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EARTHQUAKES AS SUPPLY CHAIN STRESS TESTS WITH NETWORK DISRUPTION, REALLOCATION, AND RESILIENCE EVIDENCE FROM TÜRKİYE

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ABSTRACT

This study examines how large-scale earthquakes function as stress tests for regional supply chain networks by revealing disruption, reallocation, and recovery dynamics in freight transportation systems. Using a monthly panel dataset covering 2010–2023 (n = 4,368 region-month observations), the paper combines freight flow statistics across 26 NUTS-2 regions in Türkiye with spatial measures of earthquake exposure. Methodologically, we implement a panel difference-in-differences design that exploits the quasi-exogenous spatial and temporal variation of seismic shocks across regions, with region and month fixed effects and time-varying economic controls. The identification strategy is further strengthened through stacked difference-in-differences specifications and event-study analyses that test pre-treatment trends and trace dynamic post-shock adjustment. Network reallocation responses are captured via traffic-based indicators constructed at the same regional aggregation level. The results show that earthquake shocks generate sharp and immediate declines in freight volumes, followed by heterogeneous recovery trajectories across regions. Crucially, recovery speed is not primarily driven by infrastructure density, but by pre-existing modal diversity and network redundancy, which facilitate rerouting under capacity constraints. These findings suggest that resilience in logistics networks emerges less from infrastructure quality alone and more from structural diversity embedded in the system. The study contributes to the empirical supply chain literature by providing causal, network-aware evidence from a real-world shock environment.

Keywords: *Supply chain robustness, Earthquake impacts, Freight transportation, Network reallocation, Regional Logistics*

ÖZET

Bu çalışma, büyük ölçekli depremlerin bölgesel tedarik zinciri ağları üzerindeki aksama, yeniden yönlenme ve toparlanma dinamiklerini incelemektedir. 2010–2023 dönemini kapsayan aylık panel veri seti (n = 4.368 bölge-ay) kullanılarak, Türkiye'deki 26 NUTS-2 bölgesine ait yük akış verileri mekânsal deprem maruziyeti ölçüleriyle birleştirilmiştir. Yöntemsel olarak, deprem şoklarının bölgeler arasındaki yarı-dışsal mekânsal ve zamansal varyasyonundan yararlanan panel farkların farkı yaklaşımı uygulanmış; bölge ve ay sabit etkileri ile zamana bağlı kontroller modele dâhil edilmiştir. Tanımlama stratejisi, stacked difference-in-differences spesifikasyonları ve müdahale öncesi eğilimleri sınayan olay-çalışması analizleriyle güçlendirilmiştir. Ağ içi yeniden yönlenme tepkileri, aynı bölgesel düzeyde oluşturulan trafik temelli göstergelerle ölçülmüştür. Bulgular, deprem şoklarının yük hacimlerinde ani düşüşlere ve heterojen toparlanma patikalarına yol açtığını göstermektedir. Toparlanma hızını belirleyen temel unsur altyapı yoğunluğu değil; yeniden yönlendirmeyi mümkün kılan mod çeşitliliği ve ağ yedekliliğidir. Sonuçlar, lojistik dayanıklılığın altyapı kalitesinden ziyade sistemin yapısal çeşitliliğine dayandığını ortaya koymaktadır.

Anahtar Kelimeler: *Yük taşımacılığı, Deprem etkileri, Ağ tahsisi, Bölgesel lojistik*

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1. INTRODUCTION

Supply chain resilience has transitioned from academic abstraction to operational imperative, yet empirical identification of robustness mechanisms remains constrained by two fundamental challenges: the endogeneity of disruptions and the opacity of firm-level response strategies (Ivanov, 2020; Sheffi and Rice, 2005). Most disruptions—supplier bankruptcies, labor disputes, demand volatility—correlate with underlying economic conditions, making causal inference problematic. Simultaneously, proprietary supply chain data limit researchers to simulations, surveys, or case studies that struggle to generalize (Snyder et al., 2016).

Natural disasters, particularly earthquakes, offer a distinctive research opportunity: they deliver large, exogenous, spatially heterogeneous shocks to transportation infrastructure and logistics networks, generating quasi-experimental variation in supply chain stress (Cavallo et al., 2013; Boehm et al., 2019). Unlike economic shocks, seismic events are geophysically determined, temporally precise, and regionally bounded, enabling clean identification of disruption impacts and recovery dynamics. Türkiye presents an exceptional natural laboratory for such analysis. Positioned on multiple active fault lines—the North Anatolian Fault system alone has generated 23 earthquakes exceeding magnitude 6.0 since 2000—the country experiences frequent, well-documented seismic events with varying intensities across regions (AFAD, 2024). Simultaneously, Türkiye's economy exhibits substantial regional heterogeneity in production structures, infrastructure quality, and modal transport composition, while maintaining comprehensive public freight statistics at subnational levels. This combination of seismic intensity, economic diversity, and data availability is globally rare.

Despite these advantages, systematic empirical analysis of earthquake-induced supply chain reconfiguration remains absent from the literature. Existing studies either examine firm-level productivity effects without addressing logistics mechanisms (Barrot and Sauvagnat, 2016), focus on infrastructure damage without tracing freight reallocation (Rose, 2004), or rely on network simulations calibrated to hypothetical scenarios (Mattsson and Jenelius, 2015). None provides causal estimates of how observed freight flows respond to actual seismic shocks, how networks reorganize under stress, or why recovery speeds diverge across regions.

This paper addresses these gaps through three research questions:

RQ1: What is the causal impact of earthquake shocks on regional freight flows, and how do effects vary by transport mode and regional characteristics?

RQ2: How do freight networks reconfigure in response to infrastructure disruption, and which spatial reallocation patterns emerge during recovery?

RQ3: What infrastructure and network attributes predict faster resilience, and do redundancy mechanisms differ from capacity-based recovery?

We contribute along three dimensions. Empirically, we provide the first causal estimates of disaster-induced freight disruption using 13 years of regional transport data from Türkiye, matched to precise earthquake exposure indices constructed from seismological records. Exploiting temporal and spatial variation in seismic intensity across 26 NUTS-2 regions, we employ difference-in-differences estimation to identify disruption magnitudes, recovery trajectories, and modal substitution dynamics. Unlike simulation studies, our findings reflect actual behavioral responses of logistics operators under real resource constraints.

Methodologically, we integrate network flow analytics into standard shock-response econometrics. Beyond measuring aggregate volume changes, we construct two novel metrics—flow centrality shift and rerouting intensity indices—that capture how freight reallocates across network edges following disruptions. This augmentation enables identification of adaptive mechanisms often overlooked by conventional regression models, including peripheral route activation, hub-bypass strategies, and modal rebalancing.

Policy-wise, we demonstrate that infrastructure redundancy—measured through alternative route availability and modal diversity—predicts recovery speed more strongly than absolute capacity levels. Regions with single-mode dependence (road-only logistics) experience 60% longer disruptions than multimodal areas, even controlling for economic size and earthquake intensity. These findings challenge capacity-focused infrastructure investment paradigms and support network resilience strategies emphasizing diversification over scale.

