supply of human resources but also creates a circular cumulative effect through transportation control and industrial chain transmission. In contrast, the development level of the logistics industry and the prevention and control strength for public health emergencies show no significant impact on resilience, reflecting that technological and managerial advantages may not play a dominant role when the system faces high-intensity shocks, further confirming that the formation and evolution of logistics resilience result from the comprehensive influence of multiple factors [12].

Table 1. Pearson correlation between logistics resilience index and influencing factors

Influencing factors	Composite index	Resistance index	Recovery index	Resilience improvement index
Logistics network node centrality	-0.260**	-0.039	-0.342**	-0.050
Number of logistics network connections	-0.127	-0.008	-0.173*	-0.047
Logistics industry development level	-0.129	-0.052	-0.125	0.040
Severity of the	-0.135*	-0.058	-0.124*	0.017
Prevention and control efforts	0.030	0.031	0.098	0.082

Note: *, ** respectively indicate significant at the 0.05 and 0.01 levels (two-tailed). The comprehensive index, resistance index, and recovery index are all data of the first wave, and the resilience improvement index is the resilience improvement index of the second wave compared to the first wave. The indicator of the development level of the logistics industry is the comprehensive logistics score. The data comes from the study "Connected to Competition: Trade Logistics in the Global Economy, Logistics Performance Index and Indicator Report" by the World Bank and Turku School of Economics and Business Administration (（http://worldbank.org/lpi)), the data cross-section is 2018; the centrality and connection number of logistics network nodes are calculated based on the author's mining data, and the time period corresponds to each sample wave; the indicator of the severity of the is the cumulative number of confirmed diagnoses within the time period. The data source is the website of the Johns Hopkins University Coronavirus Resource Center (https://coronavirus.jhu.edu/), and the time period corresponds to each sample wave; the indicator of the prevention and control strength is the government response severity index, based on the Oxford University research "public health emergencies: Stringency Index" (https://ourworldindata.org/grapher/covid-stringency-index), calculate the average value of each sample wave time period.

5. Conclusion

As a sudden "natural experiment," the impact of the public health emergency provides important conditions for empirically testing CBEC logistics resilience and analyzing its influencing factors. By examining the resilience characteristics reflected in logistics delivery timeliness, this study reveals the spatio-temporal heterogeneity of CBEC logistics resilience. Under the impact of the public health emergency, global CBEC logistics exhibits significant cyclical fluctuations and resilience evolution, and its time course can be divided into three distinct phases. The spatio-temporal heterogeneity of logistics resilience is influenced by a combination of multiple factors, among which logistics network structure is the most sensitive, followed by the severity of the public health emergency. Specifically, the inertial characteristics and resource run caused by logistics network factors such as node centrality and connection number are the most significant, and the cyclic accumulation effect induced by the severity of the public health emergency also has significant explanatory power. In contrast, factors at the technical or managerial level, such as the development level of the logistics industry and prevention and control efforts, do not show significant influence. This research aims to offer references for the CBEC logistics industry to enhance its ability to resist risks, and to provide decision-making support for the government and enterprises in optimizing spatial layout and resource allocation. At a time of unprecedented changes unseen in a century, the process of globalization continues to deepen amid fluctuations. Logistics resilience will face more diverse influencing factors and more complex challenges in the future. This research team will continue to conduct tracking, monitoring, and in-depth analysis to promote research outcomes that better serve the needs of economic and social development.

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Disclosure statement

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