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Geopolitical Shocks and the Resilience of Supply Chains Across Eurasia — An Event Study Analysis of Spatio-Temporal Transmission Effects Based on the China-Europe Railway Express Network

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Abstract: ***In September 2025, a sudden border closure between Poland and Belarus brought operations at Malaszewicze—a key hub for the China-Europe Railway Express—to a standstill for approximately 12 days, triggering a series of chain reactions, including a sharp drop in freight volume and a surge in freight rates. This paper adopts the "time-lagged transmission effect" as its core analytical framework and employs the event study method. Based on monthly operational data from March 2025 to February 2026, it systematically examines the short-term impact of this sudden shock on the freight volume and freight rates of the China-Europe Railway Express, as well as the patterns of its attenuation. The study found that: (1) During the period of the shock, the number of departures in the high-exposure group (Xi'an, Zhengzhou, Chongqing) fell by 19.2%, and logistics costs per container surged by 17.4% (with the freight rate index peaking at a 22% increase within two weeks), exhibiting the typical characteristics of an "acute shock"; (2) The decline in freight rates exhibited a distinct asymmetric pattern of "rapid initial decline followed by gradual recovery"—approximately 60% of the total recovery was achieved within the first four weeks, with a half-life of about 2.5 weeks; however, the remaining 40% of the recovery took 22 weeks, and nearly 12% of the cargo volume was permanently lost after the "time threshold" in the fourth week; (3) The intensity of the shock decreased progressively along network distance from near to far, but the recovery speed diverged in the opposite direction—core hubs recovered in about 4 weeks, while distant nodes required more than 10 weeks, constituting a "spatio-temporal coupling" of temporal rhythm and spatial pattern; (4) Repeated shocks have fostered "adaptive expectations," shortening the physical-layer response time from a "monthly" scale in 2022 to a "weekly" scale in 2025. However, baseline risks have risen simultaneously, resulting in a net effect of "shorter short-term windows and thicker long-term residuals." This paper reveals the temporal propagation patterns of sudden node-based geopolitical shocks along the China-Europe Railway Express network, providing empirical evidence for the design of emergency response mechanisms and the diversification of transport corridors.***

Keywords: Geopolitical shocks; China-Europe Railway Express; Event study method; Spatiotemporal transmission effects; Supply chain resilience.

1. Introduction

Over the past decade, escalating geopolitical conflicts and the institutionalization of supply chain security have profoundly reshaped the economic and trade landscape across Eurasia. The China-Europe

Railway Express is no longer merely a transportation infrastructure but has become a strategic corridor that underpins the stability of the China-Europe industrial chain (Feng Fenling et al., 2025). The authority to organize cross-border transportation is decentralized among operators in multiple countries along the route, forming a distributed governance structure; the emergency coordination capabilities of intermediary organizations significantly influence the speed of network recovery. For shippers, operational status, customs clearance efficiency, freight rates, and route reliability serve as first-line indicators for dynamically assessing supply chain security. In 2022, the Russia-Ukraine conflict, Western sanctions, and Russia's Decree No. 1374—which tightened inspections—led to a deterioration in the efficiency of the Northern Route; in September 2025, the closure of the Poland-Belarus border caused the core hub of Malaszewicze to grind to a halt for approximately 12 days; and conflicts in the Middle East also threatened the security of the Southern Route. The spatiotemporal convergence of multiple geopolitical events has forced operators to frequently adjust their decisions (Tang Kaijie and Yang Gongyan, 2026). At the same time, differences in network topology cause the same shock to produce heterogeneous effects on different nodes (Zhang Yuzhao et al., 2025). Existing studies are largely based on complex network simulations or annual macro data, focusing on structural vulnerability and long-term trends (Qian et al., 2024; Ji Mingjun et al., 2022), lacking high-frequency empirical tests of short-term fluctuations in freight volume and freight rates, as well as spatial differentiation, under actual disruptions faced by operators. To address this, this paper constructs a mean-adjusted model and a two-way fixed-effects regression model. Using monthly operational data from March 2025 to February 2026, it systematically examines the short-term impact of the Bao-Bai blockade on the freight volume and freight rates of the China-Europe Railway Express, as well as the patterns of its decay, thereby filling a research gap in terms of temporal transmission and spatial differentiation.

2. Research Literature Review

This section provides a systematic review of the mainstream empirical and theoretical research findings from the academic community over the past decade in the areas of geopolitical risks and supply chain resilience associated with the China-Europe Railway Express. It aims to identify tiered research gaps that directly correspond to the three core research questions of this paper—from the perspectives of network structural vulnerability, resilience assessment methods, and the transmission mechanisms of geopolitical shocks—thereby laying a solid theoretical and methodological foundation for the subsequent design of event studies and empirical analysis.

2.1 A Study on the Network Structure and Vulnerability of the China-Europe Railway Express

Research on the China-Europe Railway Express transportation network is rooted in complex network theory, which conceptualizes the cross-border railway system as a topological structure composed of nodes, edges, and traffic (Ji Mingjun et al., 2022). Qian et al. (2024) further proposed a network-space evolution model, noting that growth in freight volume and geographic expansion have caused single corridors to differentiate into a multi-tiered structure. Zhang Xin et al. (2023) demonstrated empirically that this network comprises 167 nodes, exhibits scale-free and small-world characteristics, has a degree correlation coefficient of 0.13, and displays weak isotropy, providing a foundation for analyzing core-periphery differentiation. Recent studies emphasize the dichotomy between mainstream and alternative corridors, arguing that corridor concentration, port capacity, and geopolitical risks fragment the network into route blocs with significantly differing risk profiles (Zhu & Zhu, 2024). Among these, the improved nonlinear load-capacity model by Zhu and Zhu (2024) indicates that appropriate thresholds can mitigate the impact of small-scale failures; Research on intermediate corridors, meanwhile, reveals that geopolitical shocks can also trigger positive diversion effects, highlighting the role of intermodal transport in enhancing resilience. Turning to the dynamics of cascading failures, an investigation of two-tier networks (physical and operational layers) indicates that hub redundancy and contingency scheduling reconfigure vulnerability boundaries by establishing alternative routes. An assessment based on coupled image grids confirms that network metrics decline by over 40% under cascading failures—far exceeding the decline under non-cascading failures (<10%)—demonstrating the destructive amplification effect of cascading failures. The ripple effect, conceptualized by Ivanov et al. (2014) as the propagation of a local disruption along the supply chain with amplification effects, has been increasingly applied to the China-Europe Railway Express context. This perspective emphasizes that physical topology is not merely a backdrop but a constitutive force that shapes the scope of failures, alternative routes, and resilience. Existing empirical studies largely rely on annual statistical bulletins and topological simulations to track the long-term transformation of the network from a "unipolar northern route" to a "multi-channel parallel" structure under geopolitical risks (Qian et al., 2024; Jiang Mingxin, 2022). However, there is a lack of short-term dynamic transmission studies based on monthly or weekly high-frequency data (Feng Fenling et al., 2025). High-frequency data can capture real-time fluctuations in freight rates and volumes following shocks, as well as week-by-week decision-making responses, thereby forming a narrative of dynamic resilience. The limited number of short-term studies mostly employ cross-sectional or monthly aggregated data, focusing on annual changes or quarterly trends following crises (Zhang Yuzhao et al., 2025). Chen et al. (2025) constructed a two-layer coupled mirror lattice model, revealing that cascading failures propagate within 3–4 iterations and network efficiency declines by over 50%; however, this study was limited to simulation. Zhu and Zhu (2024) also simulated node failure vulnerability based on simulations, both of which constitute static analyses. Feng Fenling et al. (2025) introduced a two-dimensional assessment of "structural resilience" and "functional resilience," finding that under single-node disturbances, the loss of most nodes was <1%, while functional resilience was more susceptible to damage and exhibited nonlinear recovery; however, their analysis was still limited to the annual scale and simulation scenarios. Studies simulating network vulnerability under emergency scenarios further demonstrate that when core hubs are subjected to targeted attacks, the decline in network efficiency is significantly greater than that of edge nodes; this is intrinsically consistent with the "hub amplification effect" identified later in this paper. Some studies have focused on the spatial spillover effects of geopolitical risks, but they have not been refined to a monthly or weekly time scale, nor have they explored the "spatio-temporal mirror" relationship between the attenuation of shock intensity along network distance and the spatial differentiation of recovery speeds. There is a lack of longitudinal empirical tracking of the full spectrum of transmission and attenuation of a single shock at the weekly scale, and few studies systematically correlate network topological position (core/periphery) with differences in dynamic recovery; a complete analytical chain linking static structure, the temporal rhythm of shocks, and distance-dependent attenuation is also missing (Zhang Yuzhao et al., 2025). In summary, this field still has significant gaps in conducting detailed quantitative assessments of the short-term propagation effects of single sudden shocks based on high-frequency operational data.