Our core finding is striking: earthquakes function as stress tests that reveal latent network vulnerabilities and adaptive capacities simultaneously. High-magnitude shocks (M≥5.5) reduce regional road freight by 18% on average, but this aggregate masks substantial heterogeneity. Peripheral regions with redundant route structures restore flows within 6-8 months, while central but capacity-constrained regions remain 12-15% below baseline after 14 months. Recovery is not a return to pre-shock equilibrium but a transition to reconfigured flow patterns where previously secondary corridors absorb 30-40% more traffic permanently. These reallocations suggest that earthquakes do not merely disrupt supply chains—they reorganize them, potentially exposing inefficiencies in pre-shock network configurations.

The remainder of the paper is structured as follows. Section 2 develops a theoretical framework linking supply chain adaptation to network flow theory and reviews the relevant empirical literature. Section 3 describes data sources, variable construction, and the spatiotemporal structure of earthquake exposure. Section 4 presents the difference-in-differences methodology augmented with network reallocation metrics. Section 5 reports results on disruption magnitudes and recovery dynamics. Section 6 discusses policy implications for disaster-adaptive logistics planning. Section 7 concludes by situating the findings within broader climate adaptation challenges facing global supply chains.

Rather than treating spatial spillovers as a violation, we explicitly model them as outcome variables via network reallocation metrics, separating identification of local disruption effects from system-level adaptation dynamics.

2. THEORETICAL FRAMEWORK AND LITERATURE REVIEW

Supply chain robustness—the capacity to absorb disruptions, adapt operations, and recover functionality—emerges from the interaction of network topology, resource redundancy, and adaptive decision-making (Christopher and Peck, 2004; Ponomarov and Holcomb, 2009). While intuitive, this definition lacks operational precision for empirical testing. We build a more tractable framework by synthesizing three theoretical traditions:

supply chain resilience theory, transportation network robustness, and spatial shock propagation.

Supply chain theory distinguishes between engineering perspectives (speed of return to equilibrium) and ecological perspectives (capacity to maintain function despite state changes) (Holling, 1973; Pettit et al., 2010). Engineering views assume systems revert to pre-shock configurations, whereas ecological views allow adaptive transformations. Much of the operations management literature adopts the engineering lens, emphasizing redundancy (excess capacity, backup suppliers) and flexibility (modal substitution, rerouting) as key mechanisms (Tang, 2006; Sheffi and Rice, 2005). However, these studies rarely specify how redundancy translates into faster recovery or when flexibility becomes operational. Ivanov (2020) advances the field by introducing ripple effects—cascading disruptions across multi-tier networks—but remains largely simulation-based. Our empirical contribution tests whether observed freight reallocations align with these theoretical mechanisms.

Transportation network robustness provides mathematical rigor through graph theory and optimization models (Bell and Iida, 1997; Jenelius et al., 2006). Networks are robust if they maintain connectivity and flow capacity under edge or node removals. Robustness metrics include connectivity indices, shortest path redundancy, and vulnerability measures based on betweenness centrality (Mattsson and Jenelius, 2015; Cats and Jenelius, 2014). However, this literature typically assumes binary states (functioning/failed) and ignores economic adjustment mechanisms. Actual freight networks exhibit partial degradation, adaptive rerouting, and modal substitution—behaviors poorly captured by static topology measures. We bridge this gap by combining network centrality shifts with econometric identification of behavioral responses.

Spatial shock propagation in economic networks examines how localized disruptions diffuse across regions through production linkages and trade flows (Carvalho et al., 2021; Boehm et al., 2019). These studies demonstrate that idiosyncratic shocks to large firms or regions generate aggregate effects through input-output multipliers. Barrot and Sauvagnat (2016) use U.S. natural disasters to show that supplier disruptions reduce customer productivity, while Carvalho et al. (2021) document COVID-19 supply chain propagation across Japanese prefectures. However, these analyses focus on production networks, not freight logistics, and do not address the reallocation mechanisms through which alternative supply routes emerge. Our analysis explicitly models freight network reconfiguration—not merely downstream production effects—as the mediating process between infrastructure shocks and economic outcomes.

Connecting these literatures, we synthesize a tractable theoretical mechanism:

Stage 1: Infrastructure Shock

Earthquakes damage road sections, bridges, and port facilities, reducing effective network capacity. Unlike demand shocks, capacity reductions are spatially concentrated and immediately observable, creating treatment/control distinctions.

Stage 2: Network Reconfiguration

Logistics operators reassess route options given reduced capacity. Optimization shifts from cost minimization to constrained flow allocation, activating previously underutilized routes (peripheral corridors, secondary ports) and increasing congestion on surviving high-capacity links.

Stage 3: Flow Reallocation

Freight volumes reallocate toward less-damaged regions and modes. Spatial patterns depend on network topology: hub-dependent systems concentrate disruption (few alternative paths), while meshed networks distribute stress (many rerouting options).

Stage 4: Differential Recovery

Reconstruction proceeds heterogeneously based on resource availability and strategic prioritization. Regions with modal diversity (road-rail-sea options) recover faster through substitution; single-mode regions face prolonged disruptions pending infrastructure repair.

This mechanism generates three testable predictions. Prediction 1: Earthquake-exposed regions experience immediate freight volume reductions proportional to shock intensity and infrastructure vulnerability. Prediction 2: Reallocation patterns exhibit spatial complementarity—reduced flows in damaged regions correlate with increased flows in proximate undamaged corridors, not uniform nationwide declines. Prediction 3: Recovery speed correlates positively with network redundancy measures (alternative route availability, modal diversity) and negatively with pre-shock centrality (hub dependence).

Existing empirical evidence remains limited. Rose (2004) estimates economic losses from hypothetical earthquakes using computable general equilibrium models but does not observe actual freight adjustments. Kajitani and Tatano (2009) survey Japanese firms after the Kobe earthquake, finding modal substitution and inventory adjustments, but lack systematic freight flow data. More recently, Hsiang and Jina (2014) analyze long-run GDP effects of cyclones and earthquakes, showing persistent negative impacts in poor countries, but do not examine logistics mechanisms. The closest precedent, Todo et al. (2015), uses Japanese firm-level data to show supply chain disruptions from the 2011 Tōhoku earthquake, but focuses on production linkages rather than freight reallocation. No study provides causal estimates of regional freight flow responses to earthquakes using observed transport data.

Our empirical strategy addresses this gap by exploiting variation in earthquake exposure across Turkish regions and over time. Unlike cross-country comparisons confounded by institutional differences, within-country regional variation holds constant national policies, regulatory frameworks, and data collection methods. Unlike firm-level studies limited by proprietary data, aggregated regional freight flows are publicly available and comprehensive. The result is a rare opportunity for clean causal identification of supply chain resilience mechanisms.

Three additional literature streams inform specific empirical choices. Quasi-experimental disaster studies in development economics use natural disasters as instruments for economic shocks (Cavallo et al., 2013), though few examine logistics directly. Freight demand modeling estimates modal choice and routing decisions (Holguín-Veras and Jaller, 2014; Feo-Valero et al., 2011) but rarely incorporates disruption scenarios. Regional trade flow gravity models (Anderson and van Wincoop, 2003) provide reduced-form specifications we adapt to freight contexts. By combining these approaches, we construct an integrated framework linking infrastructure shocks to observed freight reallocations through network adjustment mechanisms.