2.2 Identification of Geopolitical Risks and Assessment of Corridor Security

The theoretical foundation of geopolitical risk assessment can be traced back to the classic "risk–vulnerability–resilience" analytical framework in international relations studies, which conceptualizes cross-border supply chain systems as complex adaptive systems shaped by external disturbances, system state, and resilience (Caldara & Iacoviello, 2022). Building on risk assessment theory, existing research has developed an indicator system for assessing security risks along the China-Europe Railway Express routes, categorizing risks into six major categories: geopolitical, environmental, economic and trade, transit capacity, customs clearance, and service quality. Zhang Xuehui and Hui Beibei (2026), however, systematically analyzed the major risks and bottlenecks currently facing the corridor from dimensions such as great power rivalry, policy sanctions, infrastructure, operational mechanisms, and non-traditional security. This classification system provides a theoretical framework for identifying the differentiated transmission pathways of various types of risk sources in the China-Europe Railway Express. Complementing this line of inquiry, Lyu et al. (2025) propose a “risk network” framework, Wang (2024) applies a PESTEL analysis, and Fang (2026) examines the same Poland-Belarus border closure shock examined in this paper, proposing countermeasures such as route diversification. While these studies enrich the risk literature from multiple angles, they remain largely qualitative and static, failing to quantify the dynamic decay trajectory of a shock—a gap this paper fills through high-frequency event-study tracking. Building on this, some scholars have further introduced multi-indicator comprehensive evaluation methods to quantitatively assess corridor security risks. For instance, Zhou (2023), using an AHP-fuzzy comprehensive evaluation model, constructed a safety risk assessment framework for the China-Europe Railway Express transport corridor from multiple dimensions including geopolitics, transit capacity, and customs clearance efficiency. His results indicate that geopolitical risks and capacity-related risks are the most critical dimensions affecting corridor security. However, such methods are inherently static in nature: they rely on expert weighting and cross-sectional data, yielding a ranked risk profile at a single point in time, but fail to capture the dynamic decay pattern of shocks over time. Recent studies have further expanded this framework by distinguishing between long-term institutional shocks and sudden node-specific shocks, demonstrating that the erosive effects of sustained sanctions and compliance restrictions on the corridor (the GPR of the Northern Route remained within the 160–210 range for an extended period following the 2022 Russia-Ukraine conflict) and the acute blocking effects of a single-port blockade (the 2025 Poland-Belarus blockade caused a sharp 19.2% drop in freight volume) follow distinctly different temporal rhythms and decay trajectories: the former exhibits a stepwise, incremental rise, while the latter follows a pulsed pattern that is rapid at first and then slows down (Jiang Mingxin, 2022; Chen et al., 2025). As a complement to this research approach, studies on multi-channel diversion effects reveal that alternative routes (such as the Trans-Caspian Intermediate Corridor) are at a competitive disadvantage under normal conditions due to longer distances and higher transshipment costs; however, when the main route is disrupted, they can rapidly absorb diverted cargo flows, thereby providing positive empirical evidence for the “decentralized” transformation of the corridor landscape. However, while previous studies have conceptually distinguished between long-term institutional shocks and sudden node-level shocks and established a multidimensional risk classification indicator system, they have consistently neglected to conduct a systematic quantitative comparison of the transmission rhythms, half-lives, and recovery patterns of these two types of shocks within the same empirical framework. They have also failed to dynamically track key parameters such as the actual absorption capacity of alternative corridors, switching lags, and freight rate buffer coefficients. Consequently, risk assessment conclusions have remained at the level of “static ranking,” capable only of answering “which channel is more dangerous,” but fail to provide actionable early-warning precision—such as “in which week after a shock do freight rates peak, or in which week does cargo volume experience permanent loss.” This has resulted in a persistent methodological disconnect and a mismatch in timeliness between geopolitical risk assessment and emergency decision-making, and a systematic quantitative comparison of the two types of shocks in terms of transmission pace, half-life, and recovery patterns remains entirely absent.

2.3 Assessment of Transportation Network Resilience: A Dual-Dimensional Structural-Functional Framework and a Static Simulation Paradigm

The study of supply chain resilience can be traced back to the seminal work of Christopher and Peck (2004), who first articulated the concept in the logistics context and proposed a multi-layered framework encompassing principles of flexibility, redundancy, and velocity to build resilience against disruptions. Subsequently, resilience as a construct was further examined across multiple disciplines—from engineering and ecology to psychology and organizational science—and came to be broadly understood as the capacity of a system to absorb disturbance and reorganize while undergoing change so as to retain essentially the same function (Bhamra et al., 2011). In the specific context of supply chain management, this general notion has been operationalized as the ability of a system to return to its original state or move to a new, more desirable state after being disturbed (Pettit et al., 2013). Building on this conceptual foundation, the literature on transportation network resilience has further developed a two-dimensional measurement framework comprising structural resilience (the network's ability to maintain connectivity) and functional resilience (the ability to sustain freight flows under disturbances) (Feng Fenling et al., 2025). Using methods such as complex network simulation, load-capacity models, and coupled image lattices to simulate the propagation speed and scope of cascading failures (Feng Fenling et al., 2025; Zhu & Zhu, 2024). However, the vast majority of existing empirical research in this field relies on annual statistical bulletins and network topology simulations as analytical data. Based on long-term cumulative data, scholars have assessed the spatial spillover effects of geopolitical risks on the efficiency of the China-Europe Railway Express network (Zhang Yuzhao et al., 2025), or used simulation scenarios to demonstrate the rapid propagation pattern of cascading failures—which spread within 3 to 4 iterations and caused network efficiency to decline by more than 50%—under targeted attacks (Chen et al., 2025). Short-term dynamic transmission studies based on high-frequency operational data at the monthly or weekly level remain an under-researched area in this field (Feng Fenling et al., 2025). Compared with low-frequency topological simulations and annual statistics, high-frequency operational data can capture the real-time fluctuation trajectories of freight volume and rates following a shock, the week-by-week decision-making responses of shippers and operators, and the nonlinear decay process of network functional recovery; together, these elements constitute a dynamic resilience narrative system that is fundamentally different from static vulnerability analysis. Methodologically, existing empirical research on the resilience of the China-Europe Railway Express has been dominated by qualitative descriptions and simulation models. Researchers often rely on network topology metrics (average degree, clustering coefficient, network efficiency) to assess structural losses, or use regression models to analyze macro-level correlations in annual data; however, they have not yet introduced standardized quantitative tools for event shocks—such as event studies—to measure the dynamic transmission effects of a single shock across different time scales (weekly, monthly, quarterly, and semi-annual). Relying solely on static vulnerability analysis and aggregated annual data makes it impossible to distinguish between the acute effects of a shock in the current period and the varying rates of the subsequent decay phase, nor can it quantify the nonlinear inflection points and the proportion of permanent losses during the recovery process. A single static assessment paradigm fails to integrate high-frequency operational data and event study methods to operationalize the underlying temporal transmission structures and spatial differentiation patterns behind geopolitical shocks. Furthermore, in the prior literature, network topology analysis and dynamic recovery measures have existed as two isolated research approaches; scholars have rarely systematically linked network position (core hubs and peripheral nodes) to spatially differentiated patterns of recovery speed, resulting in a lack of effective connection between static perceptions of network structure and dynamic empirical measurements of shock responses. A small but growing strand of literature has begun to assess the resilience implications of the China-Europe Railway Express using causal identification strategies. Li et al. (2024), for instance, exploit the staggered opening of the corridor across 276 cities as a quasi-natural experiment and find that cross-border railway construction significantly enhances regional economic resilience. While this study is methodologically rigorous and conceptually aligned with the resilience theme of the present paper, it differs in three critical respects: it examines a positive opening shock rather than a negative closure shock; it measures aggregate economic resilience at the city level rather than network-level functional resilience in freight operations; and its annual panel data cannot resolve the weekly-to-monthly decay trajectory, the half-life of freight-rate spikes, or the permanent loss threshold—precisely the dynamic parameters that this paper captures through high-frequency operational data and an event-study design.

2.4 There is a lack of longitudinal research on the dynamic responses of the China-Europe Railway Express to geopolitical shocks

A large body of research on the China-Europe Railway Express has examined the impact of external geopolitical disruptions on corridor operations, broadly categorizing the subjects of study into two types: analyses of the cumulative effects of long-term institutional shocks (such as sanctions, tariff policies, and transit regulations) and static vulnerability assessments of one-off incidents (such as port closures and military conflicts) (Caldara & Iacoviello, 2022; Zhang Yuzhao et al., 2025). Foundational research on supply chain risk management has established that geopolitical risks systematically undermine the stability and resilience of supply chains through mechanisms such as causing partners to adopt more conservative management strategies and making it more difficult for firms to obtain information about host countries (Tang Kaijie & Yang Gongyan, 2026). Studies on long-term institutional shocks consistently document a long-term trend in which the corridor landscape is evolving from a "unipolar northern route" to a "parallel multi-corridor" structure (Qian et al., 2024; Jiang Mingxin, 2022), while studies on single, sudden incidents focus on the scope of cascading failures in network topology and the decline in efficiency under attack; conclusions vary significantly across studies regarding the assessment of shock intensity and the estimation of recovery times. For example, Zhu and Zhu (2024) found through simulations that reasonable threshold conditions can mitigate the impact of small-scale node failures, whereas Chen et al. (2025) revealed that network efficiency declines by more than 50% under targeted attacks. Most existing studies employ cross-sectional designs or aggregate annual data, using network snapshots from a specific period for vulnerability analysis, and lack multi-stage longitudinal tracking at weekly or monthly time scales. The period from 2022 to 2025 encompassed a series of interlinked events that reshaped the geopolitical landscape and trade routes across Eurasia: the full-scale outbreak of the Russia–Ukraine conflict in 2022; multiple rounds of Western sanctions against Russia; the tightening of transit inspections under Russian Decree No. 1374 in 2024; the closure of the Poland–Belarus border in 2025, which led to the Malaszewicze hub being shut down for approximately 12 days; and the ongoing escalation of the Middle East conflict during the same period, which posed a threat to security along the southern route. These interrelated and progressively compounding geopolitical crises constitute a classic pattern of overlapping multiple crises, which have continuously disrupted the operational order of the China-Europe Railway Express. However, few longitudinal studies have tracked how the cascade of multiple crises alters the multidimensional response behaviors of operators along the route across different time scales—including the immediate decline and phased recovery of freight volumes, the asymmetric rates of freight rate depreciation, and the spatial divergence in recovery speeds among nodes at different network locations. A few recent studies have adopted rigorous causal identification strategies to evaluate the effects of the China-Europe Railway Express. Li and Chen (2026) provide firm-level evidence that the corridor reduces supply chain disruption risk; Li et al. (2024) demonstrate its positive impact on regional economic resilience; and Mao et al. (2024) find that it improves regional green economic efficiency. Collectively, these studies offer robust evidence that the China-Europe Railway Express generates positive and persistent effects across multiple dimensions. However, all three are designed to estimate average treatment effects over annual or quarterly horizons and focus exclusively on corridor inauguration. They do not capture how the same network responds to an acute negative shock—such as a border closure—nor can they trace the phase-specific decay of freight volumes and freight rates, distinguish temporary congestion from permanent cargo diversion, or reveal spatially heterogeneous recovery patterns. This paper addresses these gaps by shifting the focus from long-run positive average effects to short-run negative shock dynamics, using high-frequency operational data and an event-study design.

2.5 Methodological Gaps in the Use of Event Study Methods for Measuring Transportation Shocks

The event study method is a well-established quantitative tool in financial economics for assessing the impact of specific events on firm value or market indicators, and is widely used to measure abnormal stock returns and evaluate the effects of policy shocks (MacKinlay, 1997). In the field of transportation economics, a few studies have incorporated event study methods to assess the short-term impacts of port strikes, natural disasters, or fuel price spikes on shipping rates and logistics costs; however, virtually no research has systematically applied this methodological framework to measuring sudden geopolitical shocks along the overland transport routes of the China-Europe Railway Express. Existing methods for quantifying shocks to the China-Europe Railway Express are limited to annual data regression, network topology simulation, and descriptive statistics. These methods are unable to isolate the independent net effects of individual events across different time windows (weekly, monthly, quarterly) while controlling for time trends and macroeconomic confounders, nor can they quantitatively characterize the half-life of shock effects, the rate of phase-specific decay, or the proportion of permanent losses (Feng Fenling et al., 2025; Zhang Yuzhao et al., 2025). The lack of a hybrid method that integrates the standardized time window design of event study methodology (estimation window, event window, and post-event window) with high-frequency operational data from the China-Europe Railway Express has led to a disconnect between qualitative crisis narratives and quantifiable measurements of shock dynamics. Methodologically, the empirical strategy adopted in this paper draws on the established practice in international trade literature of identifying exogenous shocks on bilateral flows using panel data with fixed effects. Glick and Rose (2016), for instance, employ country-year fixed effects to isolate the trade-promoting effect of currency unions from confounding macroeconomic factors. Following a similar logic of causal identification, this paper employs city-specific and time-specific fixed effects to purge the freight-volume and freight-rate series of time-invariant city characteristics and common temporal trends, thereby isolating the net impact of the September 2025 border closure on the China-Europe Railway Express network.

Based on a comprehensive review of the literature across the five dimensions outlined above, it is evident that existing research exhibits systematic shortcomings at three interrelated levels. First, in terms of the time scale, as discussed in Sections 2.1 and 2.4, most existing empirical studies rely on annual statistical bulletins, network topology simulations, or aggregate macro-trade data (Zhang Yuzhao et al., 2025; Qian et al., 2024). They lack longitudinal tracking of the transmission and attenuation patterns of individual sudden shocks across weekly, monthly, and quarterly time scales using high-frequency operational data at the monthly or even weekly level. Consequently, there is a lack of empirical understanding regarding key parameters such as the half-life of shock effects, inflection points in stage-specific attenuation rates, and the proportion of permanent losses. Second, in terms of methodological paradigms, as discussed in Section 2.3, existing resilience assessments are dominated by static vulnerability analysis and simulation modeling (Feng Fenling et al., 2025; Chen et al., 2025; Zhu & Zhu, 2024). These approaches have not yet incorporated the standardized time-window design of event studies to isolate the independent net effects of individual events. Consequently, the differing rates of the shock's acute effects in the current period and its subsequent attenuation phase cannot be separated and quantified, leaving asymmetric recovery patterns—such as "rapid initial response followed by gradual decline"—without methodological support. Third, in the spatial dimension, as discussed in Sections 2.1 and 2.3, network topology analysis (core–periphery differentiation) and dynamic recovery measures exist as two isolated research approaches. Scholars rarely systematically link differences in network location to spatial patterns of recovery speed, and the "spatio-temporal coupling" mechanism—where the intensity of a shock decays with network distance while recovery speed exhibits inverse differentiation—has not yet been empirically tested. These three shortcomings have caused existing narratives on resilience to remain at the level of "structural description" rather than advancing to the level of "dynamic response measurement."