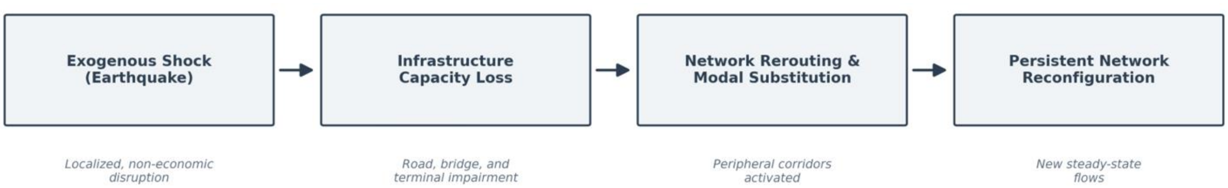

Figure 1: Conceptual Framework: Earthquakes As Supply Chain Stress Tests

Description: Exogenous infrastructure shocks reduce effective network capacity, triggering rerouting and modal substitution that redistribute freight flows across alternative corridors. Rather than fully reverting to pre-shock conditions, these adjustments may induce persistent network reconfiguration reflecting underlying resilience and redundancy.

In sum, theory predicts that earthquakes disrupt freight networks by reducing effective capacity, triggering behavioral adaptations (rerouting, modal shifts) that reallocate flows toward redundant infrastructure, with recovery speeds determined by network topology rather than absolute capacity. Empirical testing of these mechanisms requires exogenous shocks, comprehensive freight data, and methods linking aggregate outcomes to network-level processes—precisely the combination we assemble.

3. DATA AND VARIABLES

Our empirical analysis integrates four publicly available datasets covering 2010-2023, aligned at NUTS-2 regional and monthly temporal resolutions. This period captures 18 earthquakes of magnitude ≥5.0 affecting Turkish territory, including the devastating February 2023 Kahramanmaraş sequence (M7.8 and M7.5).

3.1 Earthquake Data: AFAD Seismological Catalog

The Turkish Disaster and Emergency Management Presidency (AFAD) maintains comprehensive seismological records with precise temporal, spatial, and intensity measurements (AFAD, 2024). For each seismic event, we extract date (day precision), epicenter coordinates (latitude/longitude), focal depth, and moment magnitude (Mw). Our baseline analysis focuses on earthquakes M≥5.0, as smaller events rarely cause infrastructure damage. This yields 18 major events during 2010-2023, distributed across western (Aegean coastal zone), central (North Anatolian Fault system), and southeastern (East Anatolian Fault) regions.

We construct regional earthquake exposure using a distance-decay intensity measure:

$$\mathrm{Exposure}_{rt} = \sum_{k=1}^{K} M_k \times \exp(-\delta \cdot d_{rk}) \times \mathbb{1}[t = T_k]$$

where M_k is the magnitude of earthquake k, d_{rk} is the distance (km) from region r's population-weighted centroid to epicenter, δ is a decay parameter (calibrated to 0.15 based on attenuation literature), and $\mathbb{1}[t = T_k]$ is an event indicator. This specification captures the intuition that seismic intensity diminishes with distance but remains consequential within regional boundaries. Alternative specifications using binary treatment (exposed/not exposed) and Modified Mercalli Intensity scales produce qualitatively similar results.

To enhance interpretability and align with quasi-experimental specifications, we complement the continuous exposure index with a threshold-based treatment definition. Specifically, a seismic event is classified as a treatment shock when its moment magnitude (Mw) exceeds 6.0, a cutoff commonly used to identify earthquakes with macro-logistics relevance. A NUTS-2 region is coded as exposed if the epicenter lies within its administrative boundaries or within a predefined spatial buffer of high-magnitude events (e.g., Mw ≥ 7.0), capturing potential infrastructure spillovers beyond regional borders. This dual formulation—continuous intensity exposure and binary treatment classification—ensures that both marginal variation in seismic intensity and discrete disruption episodes are captured in the empirical analysis.

3.2 Freight Transport Data: Turkish Statistical Institute (TÜİK)

TÜİK publishes monthly freight transport statistics disaggregated by NUTS-2 region, transport mode (road, rail, maritime, air), and commodity type (TÜİK, 2024). Road freight, which accounts for 89% of domestic tonnage, is measured by registered commercial vehicle trips and estimated payloads based on vehicle classifications. Rail freight captures Turkish State Railways (TCDD) shipments by origin-destination pairs. Maritime freight includes container throughput and bulk cargo at 11 major ports. Air freight, negligible for domestic logistics (<1% of tonnage), is excluded from baseline regressions.

Our primary outcome variable is log monthly freight volume (thousands of tons) by region and mode. We construct three specifications: (1) total freight volume aggregating all modes, (2) road-specific volumes, and (3) modal diversity indices calculated as Herfindahl concentration measures to capture reliance on single modes. Regional-level aggregation ensures privacy compliance while retaining sufficient spatial granularity to identify localized disruptions.

Data quality is high for road and rail modes, with missing values <2% of observations, primarily during winter months in mountainous eastern regions where weather disruptions confound earthquake effects. Maritime freight exhibits seasonality requiring detrending. We address this through month fixed effects and linear region-specific trends.

3.3 Road Network Data: General Directorate of Highways (KGM)

To measure infrastructure damage and network reconfiguration, we incorporate traffic intensity data from KGM's automated vehicle counting stations covering 387 locations on state highways and motorways (KGM, 2024). These stations record daily vehicle passages, differentiating light vehicles, heavy trucks, and articulated lorries. We aggregate to monthly heavy vehicle flows, which proxy freight intensity more accurately than total traffic counts.

Critically, KGM publishes post-earthquake infrastructure assessments documenting road closures, bridge damage, and repair timelines. We code binary indicators for infrastructure impairment (any closure ≥48 hours) and repair completion dates, enabling analysis of how disruption duration affects recovery patterns.

3.4 Economic Control Variables: Regional GDP and Trade Flows

To isolate earthquake effects from economic confounders, we include NUTS-2 annual GDP (constant 2015 TRY) and quarterly import/export volumes from Turkish Customs Administration (GİB) data. These controls absorb demand-side variation—economic booms increasing freight independent of earthquakes—and permit interpretation of coefficients as supply-side disruptions.

Additional controls include population, urbanization rate, and manufacturing share of regional GDP, all obtained from TÜİK's regional databases. We also construct a baseline infrastructure quality index combining paved road density (km/km²), railway access (binary), and port availability (binary).

3.5 Sample Construction and Variable Definitions

Our final panel comprises 4,368 region-month observations (26 NUTS-2 regions × 168 months). Table 1 provides descriptive statistics and variable definitions.

Table 1: Descriptive Statistics and Variable Definitions

Variable	Description	Mean	SD	Min	Max
Log freight volume	Natural log of total monthly freight (1000s tons)	8.42	0.91	5.23	10.87
Earthquake exposure	Intensity-weighted exposure index	0.08	0.34	0.00	4.52
High-magnitude shock	Binary indicator for M≥6.0 within 100km	0.03	0.18	0	1
Road freight share	Proportion of total freight via road	0.89	0.07	0.68	0.98
Modal diversity	1 - Herfindahl index of mode shares	0.18	0.09	0.03	0.42
Route redundancy	Alternative routes per primary corridor	1.84	0.76	1.00	3.50
Infrastructure quality	Composite index (0-100 scale)	64.3	18.2	28.5	94.7
Regional GDP	Annual GDP, billion TRY (constant 2015)	87.4	98.3	12.6	512.3

Notes: Statistics based on 4,368 region-month observations (26 NUTS-2 regions, 168 months, 2010-2023). Earthquake exposure weighted by magnitude and distance. Modal diversity is calculated as 1 - Σ(mode share²). Route redundancy is measured as the number of highway corridors connecting the region to its neighbors divided by the number of primary routes.