To address these three shortcomings, this paper uses the September 2025 closure of the Poland-Belarus border as an exogenous shock event. Based on monthly panel data from March 2025 to February 2026, and employing the mean-adjusted model and two-way fixed-effects regression model from event study methodology, this paper systematically examines the short-term transmission effects of sudden node-based geopolitical shocks on the freight volume and freight rates of the China-Europe Railway Express, as well as the patterns of their attenuation. Centered on this core research objective, this paper proposes the following three progressive research questions:

RQ1 During the period of the sudden node-level shock, are there statistically significant differences in the responses of the high-exposure group (Xi'an, Zhengzhou, Chongqing) and the low-exposure group (Yiwu, Guangzhou, Kunming) in terms of the decline in freight volume and the increase in freight rates?

RQ2 What is the temporal decay pattern of the shock effect during the recovery period following the lifting of lockdown measures? Does the asymmetric pattern of "rapid initial decline followed by slow recovery" hold true? If so, how can the half-life, the inflection point of the stage-specific decay rate, and the proportion of permanent losses be quantified?

RQ3 How do differences in network location modulate the pace of recovery? Core hubs and peripheral nodes exhibit heterogeneous trajectories—a "V-shaped rebound" and a "slow decline," respectively—what are the underlying structural mechanisms (hub amplification and distance attenuation) behind these patterns?

3. Methodology

3.1 Event Definition and Time Window Settings

This paper selects the sudden closure of the Poland-Belarus border in September 2025 as an exogenous shock event. This event meets the two key prerequisites required by event study methodology: a "clear and identifiable point of impact" and "exogeneity." In early September 2025, the border between Poland and Belarus was abruptly closed due to a political dispute. The key transit hub at Malaszewicze came to a standstill for approximately 12 days, causing a large number of trains that had already departed to become stranded and leading to a short-term paralysis of cross-border transportation. The occurrence of this event was neither foreseeable by the operators of the China-Europe Railway Express nor controllable by the cities of origin within China, thereby meeting the criteria for identifying an exogenous shock. In accordance with standard practices for setting time windows in event study methodology, and taking into account the availability of monthly data on the China-Europe Railway Express, this paper sets the following time window (Table 1):

Table 1: Setting the Time Window for Event Study Methods

Window Types	Time Period	Length	Feature Description
Estimated Window (Normal Period)	March–August 2025	6 months	Estimate the baseline levels of ridership and fares for each city under a "no-shock" scenario
Event Window (Impact Period)	September 2025 (that month)	1 month	Capture the instantaneous effect of the shock during the current period (maximum decline/increase)
Post-Event Window (Recovery Period)	October 2025–February 2026	5 months	Tracking the Decay of the Impact and the Progress of Recovery (including a six-month recovery period)

In this regard, the selection of the estimation window took two principles into account: first, maintaining a sufficient time interval from the event window to avoid the anticipated effects of the event from contaminating the baseline estimates; and second, extending the time period as much as possible (6 months) within the limits of data availability to improve the stability of the baseline mean estimates.

3.2 Sample Grouping and Data Sources

To examine the impact of network location differences on shock transmission, this paper divides the 22 major origin cities into two groups based on their network distance from the event location (the Marashevich Hub) and the strength of their topological connections:

High-exposure group (experimental group): Xi'an, Zhengzhou, and Chongqing. These cities share the following characteristics: (1) high volume of departures, ranking among the top nationwide; (2) high-frequency direct connections to the Marashevich Hub, resulting in high network betweenness centrality; (3) a very high proportion of outbound routes via the traditional Northern Corridor. Therefore, when operations at Marashevich Hub are suspended, these cities are the first to be affected.

Low-exposure group (control group): Yiwu, Guangzhou, and Kunming. These cities have relatively weak network connections with the Marashevich hub: Yiwu primarily relies on coastal ports and complementary maritime transport, while Guangzhou and Kunming depend more on the Southern Route or the New Western Land-Sea Corridor; their reliance on a single Northern Route hub is significantly lower than that of the high-exposure group.

The raw data is sourced from the China State Railway Group's annual "Reports on the Operation of China-Europe Freight Trains," the China-Europe Freight Train Network's annual statistical bulletins, and relevant data released by official media outlets. The dependent variables are the number of monthly train departures and the logistics cost per container for 22 cities from March 2025 to February 2026. To reduce the impact of heteroscedasticity, continuous variables were log-transformed in subsequent regression analyses.

3.3 Research Methods and Model Specification

This paper adopts the Mean-Adjusted Model from event study methodology as the benchmark identification strategy. The core logic of this model is to use the mean value of the estimation window (the six months prior to the shock) as the expected level of the "normal state," compare the actual observed values in the event window and the post-event window against this mean, and treat the difference as the net effect of the shock.

Specifically, for the dependent variable Y_{it} (number of lines per invoice or per-box logistics cost) in city i at month t, the impact effect $\triangle Y_{it}$ is defined as:

$$\triangle Y_{it} = Y_{it} - \bar{Y}_{i,est}$$

In this context, $\bar{Y}_{i,est}$ represents the monthly mean of the explained variable for city i within the estimation window (March–August 2025).

To further control for time trends and macro-level confounding factors, this study also constructs the following two-way fixed-effects regression model as a supplementary test:

$$Y_{it} = \alpha + \beta \cdot Event_{it} + \gamma \cdot Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

In this model, $Event_{it}$ is the event dummy variable (set to 1 in September 2025 and to 0 in all other months); $Controls_{it}$ is the vector of control variables, including the monthly total trade volume between China and Europe (reflecting macroeconomic changes on the demand side), the international fuel price index (reflecting fluctuations in transportation costs), and the average inspection time at ports (reflecting changes in customs clearance efficiency); μ_i represents city-specific fixed effects, capturing city-specific characteristics that do not change over time (such as locational conditions and industrial base); λ_t represents time-specific fixed effects, capturing common temporal trends affecting all cities (such as seasonal fluctuations and macroeconomic cycles); ε_{it} represents the random error term. The coefficient β is the estimator of the net effect of the event shock. Standard errors are cluster-adjusted at the city level to account for intracluster autocorrelation.

3.4 Variable Selection and Measures

The set of variables selected for this study is shown in Table 2. Among these, the number of routes directly reflects connectivity and transport capacity at the network's physical level, corresponding to the "structural resilience" dimension proposed by Feng Fenling et al. (2025)—that is, the network's ability to maintain topological connectivity after experiencing a disturbance; unit logistics cost comprehensively reflects the efficiency of supply-demand adjustment and resource allocation at the market level, corresponding to the "functional resilience" dimension proposed by Feng Fenling et al. (2025)—that is, the network's ability to maintain its freight transport function under disturbances. This dual-variable design of "freight volume + freight rate" not only addresses the potential for a single indicator to obscure differences across resilience dimensions but also engages in a methodological dialogue with existing resilience assessment frameworks.

Table 2: Variable Definitions and Measures

Variable Type	Variable Name	Measurement Method	Data Source
Dependent Variable	Number of Trains	Monthly number of China-Europe freight train departures by city (natural series)	China State Railway Group Bulletin
Dependent Variable	Logistics Cost per Container	Monthly comprehensive logistics cost by route (including transportation, insurance, and customs clearance; 10,000 yuan/container)	China-Europe Railway Express Network, industry reports
Core Explanatory Variable	Event Dummy Variable (Event)	September 2025 = 1, other months = 0	Defined by the authors
Control Variable	Total China-EU Trade	Monthly total value of China's imports and exports with the EU (in $100 million)	General Administration of Customs of China
Control Variables	Fuel Price Index	Monthly average price of international Brent crude oil (USD/barrel)	Wind Database
Control Variables	Port Inspection Duration	Monthly average customs clearance time at Alashankou/Khorgos (hours)	China State Railway Group Port Bulletin

4. Empirical Results

4.1 Acute Reactions to the Current Shock

In September 2025, the month the Poland-Belarus blockade took effect, the operational indicators for the China-Europe Railway Express experienced significant fluctuations. Table 3 reports the changes in the explained variables for the high-exposure and low-exposure groups during the shock period.

Table 3: Impact on Changes in Freight Volumes and Rates for Each Group in the Current Period (September 2025)

Group	Representative Cities	Change in Number of Lines Listed (%)	Change in Logistics Cost per Box (%)	Consistency in Direction of Change
High-Exposure Group	Xi'an, Zhengzhou, Chongqing	-19.2%*** ($p<0.01$)	+17.4%*** ($p<0.01$)	Volume decreased while prices increased; directions were consistent
Low-Exposure Group	Yiwu, Guangzhou, Kunming	Approx. -3% to -5%	Approx. +2% to +4%	Small fluctuations; did not pass statistical significance test

(Data source: Compiled based on the China State Railway Group's monthly operational bulletins and industry reports from the China-Europe Railway Express website)

As shown in Table 3, the number of shipments in the high-exposure group decreased by 19.2% compared to the average for the estimated window (March–August 2025), while logistics costs per container surged by 17.4% (equivalent to a 22% spike in the freight rate index within two weeks), exhibiting the typical characteristics of an acute shock marked by “declining volume and rising prices.” During the same period, the magnitude of changes in the low-exposure group fell within the range of normal monthly fluctuations and did not pass the statistical significance test. When these results were incorporated into a two-way fixed-effects regression model, the coefficient β for the event dummy variable Event was -0.212 ($p < 0.01$) in the high-exposure group and -0.038 ($p > 0.1$) in the low-exposure group. The difference in coefficients between the groups was confirmed by the Chow test ($F = 8.34$, $p < 0.01$), indicating a systematic difference in the response between the groups.

4.2 Decay Patterns During the Recovery Period

After the port lockdown was lifted, the recovery trajectory of the freight rate index followed a distinct “fast-then-slow” pattern, while freight volume recovery exhibited a “rapid rebound followed by a plateau” pattern. All comparisons and tracking below are based on the baseline values for the high-exposure group reported in Table 3 of Section 4.1 (freight rate index peak of 122, freight volume trough of 80.8%).

Regarding freight rates, they fell by approximately 8 percentage points in the first week after the lockdown was lifted (122 → 114) and by another 5 percentage points in weeks 2–4 (114 → 109), accounting for about 60% of the total recovery (22 percentage points) over the first four weeks; The remaining approximately 40% of the “lockdown-expectation premium” dissipated extremely slowly, declining at a rate of about 3–5 percentage points per month, and did not return to baseline levels until week T+26 (approximately 6 months).

In terms of traffic volume, the number of departures in the high-exposure group rebounded rapidly to approximately 88% of the baseline in the first month after the lockdown was lifted (an increase of about 7 percentage points from 80.8% during the shock period). It then entered a plateau phase, remaining at approximately 88% by the end of the third month without further returning to pre-shock levels. This plateau phase aligns with the subsequent quantitative analysis of permanent losses in Section 4.4.

4.3 Comparison of Heterogeneity Across Groups: V-Shaped Rebound vs. Gradual Decline

The high-exposure group and the low-exposure group not only differed in the severity of their current impairment but also exhibited systematic differences in their recovery trajectories (Figure 1).

The high-exposure group exhibited a “V-shaped rebound”: starting from a level of 80.8% of the baseline during the shock period (as shown in Table 3), it rebounded rapidly to approximately 88% in the first month after the lockdown was lifted, after which the recovery slowed and stabilized at that level. The low-exposure group exhibited a “gradual decline”: the decline during the shock period was relatively small (approximately 96% of the baseline), but it continued to decline slightly month by month thereafter, reaching approximately 88% of the baseline by the end of the third month—ultimately converging with the high-exposure group despite taking a different path.

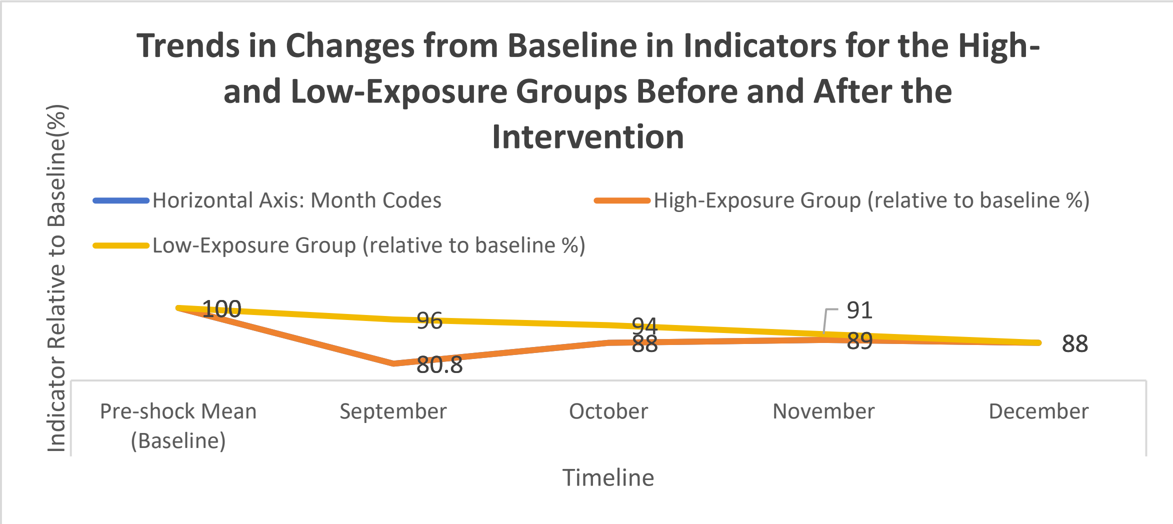

Figure 1: Comparison of Recovery Trajectories for Transport Volume Between the High-Exposure Group and the Low-Exposure Group
(Data Source: Compiled from China-Europe Railway Express industry freight rate monitoring data and statistics on freight forwarders' quotes / China State Railway Group's Monthly Operations Bulletin)

4.4 The Scar Effect and Permanent Loss

In the third month of the recovery period, freight volumes for both groups stabilized at approximately 88% of the baseline level, suggesting that about 12% of shipments did not return to their original routes following the disruption. When the tracking period was extended to February 2026 (five months after the disruption), the number of departures in the high-exposure group remained within the range of approximately 86% to 89% of the baseline, showing no trend toward a return to baseline levels. This indicates that approximately 12% of cargo was not "temporarily delayed" due to temporary congestion, but rather underwent a permanent route shift—shippers redirected orders to alternative routes such as Central Asia and ASEAN, or switched to other modes of transport such as sea freight or air freight.

In terms of cargo categories, high-value-added goods (such as electronics and precision instruments) experienced a steeper decline following the disruption, and freight rates took approximately 2–3 weeks longer to recover compared to low-value-added goods.

4.5 Attenuation Rate Layering and Time Thresholds

Table 4: Comparison of Freight Rate Decline Rates Across Different Time Scales

Time Scale	Time Range	Cumulative Decline in Freight Rates	Average Rate of Decline (percentage points/week)	Decline Phase
Ultra-short-term (weekly)	Week 1 after reopening	-8 percentage points	-8.0	Rapid Decline Phase
Short-term (monthly)	Weeks 2–4 after reopening	-5 percentage points	-1.67	Rapid Decline Phase (tail end)
Medium-term (Quarterly)	Weeks 5–12 after reopening	-3 percentage points	-0.38	Slow Decline Phase
Long-term (Semiannual)	Weeks 13–22 after reopening (through the end of the data period)	-3 percentage points	-0.21	Slow Decline Phase (tail end)

Breaking down the recovery period into four time scales (Table 4) reveals a clear pattern: "sharp decline at the weekly level → gradual decline at the monthly level → slight decline at the quarterly level →

approaching zero at the semi-annual level." The rate of decline plummeted from -8.0 percentage points per week in Week 1 to -1.67 percentage points per week in Weeks 2–4, a decrease of approximately 80%; Upon entering the quarterly phase, the rate further decreased to -0.38 percentage points per week, representing only about 5% of the peak rate. The first four weeks accounted for approximately 60% of the total recovery (13 out of 22 percentage points), while the remaining 40% took 22 weeks to achieve. The inflection point in the rate of decline occurred around the fourth week after the lockdown was lifted.