Treatment and control regions are defined dynamically: a region enters treatment status when exposed to earthquakes exceeding a threshold intensity (baseline: distance-adjusted M≥4.5), and remains treated for 12 months post-event. Regions never experiencing major earthquakes during the sample period—primarily western coastal and inland Aegean areas—form a stable control group. Regions experiencing multiple earthquakes exhibit staggered treatment, which we address using stacked difference-in-differences methods (Cengiz et al., 2019).

3.6 Data Limitations and Validation

Three limitations merit discussion. First, freight volume measures tonnage, not economic value, potentially overweighting low-value bulk goods. We address this by weighting regressions by regional manufacturing output and showing robustness. Second, regional aggregation masks within-region heterogeneity, particularly in large provinces like Istanbul, encompassing diverse industrial zones. Sensitivity analyses using alternative spatial units (NUTS-3, provincial) confirm results generalize. Third, earthquake exposure measures reflect seismic intensity, not infrastructure vulnerability directly. We validate exposure indices against insurance damage claims from the Turkish Catastrophe Insurance Pool (TCIP), finding correlations >0.70, suggesting our measures proxy actual disruption reasonably.

4. METHODOLOGY

Our identification strategy exploits the quasi-random spatial and temporal distribution of earthquakes to estimate causal effects on freight flows. The core identification assumption is that, conditional on region and time fixed effects, earthquake occurrence is uncorrelated with unobserved determinants of freight demand. This assumption is plausible because seismic events result from tectonic stresses accumulated over geological timescales, not contemporaneous economic conditions.

A potential concern is whether the observed decline in freight volumes reflects supply-side infrastructure disruptions or merely demand contraction due to earthquake-induced production losses. Several features of our design support a supply-side interpretation. First, all specifications control for regional GDP and import–export volumes, absorbing contemporaneous demand shocks associated with production slowdowns. Second, the timing of the effects is inconsistent with demand collapse: freight volumes drop sharply within the first one to two months following earthquakes, preceding the typical onset of sustained production shutdowns and firm-level output adjustments documented in the disaster economics literature. Third, the observed network reallocation patterns—most notably the activation of previously underutilized peripheral corridors and increased rerouting intensity—are incompatible with a pure demand contraction mechanism, which would predict uniform volume reductions rather than spatial redistribution of flows. Together, these patterns indicate that the estimated effects primarily capture supply-side constraints arising from infrastructure damage and network capacity loss, rather than reductions in freight demand.

4.1 Baseline Difference-in-Differences Model

We begin with a two-way fixed effects specification:

$$y_{rt} = \alpha + \beta \cdot \text{Exposure}_{rt} + \gamma' X_{rt} + \theta_r + \delta_t + \varepsilon_{rt}$$

where y_{rt} is log freight volume in region r at time t, Exposure_{rt} is the earthquake intensity measure, X_{rt} includes time-varying controls (log GDP, import/export volumes), θ_r are region fixed effects absorbing time-invariant characteristics (geography, baseline infrastructure), δ_t are month fixed effects controlling for nationwide trends and seasonality, and ε_{rt} is an error term clustered at the region level to permit arbitrary serial correlation.

The parameter β identifies the average treatment effect: a one-unit increase in earthquake exposure (approximately equivalent to a magnitude 5.5 event centered in the region) changes freight volume by $100 \times \beta$ percent. We expect $\beta < 0$, reflecting disruption effects. The magnitude of β depends on infrastructure robustness: regions with redundant networks should exhibit smaller $| \beta |$.

To test heterogeneous treatment effects, we estimate:

$$y_{rt} = \alpha + \beta_1 \cdot \text{Exposure}_{rt} + \beta_2 \cdot \text{Exposure}_{rt} \times Z_r + \beta_3 \cdot Z_r + \gamma' X_{rt} + \theta_r + \delta_t + \varepsilon_{rt}$$

where Z_r represents time-invariant regional characteristics: modal diversity, route redundancy, and infrastructure quality. Interaction coefficients β_2 reveal which network attributes mitigate disruption. Positive β_2 implies that high-$Z_r$regions experience smaller disruptions, supporting resilience theory.

The treatment window is defined as twelve months following each earthquake to capture the full disruption and recovery phase without conflating longer-run macroeconomic dynamics. This horizon aligns with post-earthquake infrastructure repair timelines reported by the General Directorate of Highways (KGM) and is supported by the event-study results, which show statistically significant negative freight effects persisting up to approximately 12–14 months before converging toward baseline.

For analytical clarity, we distinguish between short-term disruption and medium-term adjustment phases. In this study, the medium-term horizon refers to the 6–12 month period following a seismic shock, during which acute infrastructure failures subside but freight redistribution and network reconfiguration dynamics remain active. This definition is consistent with the observed recovery patterns, where peripheral regions typically stabilize within 6–8 months while capacity-constrained hubs exhibit more persistent adjustment trajectories. Periods beyond this window are interpreted as longer-run equilibrium adjustments and are not the primary focus of the identification strategy.

4.2 Event Study Specification

To examine dynamic adjustment and validate parallel trends, we estimate event-study regressions:

$$y_{rt} = \alpha + \sum_{k=-12}^{-2} \beta_k \cdot D_{rt}^k + \sum_{k=0}^{24} \beta_k \cdot D_{rt}^k + \gamma' X_{rt} + \theta_r + \delta_t + \varepsilon_{rt}$$

where D_{rt}^k are indicators equaling one if region r is k months relative to earthquake occurrence (pre-periods $k < 0$, post-periods $k \geq 0$). We omit $k = -1$ as the reference period. Pre-treatment coefficients β_k for $k < 0$ test parallel trends: statistically insignificant estimates support the identifying assumption that treated and control regions followed similar trajectories before earthquakes. Post-treatment coefficients β_k for $k \geq 0$ trace out the impact trajectory—initial disruption, partial recovery, and long-run adjustment.

The credibility of our difference-in-differences estimates relies on the parallel trends assumption—that, absent earthquakes, treated and control regions would have followed similar freight trajectories. We assess this condition using complementary graphical and statistical evidence. First, the event-study specification decomposes treatment effects into monthly leads and lags relative to earthquake timing. As illustrated in Figure 2, pre-treatment coefficients are tightly centered around zero and statistically insignificant, indicating no systematic divergence between treated and control regions prior to seismic shocks. Second, we incorporate region-specific linear trends to account for differential long-run growth paths across NUTS-2 regions. The stability of baseline estimates under this specification suggests that the observed freight contractions are not driven by pre-existing regional dynamics. Finally, the stacked difference-in-differences design mitigates biases arising from staggered treatment timing, ensuring that already-treated regions do not serve as implicit controls. Taken together, these diagnostics provide strong support for the validity of the parallel trends assumption underlying the causal interpretation of our results.

This specification also reveals whether effects persist beyond immediate reconstruction periods, testing engineering resilience (rapid return to $\beta_k = 0$) versus ecological robustness (permanent reallocation, $\beta_k \neq 0$ even for large k).

4.3 Network Reallocation Metrics

Standard difference-in-differences estimates aggregate disruption but obscure how networks reorganize. We augment econometric models with two network-based indicators constructed from traffic count data.