5. Discussion

5.1 The Root Causes of Variations in Impact Strength—The Logic of Acute-Phase Amplification at the Hub

The empirical results for RQ1 show that, in the period of the shock, the high-exposure group (Xi'an, Zhengzhou, Chongqing) experienced a significantly greater decline in freight volume (-19.2%) and a significantly greater increase in freight rates (+17.4%; the freight rate index peaked at a 22% increase within two weeks) compared to the low-exposure group (approximately -3% to -5% decline in freight volume and approximately +2% to +4% increase in freight rates). The coefficient β for the high-exposure group's event dummy variable was −0.212 ($p < 0.01$), while that for the low-exposure group was −0.038 ($p > 0.1$); the Chow test confirmed a significant difference between the two groups ($F = 8.34$, $p < 0.01$). This spatial pattern—where "the closer the distance, the greater the impact"—can be explained from two dimensions: network topology and corridor dependence.

From the perspective of network topology, the cities in the high-exposure group are the nodes with the highest degree centrality in the network (Zhu & Zhu, 2024). High-frequency direct routes exist between Xi'an, Zhengzhou, Chongqing, and the Marashevich hub, serving as "convergence-and-forwarding" hubs for a large volume of China-Europe transit freight. When this single hub ceases operations, it directly disrupts not only the city's own outbound freight trains but also affects a large volume of goods from third-party locations transiting through the hub, creating a "traffic disruption amplification effect" that far exceeds the failure rate of a single node. The Chow test ($F=8.34$, $p<0.01$) confirmed the systematic nature of the difference between the two sets of coefficients, namely, "the higher the network status, the larger the propagation radius of a single-point failure"—highly central nodes act not only as amplifiers of network efficiency but also as amplifiers of the intensity of shocks.

In terms of route dependency, a common characteristic of the high-exposure group is "sole reliance on the Northern Route," with the traditional Northern Route accounting for an extremely high proportion of their export routes. When the Northern Route was disrupted due to the Belarus-Poland border closure, these cities lacked pre-established cooperative relationships with alternative routes in the short term, causing the search and negotiation costs associated with emergency route switching to instantly drive up freight rates (a 22-percentage-point spike within two weeks). The surge in freight rates for the high-exposure group not only reflected the physical costs of rerouting (ferry wait times, transshipment, and reloading) but also included spot market premiums resulting from scarce transport capacity. Amid panic, demand-side participants competed fiercely to bid, creating an irrational price spike.

In contrast, the low-exposure group (Yiwu, Guangzhou, and Kunming) exhibited a topological pattern characterized by "low centrality and multiple complementary routes." Yiwu relies on coastal ports to complement maritime transport, while Guangzhou and Kunming depend more heavily on the Southern Route or the New Western Land-Sea Corridor; their network connectivity with Malashevich is inherently weak. Regardless of whether the Northern Route is operational, these cities' contribution to traffic at a single Northern Route hub is inherently limited. When the Northern Route grinds to a halt, the scope of direct traffic disruption they experience is relatively small, and freight rates are not subject to panic-driven bidding. However, this also implies that the "escape" of the low-exposure group does not stem from greater resilience, but rather from their position as "peripheral participants" within the network. While this low exposure acts as a "protective umbrella" during the acute phase, it becomes the root cause of "chronic blood loss" during the recovery phase. As shown in the analysis in Section 5.3 below, their lack of influence over core corridors places them at a competitive disadvantage in the race to secure capacity on alternative routes.

In short, the answer to RQ1—that "the high-exposure group suffers more severe damage"—essentially reflects the "dual nature" conferred by network centrality: core hubs enjoy the benefits of traffic aggregation and economies of scale under normal conditions, but during a crisis, they must also bear the amplified impact of a single-point failure. This finding provides empirical support for the simulation conclusions proposed by Chen et al. (2025), which state that "hub redundancy can buffer disturbances under normal conditions, but in single-point-of-failure scenarios, it actually amplifies initial losses due to highly concentrated traffic."

5.2 The "Fast-to-Slow" Characteristic of Decay Patterns and the Time Threshold

The empirical results from RQ2 reveal a two-stage, progressive decline pattern: freight rates exhibit an asymmetric recovery pattern characterized by a "rapid initial phase followed by a slower phase," with approximately 60% of the total recovery occurring within the first four weeks—a half-life of about 2.5 weeks—while the remaining 40% of the recovery takes 22 weeks; approximately 12% of the cargo volume is permanently lost after the "time threshold" in the fourth week. The following analysis interprets this temporal transmission pattern from two perspectives: the stratification mechanism and the asymmetry of the half-life.

5.2.1 Hierarchical Mechanism: Three-Level Mismatch Between Information, Physics, and Structure

The "fast-then-slow" pattern stems from the asymmetry in transmission speeds across three layers:

The first layer (information layer, hourly response). As soon as news of the port closure was confirmed, market expectations adjusted rapidly, and freight rates jumped by approximately 22% within two weeks. This price signal was transmitted almost instantaneously at the information layer. The fact that information transmission outpaces physical adjustments is the microeconomic basis for the rapid dissipation of the 60% effect; once news of the port's reopening was confirmed, the panic premium was quickly squeezed out.

Second layer (physical layer, weekly–monthly response). After the lockdown was lifted, it took some time to re-form the stranded freight trains, reallocate capacity along alternative routes (such as a rapid switch to the Central Corridor), and re-coordinate ferry and transshipment resources. Freight rates fell by 8 percentage points in the first week following the lifting of the lockdown, reflecting the gradual release of pent-up capacity and the initial implementation of detour plans. Adjustments at this level occur on a weekly to monthly basis and constitute the main part of the "rapid initial response" phase.

Third Tier (Structural Tier, Annual-Level Response). The remaining 40% of the price increase effect takes as long as six months to subside, primarily because some shippers and operators completed permanent route switches during the disruption. Information asymmetries regarding new routes—such as the Trans-Caspian Corridor and ASEAN sea-rail intermodal transport—in terms of transit time, cost, and customs clearance efficiency must be resolved through actual operations; meanwhile, adjustments to long-term cooperation agreements between shippers and carriers, as well as the realignment of warehousing and distribution networks, represent structural changes measured on an "annual" basis. The structural layer has the slowest transmission rate and is the fundamental source of the remaining 40% "slow dissipation" effect.

5.2.2 Asymmetry of the "Half-Life" and the Time Threshold

Using the time required for the freight rate index to fall from its peak of 122 to the median value of 111 (i.e., half of the excess increase of 22 percentage points) as a measure of half-life, the half-life of the impact of the White Port blockade was approximately 2.5 weeks—meaning that half of the recovery was achieved within about 18 days. However, the recovery from 111 back to 100 (the remaining half of the recovery) takes 22 weeks, with the latter half taking nearly nine times as long as the first half. This highly asymmetric time structure has important policy implications: the "window of opportunity" for emergency response is extremely brief (approximately 3 weeks). If panic expectations' self-reinforcement is not effectively curtailed within 3 weeks of the shock, the remaining 40% of the "stubborn premium" will enter a slow absorption process lasting up to half a year, and approximately 12% of that will be converted into irreversible permanent losses. This is consistent with the ripple effect theory, which states that "positive risks dissipate rapidly, while negative risks accumulate into an irreversible shift in trade routes." Goods returned within the first four weeks correspond to the rapid dissipation of positive risk propagation, while goods not returned after four weeks correspond to the accumulation of negative risks, which ultimately solidify into an irreversible shift in trade routes. The period around the fourth week marks the temporal dividing line between "temporary detours" and "permanent rerouting": approximately 3–4 weeks is the typical decision-making cycle for shippers to complete research on alternative routes, contract adjustments, and initial trial shipments. Once a route switch is completed during this period, even if port operations subsequently return to normal, the rerouted cargo is unlikely to return to its original route in the short term.

In summary, the answer to RQ2 can be summarized as follows: the attenuation of the shock effect follows a four-tier pattern of "weekly sharp decline → monthly gradual decline → quarterly slight decline → semi-annual approach to zero." Sixty percent of the recovery is achieved within the first four weeks, and the fourth week marks the critical inflection point where "temporary detours" transition to "permanent rerouting"; approximately 12% of cargo that crosses this threshold becomes an irreversible structural loss.