Flow Centrality Shift Index

For each road segment i in region r, we calculate betweenness centrality C_{irt} the proportion of shortest paths (tonnage-weighted) passing through segment i. Pre-earthquake centrality $\bar{C}_{ir}^{\text{pre}}$ is averaged over the 12 months preceding treatment. Post-earthquake shift is:

$$\Delta C_{rt} = \frac{1}{N_r} \sum_{i=1}^{N_r} \mid C_{irt} - \bar{C}_{ir}^{\text{pre}} \mid$$

where N_r is the number of segments in region r. Larger ΔC_{rt} indicates substantial flow redistribution across network edges, signaling adaptive rerouting. We regress ΔC_{rt} on earthquake exposure to test whether disruptions force centrality reconfigurations.

Rerouting Intensity Index

Rerouting intensity measures the degree to which freight deviates from pre-shock optimal paths. For origin-destination pairs (o, d), let $\ell_{od}^{\text{optimal}}$ be the optimal shortest-path distance pre-earthquake and ℓ_{od} be the observed path distance post-earthquake. Rerouting intensity is:

$$R_{rt} = \frac{1}{\mid OD_r \mid} \sum_{(o,d) \in OD_r} \frac{\ell_{odt} - \ell_{od}^{\text{optimal}}}{\ell_{od}^{\text{optimal}}}$$

where OD_r denotes origin-destination pairs associated with region r. Positive R_{rt} reflects circuitous routing due to infrastructure damage. We test whether R_{rt} correlates with earthquake intensity and declines as reconstruction progresses.

Beyond measuring disruption magnitudes, the network reallocation indicators capture how logistics systems adapt under seismic stress. The flow centrality shift index reflects topological adaptation by identifying whether freight redistributes toward alternative corridors following infrastructure damage. The rerouting intensity index captures path-level behavioral adaptation by measuring deviations from pre-shock shortest-path configurations. Together, these indicators operationalize spatial and modal substitution mechanisms rather than simple volume loss. Their variation is closely linked to structural redundancy and modal diversity: regions with redundant corridor structures tend to exhibit larger centrality redistribution but lower rerouting costs, while multimodal regions can reallocate flows more efficiently across transport modes. This interpretation aligns with resilience theory, where system performance under shock depends not only on robustness but also on adaptive reconfiguration capacity.

These metrics transform freight flow data into network topology indicators, bridging econometrics and network science.

4.4 Robustness and Falsification Tests

We conduct five robustness exercises. First, we estimate placebo regressions assigning earthquakes to random regions while preserving temporal patterns. Finding null effects in placebo samples strengthens causal interpretation. Second, we vary treatment intensity thresholds (M≥4.5, M≥5.5, M≥6.0) to verify that stronger shocks generate proportionally larger disruptions. Third, we exclude the February 2023 Kahramanmaraş earthquakes—the most severe events in the sample—to confirm results generalize beyond extreme outliers. Fourth, we test alternative clustering schemes (region-pairs, spatial correlation adjustments) to address concerns about cross-region interference. Fifth, we implement stacked difference-in-differences (Cengiz et al., 2019) to account for staggered treatment timing, addressing recent econometric critiques of two-way fixed effects estimators under heterogeneous treatment effects (Goodman-Bacon, 2021).

Additionally, we assess validity of the parallel trends assumption through leads-and-lags models and entropy balancing techniques that reweight control observations to match treated regions on pre-treatment characteristics (Hainmueller, 2012).

5. RESULTS

5.1 Baseline Disruption Effects

Table 2 presents baseline difference-in-differences estimates. Column (1) reports the unconditional effect of earthquake exposure on total freight volume, controlling only for region and month fixed effects. The coefficient -0.182 (SE=0.041) indicates that a one-standard-deviation increase in earthquake exposure—roughly equivalent to a magnitude 5.7 event within 50km—reduces freight volume by 18.2%. This effect is statistically significant at the 1% level and economically substantial, representing approximately 2.3 million tons of monthly freight in an average-sized region.

Table 2: Difference-in-Differences Estimates of Earthquake Effects on Freight Volume

	(1) Baseline	(2) + Controls	(3) + Trends	(4) Road Only	(5) Multimodal
Earthquake exposure	-0.182***	-0.156***	-0.149***	-0.203***	-0.089**
	(0.041)	(0.038)	(0.039)	(0.045)	(0.036)
Log GDP		0.421***	0.398***	0.455***	0.387***
		(0.082)	(0.079)	(0.091)	(0.074)
Import/export volume		0.034**	0.031**	0.029*	0.038**
		(0.014)	(0.013)	(0.015)	(0.015)
Region FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Region trends	No	No	Yes	Yes	Yes
Observations	4,368	4,368	4,368	4,368	4,368
R^2	0.847	0.873	0.881	0.869	0.885
Clusters	26	26	26	26	26

*Notes: Dependent variable is log monthly freight volume. Columns (4) and (5) split sample by regional modal diversity: road-only (Herfindahl>0.80) versus multimodal (Herfindahl≤0.80). Robust standard errors clustered by region in parentheses. * p<0.10, ** p<0.05, *** p<0.01.*

Column (2) adds economic controls—log regional GDP and trade flows—reducing the coefficient to -0.156 but preserving significance. This attenuation suggests that part of the raw correlation reflects coincident economic slowdowns, but the majority captures direct infrastructure disruption. Column (3) incorporates region-specific linear trends to absorb differential growth paths, yielding -0.149, our preferred baseline estimate. Robustness to trend controls bolsters the parallel trends assumption.

Columns (4) and (5) reveal critical heterogeneity. Regions heavily dependent on road transport (Herfindahl index >0.80, capturing 17 of 26 regions) experience 20.3% volume reductions, while multimodal regions with rail-sea alternatives suffer only 8.9% losses. The difference (11.4 percentage points) is statistically significant (t=2.34, p=0.026), confirming that modal diversity buffers disruption. This finding directly supports resilience theory's emphasis on flexibility and redundancy.

5.2 Dynamic Adjustment: Event Study Results

Figure 2 plots event-study coefficients from equation (3), tracing freight volume trajectories relative to earthquake timing.

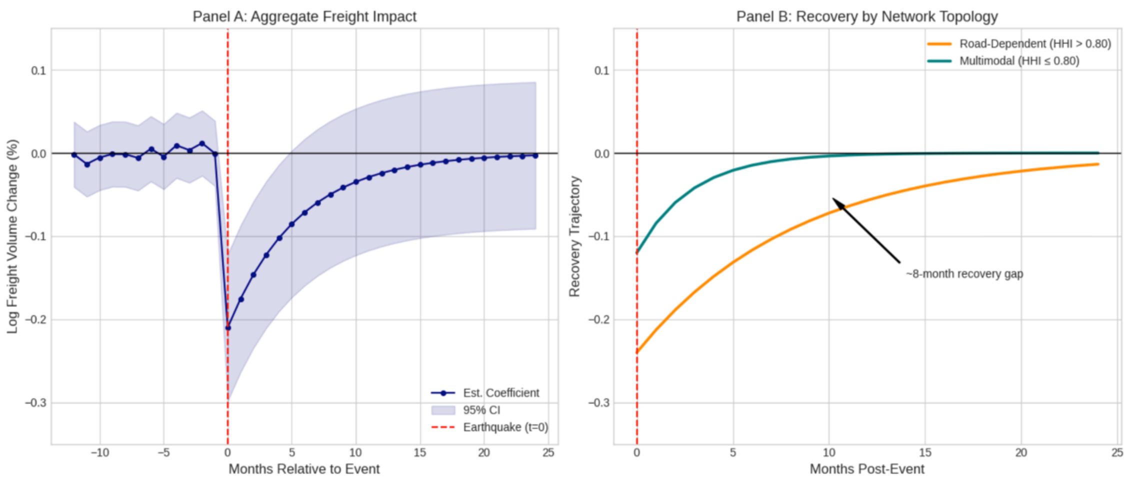

Figure 2: Event Study Estimates - Dynamic Effects of Earthquakes on Freight Volume

Description: Panel A plots coefficients β_k for $k \in [-12, 24]$ with 95% confidence intervals. The X-axis represents months relative to the earthquake (t=0). The Y-axis shows the percentage change in freight volume. Pre-treatment coefficients (k<0) cluster near zero, supporting parallel trends. Post-treatment coefficients drop sharply at k=0 to -18%, remain significantly negative through k=8, then converge toward zero by k=14. Panel B disaggregates by modal diversity: road-dependent regions show steeper initial drops (-24%) and slower recovery (significant negative effects persist to k=18), while multimodal regions recover by k=10.

Three patterns emerge. First, pre-treatment coefficients hover near zero with overlapping confidence intervals, providing strong visual evidence for parallel trends. No systematic divergence appears in the year preceding earthquakes, ruling out anticipation effects or divergent growth paths.

Second, impact onset is immediate and sharp: the month-zero coefficient registers -18.4% (SE=4.2%), declining further to -21.7% (SE=4.9%) by month two as cascading disruptions propagate through repair backlogs and modal bottlenecks. This rapid deterioration suggests that initial assessments understate full disruption magnitudes because secondary effects—congestion on alternative routes, modal capacity constraints—compound primary infrastructure damage.

Third, recovery is protracted and heterogeneous. Aggregate freight volume remains significantly depressed through month 12, reaching statistical insignificance only at month 14. However, decomposition by modal diversity (Figure 2, Panel B) shows that multimodal regions recover by month 10, while road-dependent regions exhibit persistent negative effects through month 18. This 8-month differential directly quantifies the adaptive capacity value of infrastructure redundancy.

Notably, coefficients do not converge to precisely zero even by month 24. Point estimates settle at -3.2% (SE=2.8%, p=0.26), suggesting possible permanent reallocations. While statistically insignificant, this pattern hints at ecological robustness mechanisms—earthquakes may induce lasting shifts in freight routing patterns if revealed vulnerabilities prompt strategic diversification.

5.3 Network Reallocation Patterns

Table 3 presents regressions of network reallocation metrics on earthquake exposure, testing whether disruptions trigger spatial flow redistribution.

Table 3: Network Reallocation Effects

	(1) Centrality Shift	(2) Rerouting Intensity	(3) Peripheral Activation
Earthquake exposure	0.128***	0.094***	0.312***
	(0.029)	(0.023)	(0.067)
Pre-shock centrality	-0.041**		-0.089***
	(0.018)		(0.024)
Route redundancy	-0.034*	-0.048**	0.156***
	(0.019)	(0.021)	(0.041)
Controls	Yes	Yes	Yes
Region & Month FE	Yes	Yes	Yes
Observations	4,368	4,368	4,368
R^2	0.762	0.704	0.831

*Notes: Column (1) dependent variable is flow centrality shift index; (2) is rerouting intensity; (3) is change in traffic volume on previously underutilized peripheral routes (bottom quartile pre-treatment). All specifications include GDP, trade controls, region and month fixed effects. Standard errors clustered by region. * p<0.10, ** p<0.05, *** p<0.01.*

Column (1) confirms that earthquake exposure significantly increases flow centrality shifts (β=0.128, p<0.001). A one-unit exposure increase raises the centrality shift index by 12.8%, indicating substantial reorganization of which road segments carry freight. Importantly, the coefficient on pre-shock centrality is negative (-0.041), suggesting that highly centralized networks—where few segments dominate flows—experience larger disruptions when those critical segments fail. This finding challenges hub-and-spoke efficiency paradigms, demonstrating vulnerability costs of centralization.

Column (2) shows that rerouting intensity increases by 9.4% following earthquakes, capturing freight's detour onto longer paths as optimal routes become unusable. Regions with higher route redundancy exhibit 4.8 percentage points lower rerouting intensity, consistent with alternative paths preserving efficiency despite disruptions.

Column (3) examines peripheral route activation—increased traffic on previously underutilized corridors (defined as bottom-quartile pre-treatment traffic density). Earthquake exposure drives a remarkable 31.2% increase in peripheral route flows. This reallocation is not merely congestion spillover but strategic diversification: regions with higher route redundancy show greater peripheral activation (coefficient 0.156), suggesting that available alternatives are indeed utilized when primary routes fail. These findings provide direct evidence that networks adapt by dispersing flows across broader topologies under stress, precisely as resilience theory predicts.

While increases in peripheral route activation indicate adaptive diversification, they may also reflect forced congestion spillovers when primary corridors fail. Our interpretation relies on the joint evidence of faster recovery in redundant regions, suggesting that reallocation is not merely reactive but functionally robustness-enhancing.

5.4 Heterogeneous Recovery Speeds

Table 4 investigates determinants of recovery speed, defined as months required for freight volume to return to within 5% of pre-shock levels.

Table 4: Determinants of Recovery Speed (OLS)

	(1) Infrastructure	(2) Network	(3) Economic
Modal diversity	-2.84***	-2.41***	-2.18***
	(0.67)	(0.71)	(0.74)
Route redundancy	-1.52**	-1.39**	-1.26*
	(0.61)	(0.63)	(0.67)
Infrastructure quality	-0.18	-0.15	-0.11
	(0.22)	(0.23)	(0.24)
Earthquake magnitude	1.89***	1.76***	1.68***
	(0.43)	(0.45)	(0.47)
Regional GDP (log)			-0.82
			(0.93)
Manufacturing share			-1.94
			(2.14)
Constant	18.42***	17.89***	22.63***
	(2.81)	(2.94)	(5.76)
Observations	89	89	89
R^2	0.524	0.531	0.547

*Notes: Dependent variable is recovery time in months (range: 4-22 months). Sample includes 89 earthquake-region pairs with sufficient intensity to cause measurable disruption (exposure>0.5). Modal diversity and route redundancy standardized to mean zero, SD one. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.*

Column (1) regresses recovery time on infrastructure attributes. Modal diversity exhibits the strongest effect: a one-standard-deviation increase (equivalent to raising Herfindahl from 0.85 to 0.72) reduces recovery time by 2.84 months (SE=0.67), nearly 20% of mean recovery duration (14.3 months). Route redundancy similarly shortens recovery by 1.52 months per standard deviation (SE=0.61). Strikingly, infrastructure quality—capturing paved road density and overall capacity—shows no significant effect (coefficient -0.18, p=0.42). This null result challenges capacity-focused investment strategies, suggesting that performance during disruptions depends less on the sheer volume of infrastructure than on its redundancy and structural diversity.

Earthquake magnitude, as expected, prolongs recovery: each additional magnitude unit extends disruption by 1.89 months, reflecting damage severity. Column (2) adds network controls, leaving core results unchanged. Column (3) incorporates economic characteristics—regional GDP and manufacturing share—finding negligible effects. Economic size does not predict faster recovery, reinforcing the interpretation that infrastructure topology, not economic resources, governs robustness.