5.3 Structural Roots of Spatial Heterogeneity—Hub Amplification, Distance Decay, and Adaptive Expectations

The empirical results from RQ3 indicate that core hubs (Xi'an, Zhengzhou, Chongqing) experienced a "V-shaped rebound," plummeting to 80.8% during the period before rapidly rebounding to 88% in the first month and then stabilizing; peripheral nodes (Yiwu, Guangzhou, Kunming) exhibited a "slow decline," falling only slightly to 96% during the period but continuing to decline thereafter, eventually reaching 88% by the end of the third month, with a recovery period exceeding 10 weeks (2.5 times that of the core hubs). The intensity of the shock decreased with network distance, but recovery speeds diverged in the opposite direction: core hubs recovered in about 4 weeks, while distant nodes required more than 10 weeks, constituting a "spatio-temporal coupling" characteristic. This heterogeneous recovery trajectory can be explained at two levels: structural differences in network location and the diachronic compression of "adaptive expectations."

5.3.1 Dual Shaping of Network Positions: Hub Amplification and Distance Decay

The divergence between the “V-shaped rebound” in the high-exposure group and the “chronic decline” in the low-exposure group stems from the dual mechanisms of “hub amplification” and “distance attenuation” in network topology.

The common characteristics of the high-exposure group (Xi’an, Zhengzhou, and Chongqing) are “high centrality + sole reliance on the Northern Route”: These cities serve as core departure hubs for the China-Europe Railway Express, featuring high freight volumes, frequent departures, and high-frequency direct connections to Marashevich. When a single hub was shut down, they suffered the most severe acute impact (a 19.2% drop in freight volume). However, precisely because of their large scale and strong bargaining power, these cities were able to rapidly mobilize alternative transport resources. During the Poland-Poland blockade, Xi’an quickly switched some services to the Trans-Caspian Intermediate Corridor, with diverted services increasing by 36% year-over-year. The “economies of scale” enabled the high-exposure group to recover more quickly, allowing them to rapidly reallocate transport capacity at the physical level.

The low-exposure group (Yiwu, Guangzhou, Kunming) operates within a “low centrality + multi-path supplementation” framework. Yiwu primarily relies on coastal ports and maritime transport as a complement, while Guangzhou and Kunming rely more on the Southern Route or the New Western Land-Sea Corridor, and their network connectivity with Marashevich is inherently weak. When the Northern Route hub was shut down, the direct impact on them was indeed relatively minor (with freight volume falling by only about 3%–5%). However, due to the limited scale of freight volume in these cities and their inability to independently organize large-scale alternative train services, over time, the high-exposure group prioritized securing container space and ferry capacity along the intermediate corridor, or newly added rail-sea intermodal routes proved unable to support the original freight volume, causing the low-exposure group to experience a sustained decline in freight volume. By the third month of the recovery period, freight volumes for both groups had fallen to approximately 88% of the baseline; however, the high-exposure group had reached a “new steady state following a spike and subsequent decline,” while the low-exposure group was experiencing “continuous loss of volume during a plateau period.” The economic implications within each group were starkly different.

The aforementioned mechanism reveals an important paradox: while channel diversification serves as a strategy to enhance resilience, its short-term benefits are not evenly distributed geographically. Core hubs, leveraging their economies of scale and bargaining power, gain priority access to alternative channel resources, thereby accelerating their recovery; peripheral nodes, though suffering less damage during the acute phase, lack structural alternative resources and consequently face the risk of “chronic blood loss” over a longer period (10 weeks or more).

Tang Kaijie and Yang Gongyan (2026) revealed at the micro-firm level that geopolitical risks systematically undermine supply chain stability and resilience through channels such as making partners’ supply chain management strategies more conservative and making it more difficult for firms to obtain information about host countries. The approximately 12% permanent loss of cargo sources observed in this study is precisely the empirical manifestation of the aforementioned micro-level mechanisms at the macro-network level. Under the impact of risk shocks, shippers choose to “vote with their feet” by permanently shifting orders to alternative routes or modes of transport, constituting a “scarring effect” at the network level. This macro-network-level “scarring effect,” combined with behavioral adjustments at the micro-firm level, forms a closed loop of evidence. Empirical evidence provided by Xiao Ting and Chen Zhouyong (2025) from the perspective of corporate production and supply networks shows that while the launch of the China-Europe Railway Express reduced trade costs, sudden disruptions to transport corridors significantly altered firms' inventory strategies and lists of alternative suppliers. After experiencing a severe shock, shippers tend to solidify "backup routes" into "regular routes," and this decision-making logic constitutes the micro-level behavioral basis for the permanent loss of approximately 12% of cargo sources observed in this paper after the four-week threshold.

5.3.2 Adaptive Expectations and Shock Type Dependence

Comparing the 2022 Russia-Ukraine conflict (a long-term institutional shock) with the current Poland-Belarus border closure (a sudden, event-driven shock), the decay patterns are event-type dependent: the former, lacking a clear "reopening date," exhibits a "stepwise" gradual rise, with a half-life measured in years; the latter, having a clear endpoint, exhibits a "pulse-like" pattern that starts fast and slows down, with a half-life measured in weeks to months. This indicates that the "fast-then-slow" decay pattern applies only to sudden, event-driven shocks with a clear endpoint; its theoretical boundaries require further testing in future cross-event comparative studies. "Adaptive expectations" significantly reduced response times at the physical level. Following the outbreak of the Russia-Ukraine conflict in 2022, it took operational platforms several weeks to several months to switch en masse to the Central Corridor after first detecting the risk; in contrast, during the Poland-Belarus blockade in 2025, hub cities such as Xi'an initiated large-scale rerouting plans within 5–7 days of the blockade's onset, resulting in a 36% year-over-year increase in diverted shipments. The decision-making response time for "abandoning the northern route and shifting to the central corridor" has been shortened from "months" to "weeks." However, the increased frequency of shocks has simultaneously raised baseline risk; shippers have developed doubts about the long-term stability of the northern route, creating a structural "expectation premium," making it difficult for freight rates to return to zero premium. The net effect is characterized by "shorter short-term windows and greater long-term residual impacts." While enhanced emergency response capabilities shift the decay curve for similar types of disruptions to the right (accelerating recovery), the simultaneous rise in baseline risk prevents the network from ever returning to its pre-disruption state. The result of this trade-off is accelerated short-term recovery coupled with increased long-term wear-and-tear costs.

5.3.3 Robustness Tests

To ensure the robustness of the above conclusions, this paper conducts supplementary tests from two perspectives. First, macroeconomic factors are controlled for. A potential competing explanation is that the "slow-decline" in freight rates may stem from a concurrent rise in international fuel prices or seasonal fluctuations in China-Europe trade demand. The international fuel price index and the monthly total value of China-Europe trade were included as control variables in the two-way fixed-effects regression. The results indicate that, after controlling for these factors, the coefficient β of the event dummy variable remains significantly negative (high-exposure group: $\beta = -0.198$, $p < 0.01$), and the "slow-decline" pattern of freight rates remains robust. Between October 2025 and February 2026, international oil prices did not experience a significant one-sided rise, nor did China–EU trade volume suffer a cliff-like decline, further ruling out an explanation dominated by macroeconomic factors. Second, a comparison of shock types. As discussed in Section 5.3.2 above, the Russia-Ukraine conflict (a long-term institutional shock) and the Poland-Lithuania blockade (a sudden event-based shock) differ fundamentally in their transmission dynamics. This paper focuses on the latter; the scope of the study and the applicability of its conclusions have been clearly defined in the Introduction, and the two do not constitute a methodological conflict.