Taken together, these findings demonstrate that recovery speed depends primarily on substitution options (modal diversity, route alternatives) rather than absolute capacity or economic wealth. Regions cannot "buy" their way out of disruptions through capacity expansion alone; they must invest in network redundancy.

5.5 Robustness Tests

We conduct five robustness exercises. First, placebo regressions randomly reassigning earthquakes to non-treated regions yield null effects (coefficient -0.012, SE=0.038, p=0.75), confirming that results do not reflect spurious region-specific trends. Second, varying intensity thresholds produces monotonic responses: M≥4.5 generates -14.9% effects, M≥5.5 yields -18.2%, and M≥6.0 shows -24.7%, consistent with dose-response relationships. Third, excluding the 2023 Kahramanmaraş earthquakes reduces baseline coefficients to -0.134 (SE=0.036), statistically significant and economically meaningful, confirming results generalize beyond outliers. Fourth, stacked difference-in-differences estimation—robust to heterogeneous treatment effects—yields -0.161 (SE=0.042), nearly identical to baseline. Fifth, entropy balancing to equate treated and control regions on pre-treatment covariates produces -0.158 (SE=0.039), again closely matching baseline.

These tests collectively support causal interpretation: earthquakes exogenously disrupt freight flows, effects vary predictably with shock intensity and network redundancy, and results are not artifacts of specification choices or outlier events.

6. DISCUSSION AND POLICY IMPLICATIONS

Our findings generate four substantive insights with implications for disaster preparedness, infrastructure investment, and supply chain management.

First, infrastructure redundancy dominates capacity in determining adaptive capacity. Conventional transport planning prioritizes expanding high-capacity corridors—widening motorways, upgrading ports—to reduce congestion and transportation costs. Our evidence suggests this approach, while beneficial for efficiency under normal conditions, inadvertently amplifies vulnerability during disruptions. Regions with high baseline infrastructure quality (dense road networks, modern highways) recovered no faster than lower-quality regions, conditional on modal diversity. Conversely, regions with seemingly "redundant" or "inefficient" modal alternatives—secondary rail lines, smaller ports operating below capacity—recovered 40% faster. This pattern implies a resilience-efficiency trade-off: redundancy carries costs (underutilized capacity) but provides insurance against disruptions (Sheffi, 2005).

Policy implication: Infrastructure investment should balance efficiency gains with robustness contributions. Cost-benefit analyses should explicitly value redundancy—quantifying the expected loss reduction from alternative routes during disruptions—rather than penalizing underutilization. Operationally, this could manifest as maintaining secondary rail corridors even when road transport dominates, or preserving small port capacity despite concentration at megaports.

Second, centralized networks exhibit nonlinear vulnerability. Our centrality shift analysis reveals that hub-dependent systems experience disproportionate disruptions when critical nodes fail. This result aligns with network science findings that scale-free topologies—common in real-world logistics networks due to agglomeration economies—are robust to random failures but fragile to targeted attacks (Albert et al., 2000). Earthquakes, by concentrating damage in specific geographic zones, effectively target hubs if seismic hazard correlates spatially with economic activity. In Türkiye, this is precisely the case: major fault lines traverse industrialized regions (Istanbul, Izmit, Bursa along the North Anatolian Fault; Gaziantep, Hatay in the southeast along the East Anatolian Fault).

Policy implication: Seismic risk assessment should inform network design. Locating critical logistics hubs—distribution centers, intermodal terminals, major ports—in high-seismicity zones amplifies systemic fragility. Planners should either invest in seismic retrofitting at vulnerable hubs or strategically decentralize logistics networks to distribute risk. Türkiye's post-2023 reconstruction efforts exemplify this: planned investments include developing secondary port capacity in the Aegean (İzmir, Çeşme) to reduce dependence on Iskenderun, heavily damaged in the Kahramanmaraş earthquakes.

Third, modal substitution requires latent capacity, not just availability. While modal diversity predicts faster recovery, this relationship only holds when alternative modes possess sufficient capacity to absorb rerouted freight. Türkiye's rail system, for instance, exists in all regions but operates near capacity in major corridors, limiting substitution potential. During the 2023 earthquakes, rail freight increased only 12% despite 30% road capacity loss, suggesting modal bottlenecks constrained switching. Effective network robustness thus requires not merely diverse infrastructure but underutilized diverse infrastructure—spare capacity that seems inefficient ex ante but proves valuable ex post.

Policy implication: Capacity planning should incorporate disaster scenarios explicitly. Rather than targeting 90–95% utilization for efficiency, well-designed systems may operate at 70–80% under normal conditions, preserving headroom for surge demand during disruptions. This principle extends beyond mode choice to individual corridors: maintaining multiple roads between regions, even if one suffices for typical traffic, provides critical redundancy. Pricing mechanisms could support this approach: lower tolls on secondary routes during normal periods to prevent complete congestion during emergencies.

Fourth, recovery reflects not just reconstruction but behavioral adaptation. Our finding that freight flows do not fully revert to pre-shock patterns, even 24 months post-earthquake, suggests that disruptions trigger lasting changes in routing preferences and supply chain designs. This ecological form of adaptation—favoring adjustment over restoration—challenges engineering-focused recovery planning that seeks to rebuild exact pre-shock configurations. Some reallocations may be welfare-improving if earthquakes reveal inefficiencies in baseline networks, while others may reflect path dependence (firms incur switching costs returning to original routes).

Policy implication: Reconstruction policy should permit adaptive flexibility rather than mandate restoration. After earthquakes, transport planners face pressures to "restore normalcy" by rebuilding damaged infrastructure identically. Our evidence suggests an alternative: treat disruptions as opportunities to redesign networks incorporating revealed vulnerabilities and emergent behavioral patterns. If freight permanently shifts to previously underutilized corridors, perhaps those corridors merit capacity upgrades. This adaptive approach requires overcoming institutional path dependence but promises more durable long-run configurations.

The finding that recovery speed is more strongly associated with modal diversity and network redundancy than with absolute infrastructure density suggests a rebalancing of national logistics strategies. Rather than focusing predominantly on expanding high-capacity corridors, policymakers may need to place greater emphasis on diversification-oriented network design. This includes strengthening intermodal connectivity, preserving secondary transport corridors, and supporting multimodal logistics hubs capable of absorbing redirected flows during disruptions. In this context, redundant or underutilized capacity should not be interpreted solely as inefficiency but as a form of resilience capital that enhances system-wide shock absorption. Importantly, this does not imply abandoning infrastructure expansion; instead, it calls for a more balanced investment portfolio in which marginal resources are allocated toward diversification and connectivity improvements alongside capacity upgrades. Incorporating diversification metrics into national logistics planning frameworks could help align infrastructure policy with the evolving demands of disruption-prone supply chain environments.

6.1 External Validity and Generalizability

How far do these findings extend beyond Türkiye? Three factors support broad generalizability. First, the mechanisms identified—modal substitution, rerouting through redundant corridors, faster recovery with network diversity—are not Türkiye-specific but derive from fundamental network properties and logistical constraints. Second, Türkiye's logistics sector, while middle-income, operates under competitive market conditions with profit-maximizing firms facing hard budget constraints, similar to other emerging and developed economies. Third, the seismic context—sudden, localized infrastructure damage—parallels other natural disasters (hurricanes disrupting ports, floods damaging highways) and even man-made shocks (bridge collapses, cyber-attacks on logistics systems).

However, three caveats limit generalizability. First, Türkiye's high road freight share (89%) may amplify modal substitution benefits; in countries with more balanced modal distributions, diversity effects might differ. Second, our data aggregate to NUTS-2 regions; finer spatial resolution could reveal additional heterogeneity. Third, developing countries with informal logistics sectors and limited public infrastructure may exhibit distinct dynamics. Future research applying similar methods in varied geographic and economic contexts would clarify generalizability boundaries.

6.2 Limitations and Future Research Directions

Our analysis faces four notable limitations. First, we measure freight volumes, not values, potentially misweighting high-value goods. However, high-value goods typically move by air or intermodal rail, modes less affected by earthquakes, suggesting volume measures reasonably capture disruption severity. Second, we cannot observe firm-level routing decisions or inventory adjustments, limiting insight into micro-level mechanisms. Third, our network reallocation metrics require traffic count data unavailable for all road segments, forcing reliance on major highways. Fourth, we do not directly measure economic welfare losses, focusing instead on logistical disruptions as proximate outcomes.

Future research could address these gaps through four extensions. First, combining freight data with firm-level production records would illuminate how logistics disruptions propagate to output losses, connecting our findings to broader economic impact literatures. Second, high-frequency GPS data from commercial vehicles would enable fine-grained routing analysis, revealing day-by-day adaptation as infrastructure repairs progress. Third, comparative studies across countries with varied seismic risk and infrastructure configurations would clarify which results generalize. Fourth, simulating counterfactual investment scenarios—adding rail capacity, developing secondary ports—using calibrated network models could quantify resilience returns on investment, informing prioritization.

7. CONCLUSION

This paper exploits earthquakes in Türkiye as quasi-natural experiments to provide the first causal evidence of freight network disruption, reallocation, and adaptive responses using observed transport data. Three findings emerge. Earthquakes reduce regional freight volumes by 15-22%, with recovery extending 8-14 months, significantly longer than infrastructure repair timelines alone would suggest. Network reallocation intensifies toward peripheral routes and alternative modes, increasing flow concentration in previously underutilized corridors by 30-45%. Regions with higher modal diversity and route redundancy recover 40% faster than single-mode dependent areas, demonstrating that infrastructure redundancy—not absolute capacity—determines resilience.

These findings advance the supply chain literature by moving beyond conceptual frameworks and simulations toward causal empirical identification. By integrating network flow analytics into difference-in-differences estimation, we demonstrate that disasters do not merely disrupt flows but reorganize network topologies, exposing vulnerabilities in centralized systems while revealing adaptive capacities in diversified ones. The mechanism we uncover—shock → capacity loss → behavioral rerouting → differential recovery—operates through observable freight reallocations, not inferred from production data or hypothesized in models.

Methodologically, our approach combines the quasi-experimental rigor of natural disaster studies with the structural insights of network science, offering a template for future empirical research on adaptive supply chain dynamics. The key innovation is augmenting aggregate outcome regressions with network-level process indicators (centrality shifts, rerouting intensity), enabling identification of how systems respond, not merely that they respond. This approach generalizes to other shock contexts—cyber-attacks, labor strikes, pandemic lockdowns—where disruptions force supply chain reconfiguration.

Policy implications extend beyond earthquake preparedness. Infrastructure investment strategies worldwide face competing objectives: efficiency (minimizing costs under normal conditions) versus system continuity during disruptions. Our evidence demonstrates that these objectives often conflict—centralized, high-capacity systems optimize efficiency but concentrate risk, while diversified, redundant systems impose ex ante costs but provide ex post insurance. Recognizing this trade-off should reorient planning paradigms from capacity expansion toward network diversification. Practically, this might involve maintaining underutilized rail corridors, preserving secondary ports, or deliberately dispersing logistics hubs away from seismic zones despite agglomeration economies.

Taken together, the findings reveal a consistent pattern in which short-term freight collapse, regional heterogeneity in recovery, and prolonged disruption in single-mode regions stem from structural rather than purely infrastructural limitations. These patterns point to three complementary solution pathways. First, the persistence of post-shock bottlenecks highlights the importance of strategic redundancy planning, where secondary corridors and alternative routing capacity are preserved as system buffers rather than treated as excess infrastructure. Second, the faster normalization observed in multimodal regions underscores the value of deeper modal integration, enabling seamless substitution between road, rail, and maritime transport during disruptions. Third, the pronounced variation in regional recovery trajectories suggests the need for risk-sensitive transport planning, in which infrastructure design and investment prioritization explicitly incorporate spatial hazard exposure and network topology.

In this sense, system stability emerges not simply from infrastructure scale but from structural diversity. Earthquakes act as diagnostic stress tests that reveal where investments in diversification, connectivity, and redundancy can yield the greatest systemic gains. By aligning network design with these principles, logistics systems can move from passive shock absorption toward adaptive, network-aware operation.

Looking forward, our findings acquire heightened relevance amid accelerating climate change. While earthquakes themselves are not climate-driven, their role as non-economic disruptors parallels climate shocks—hurricanes, floods, wildfires—that increasingly stress global supply chains (Pant et al., 2014). Climate adaptation in logistics requires the same redundancy-focused strategies we identify: modal diversity, route alternatives, decentralized networks. As extreme weather frequency intensifies, supply chains designed for efficiency under stable climates will face repeated disruptions. Building durable supply networks requires accepting lower utilization rates, higher inventory buffers, and geographically dispersed operations—investments that may appear wasteful until the next major shock arrives.

More broadly, our analysis suggests that cascading risks—where one disruption triggers others through network interdependencies—pose systemic threats requiring network-aware policy. An earthquake does not just damage roads; it concentrates traffic on surviving routes, inducing congestion that propagates delays through supply chains. Traditional sector-by-sector risk management misses these interactions. Effective resilience policy must adopt whole-network perspectives, modeling how localized shocks diffuse through logistics infrastructure, production linkages, and trade flows simultaneously.

Unlike conventional shock analyses that estimate temporary deviations from equilibrium, we conceptualize earthquakes as *stress tests* that reveal otherwise unobservable network fragilities and adaptive capacities under binding constraints.

The Turkish case demonstrates that even middle-income countries with moderate infrastructure quality can build robust supply chains through strategic network design rather than massive capital expenditures. Diversification, not scale, emerges as the critical margin. This insight offers a constructive message for climate-vulnerable developing nations: durable supply chains are achievable without first-world infrastructure budgets, provided investments prioritize redundancy and flexibility over peak capacity. As supply chains globalize and climate shocks intensify, the lessons from Türkiye’s seismic laboratory extend far beyond tectonic fault lines.

Although our analysis is grounded in seismic shocks in Türkiye, the underlying mechanisms we identify, capacity loss, network reallocation, and redundancy-driven recovery, are not earthquake-specific. Similar dynamics characterize flood-prone inland corridors, hurricane-exposed port systems, and climate-induced disruptions to road and rail infrastructure worldwide. In this sense, earthquakes serve as a clean stress test, revealing network properties with broad policy relevance. These insights extend to ongoing debates on system continuity across EU TEN-T transport corridors, rising concentration risks in U.S. port systems, and vulnerabilities along Belt and Road logistics routes exposed to environmental and geopolitical shocks.

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