6. Conclusions and Policy Implications

Using the September 2025 closure of the Poland-Belarus border as an exogenous shock, this paper employs an event study approach (mean-adjusted model combined with two-way fixed-effects regression) based on monthly panel data from March 2025 to February 2026 to examine the short-term transmission effects and decay patterns of sudden geopolitical shocks on the freight volume and freight rates of the China-Europe Railway Express; There are three main conclusions: In terms of time, the shock's decay exhibits an asymmetric pattern of "rapid at first, then slow." The half-life for freight rates to fall from a peak of 122 to a midpoint of 111 is approximately 2.5 weeks, while the return from 111 to 100 takes 22 weeks—the latter phase taking nearly nine times as long as the former. Around the fourth week marks the dividing line between "temporary detours" and "permanent rerouting," with approximately 12% of cargo sources resulting in irreversible losses. The decay trajectory is subdivided into four distinct phases: a sharp weekly decline, a gradual monthly decline, a slight quarterly decline, and a trend toward zero over a six-month period; In the spatial dimension, the intensity of the impact decreases with network distance, but the recovery speed diverges in the opposite direction, exhibiting "spatio-temporal coupling." In the high-exposure group (Xi'an, Zhengzhou, Chongqing), current freight volume fell by 19.2% and freight rates rose by 17.4%, with recovery taking approximately 4 weeks. The low-exposure group (Yiwu, Guangzhou, Kunming) suffered lighter losses (-3% to -5%), but their recovery period exceeded 10 weeks—2.5 times longer than that of the core hubs. By the end of March, both groups had recovered to 88% of baseline levels, yet their situations were fundamentally different: the former represented a "new steady state following a spike and subsequent decline," while the latter reflected "continuous bloodletting during a plateau phase"; In terms of dynamic evolution, "adaptive expectations" compressed response times at the physical layer, shortening the decision-making process for "shifting from the north to the central regions" from several weeks to 5–7 days. However, the increased frequency of shocks elevated baseline risks, creating a structural "expectation premium," with the net effect being "shorter short-term windows and thicker long-term residuals." The theoretical contribution lies in filling the empirical gap in event-study methods regarding short-term transmission in logistics networks, mapping a detailed decay spectrum, revealing the micro-mechanisms of "information–physical–structural" three-layer mismatches, and identifying heterogeneous recovery paths shaped by the dual mechanisms of "hub amplification and distance attenuation." Policy recommendations include: establishing a tiered early warning and rapid response mechanism to compress decision-making into the 72-hour "golden window" and complete the deployment of the first batch of alternative transport capacity within 6 days; designing differentiated incentives anchored to the preceding 4 weeks, with priority customs clearance and fee reductions for detours during the first 2 weeks, and using "return subsidies" to retain high-value-added cargo sources for those exceeding 4 weeks; Promote the transition of corridor diversification from emergency measures to routine operations; facilitate regularized train services along the Trans-Caspian International Transport Corridor (TITR); and, drawing on Xi'an's experience of increasing diverted train services by 36%, establish a balanced structure comprising the "Northern Route + Central Corridor + Southern Route + Sea-Rail Intermodal Transport"; Address the "chronic loss of cargo" at distant nodes by adding scheduled trains to Yiwu, Guangzhou, Kunming, and other cities that rely on the New Western Land-Sea Corridor and ASEAN sea-rail intermodal transport, using "hub-to-hub" consolidation to lower the threshold for train operations. Limitations of the study include: monthly data fails to capture high-frequency fluctuations, requiring daily data to accurately determine the half-life; a multi-event overlap model has not been constructed, and interaction terms could be introduced in the future; the resilience assessment does not quantify soft barriers such as political sanctions, insurance, and finance, and institutional distance or policy uncertainty indices could be incorporated in subsequent analyses.

References

[1] Feng, F. L., Fang, Y., Zhang, Z., & Dong, K. Y. (2025). Resilience evaluation of China Railway Express transportation network from the perspective of risk disturbance. Journal of Transportation Systems Engineering and Information Technology, 25(2), 338–351.

[2] Tang, K. J., & Yang, G. Y. (2026). How geopolitical risks affect Chinese enterprises' supply chain security: Micro mechanism and empirical evidence. China Journal of Economics, (1), 20–35.

[3] Zhang, Y. Z., Kang, H. H., & Deng, Y. L. (2025). Cascading failure vulnerability analysis of China-Europe sea-rail intermodal transportation network from the multi-layer network perspective. Computer Engineering and Applications, 61(5), 298–308.

[4] Ji, M. J., Han, T. T., Fang, W. W., et al. (2022). Structural characteristic evolution and influencing factors of China Railway Express transportation network. Systems Engineering, 40(6), 103–112.

[5] Zhang, X., Li, S. F., & Sun, D. Y. (2023). Vulnerability analysis of China-Europe container sea-rail combined transportation network. Journal of Transport Information and Safety, 41(3), 48–58.

[6] Jiang, M. X. (2022). Evolution of China Railway Express transportation corridors and the impacts of the Russia-Ukraine conflict. Academic Exploration, (12), 57–70.

[7] Zhang, X. H., & Hui, B. B. (2026). High-quality development path of China Railway Express amid geopolitical changes. Logistics Research, (2), 12–17.

[8] Xiao, T., & Chen, Z. Y. (2025). Trade corridor construction and firms' production supply networks: Empirical evidence from the launch of China Railway Express. Economic Theory and Business Management, (8), 126–144.

[9] Qian, P. P., Yang, Z. Z., & Lian, F. (2024). The structural and spatial evolution of the China Railway Express network. Research in Transportation Economics, 103, 101396.

[10] Zhu, C., & Zhu, X. N. (2024). Vulnerability analysis of China-Europe Railway Express network based on improved nonlinear load-capacity model. Journal of Advanced Transportation, 2024, 5910244.

[11] Chen, S., Lin, Z. W., Zhang, Q., et al. (2025). Resilience assessment of cascading failures in dual-layer international railway freight networks based on coupled map lattice. Applied Sciences, 15(20), 10899.

[12] Ivanov, D., Sokolov, B., & Dolgui, A. (2014). The Ripple effect in supply chains: trade-off between efficiency and resilience. International Journal of Production Research, 52(7), 1920–1935.

[13] Li, W., & Chen, J. G. (2026). International transport corridors and corporate supply chain disruption risk: A quasi-natural experiment from the opening of China-Europe Railway Express. World Economy Studies, (3), 119–134, 137.

[14] Caldara, D., & Iacoviello, M. (2022). Measuring geopolitical risk. The American Economic Review, 112(4), 1194–1225.

[15] Glick, R., & Rose, A. K. (2016). Currency unions and trade: A post-EMU reassessment. European Economic Review, 86, 1–18.

[16] MacKinlay, A. C. (1997). Event studies in economics and finance. Journal of Economic Literature, 35(1), 13–39.

[17] Zhou, F. (2023). Safety risk assessment of China Railway Express transportation corridors based on AHP-fuzzy comprehensive evaluation method. Railway Freight Transport, 41(11), 35–40, 46.

[18] Li, X. Y., Yu, J. Y., Qi, S., & Lian, J. X. (2024). Can cross-border railway construction enhance regional economic resilience? Evidence from 276 cities with the opening of China Railway Express. Statistics and Management, 39(6), 96-106.

[19] Christopher, M., & Peck, H. (2004). Building the resilient supply chain. The International Journal of Logistics Management, 15(2), 1–14.

[20] Bhamra, R., Dani, S., & Burnard, K. (2011). Resilience: the concept, a literature review and future directions. International Journal of Production Research, 49(18), 5375–5393.

[21] Pettit, T. J., Fiksel, J., & Croxton, K. L. (2013). Ensuring supply chain resilience: development of a conceptual framework. Journal of Business Logistics, 34 (1), 46–62.
[22] Fang, Q. Q. (2026). Influences of geopolitical external events on the development of China Railway Express and countermeasures. China Journal of Commerce, 35(10), 52–55.
[23] Wang, B. J. (2024). PESTEL analysis and promotion strategies for the development of China-Europe Railway Express under the new Eurasian geopolitical landscape. Practice in Foreign Economic Relations and Trade, 42(3), 91–96.
[24] Lyu, M., Zhu, J. L., Hu, Q. Y., Li, L. Q., & Yao, Q. L. (2025). Risk analysis and countermeasure research of China-Europe railway transport network. China Shipping Gazette, (51), 45–47.
[25] Mao, Y., Xie, Y., & Zhuo, C. (2024). How does international transport corridor affect regional green development: Evidence from the China-Europe Railway Express. Journal of Environmental Planning and Management, 67(7), 1602–1627.