THESIS SUMMARY

Reservoir Nodes - Identifying Drivers and Structural Change in Trade and Mobility Networks

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1 Introduction

Network science provides a unified framework for examining interconnected systems across biology, sociology, technology, and economics Albert and Barabási (2002), Turnbull et al. (2018). Its relevance has increased with globalization, digitalization, and the growth of large datasets Huang and Mayer (2023), which require methods capable of handling structural complexity and dynamic interactions Havlin et al. (2012). Applications range from neural mapping Kasabov (2014) to supply chain analysis Eskandarpour et al. (2015), supported by model based approaches such as Erdős–Rényi graphs, preferential attachment, and agent based simulations Lesne (2006), Fang et al. (2007), Abar et al. (2017). These models describe diffusion Buskens (2020), cascading processes Valdez et al. (2020), and hub formation Borgatti et al. (2009). Parallel work in biology, sociology, and physics highlights recurring concepts such as clustering, resilience, and emergent patterns Zeng et al. (2017), all of which extend naturally to economics. Network econometrics incorporates structural dependence Sheng (2020), spillover effects Leung (2020), and indirect impacts of policy Guimaraes Jr et al. (2017). Networks also support the study of externalities Top et al. (2011), diffusion in markets Gregory et al. (2021), causal pathways VanderWeele and An (2013), financial contagion Galbusera and Giannopoulos (2019), labor market connections Jabbar et al. (2020), and innovation linkages Nieto and Santamaría (2007). The quality and scope of such analyses depend on full, open access databases Arzberger et al. (2004), which allow reproducibility, global comparison, and integration of trade Kurt and Kurt (2020) and mobility Kwan and Schwanen (2016) data. Open datasets enable cross disciplinary work, policy evaluation, and monitoring of systemic changes Turnes and Ernst (2015), Schultz et al. (2021). Within this landscape, the Erasmus mobility network and the BACI trade network offer two empirical systems frequently examined through network measures. Erasmus studies focus on centrality patterns, clustering, and changes in mobility flows Derzsi et al. (2011), Bruggeman et al. (2012), while BACI based analyses identify trading hubs, regional blocs, and shifts in global trade structure De Benedictis et al. (2014), Liang et al. (2019). Both networks display small world and scale free properties, implying that disruptions to central nodes can produce wide ranging effects. Despite substantial literature, several gaps remain. Temporal evolution of network indicators is often only partially modeled. Causal links between external drivers and structural changes are underexplored. Many analyses rely on aggregated units, limiting insight into product level trade patterns or regional mobility dynamics. Comparative modeling across variables, methods, and spatial or institutional units is limited, and the propagation of shocks or crises through trade or mobility networks is not fully characterized. Addressing these gaps supports a more precise understanding of interdependence, structural change, and the dynamics observed in global trade and academic mobility systems.

2 Research questions

Considering the significance of the topic and the previously stated objectives, this thesis seeks to address the following research questions:

RQ1. How do temporal dynamics and causal relationships in trade network indicators vary across products, and what do these patterns reveal about the transmission and impact of shocks, crises, and technological change?

RQ2. What do cross-level analyses (institutional, NUTS3, and national) reveal about the consistency of cultural and institutional determinants of mobility?

RQ3. What structural and causal parallels exist between trade and academic mobility networks, and how do they jointly affirm global patterns of interdependence, adaptation, and resilience?

3 Literature Review Foundations of Network Science

Network science emerged from graph theory and statistical physics as a formal approach to studying systems composed of interacting units. Early work focused on abstract representations of connectivity, where nodes and edges described relations without contextual interpretation Albert and Barabási (2002). Classical models such as Erdős–Rényi random graphs established baseline expectations for degree distributions and connectivity patterns Lesne (2006). Subsequent developments introduced preferential attachment mechanisms, demonstrating how growth processes generate heterogeneous degree distributions and highly connected hubs Fang et al. (2007). These foundational contributions showed that many empirical networks deviate systematically from random structures.

Later research expanded network representations to include direction, weight, and time dependence. Weighted and directed networks enabled the modeling of asymmetric interactions, while temporal networks allowed the study of structural evolution and dynamic processes Valdez et al. (2020). Agent based models further connected micro level behavior with macro level outcomes by simulating interaction rules among heterogeneous agents Abar et al. (2017). These methodological extensions facilitated the application of network analysis across disciplines and established a shared analytical vocabulary for studying complex systems Zeng et al. (2017).

3.1 Model Based Network Approaches Across Disciplines

Network models have been widely adopted in biology to represent metabolic pathways, protein interactions, and ecological systems Sweetlove and Fernie (2005), Delmas et al. (2019). These applications focus on robustness, tipping points, and adaptation, concepts that parallel economic concerns related to stability and shock transmission. In sociology, networks describe social interactions, trust relations, and information diffusion Molina-Morales and Martínez-Fernández (2010). Studies of cultural diffusion and influence emphasize modularity, homophily, and path dependence Gelfand and Jackson (2016), highlighting how structural constraints shape outcomes.

In physics, complex systems theory applies statistical mechanics to networks, enabling the analysis of phase transitions and emergent behavior Zeng et al. (2017). These concepts have informed economic modeling, particularly in financial systems where crises resemble systemic transitions rather than isolated events Bardoscia et al. (2021). Across disciplines, shared measures such as centrality, clustering, and assortativity provide consistent tools for describing structure while allowing domain specific interpretation Lee and Wilkinson (2019).

3.2 Networks in Economics and Econometrics

Economic systems are inherently networked, with agents connected through trade, finance, labor markets, and institutions Gao et al. (2012). Traditional econometric models often assume independence or homogeneous interactions, limiting their ability to capture spillovers and feedback effects Spanos (1995). Network econometrics incorporates structural dependence directly, allowing researchers to estimate indirect effects and policy transmission pathways Sheng (2020). This framework has been applied to the study of externalities Top et al. (2011), diffusion of innovations Gregory et al. (2021), and regional policy spillovers Leung (2020).

Causal inference in networked settings addresses violations of the no interference assumption by modeling interactions explicitly VanderWeele and An (2013). These approaches distinguish between direct, indirect, and total effects, providing more nuanced interpretations of policy outcomes Guimaraes Jr et al. (2017). Structural estimation of network formation models further enables inference on the mechanisms generating observed connections Platt (2022). Applications span labor economics, industrial organization, and innovation studies Ebbes and Netzer (2022), Álvarez et al. (2009), Nieto and Santamaría (2007).

3.3 Trade Networks and the BACI Literature

International trade networks model countries as nodes and trade flows as directed weighted edges. Early studies documented the highly centralized nature of global trade, identifying dominant hubs and regional communities De Benedictis et al. (2014). Network measures revealed dependencies and vulnerabilities that are not observable through bilateral trade statis-

tics alone Ducruet and Beauguitte (2014). Subsequent research examined structural evolution, highlighting shifts associated with globalization, technological change, and geopolitical realignment Liang et al. (2019).

The BACI database has enabled detailed empirical analysis by providing harmonized bilateral trade flows with product level resolution De Benedictis et al. (2014). Studies using BACI data have investigated trade concentration, diversification, and regional clustering Hung (2021). Product level analyses show that shocks propagate unevenly across the network, depending on product specificity and network position Cook et al. (2010). However, much of the literature remains descriptive or static, with limited integration of temporal modeling and causal inference at fine levels of aggregation.

3.4 Academic Mobility Networks and Erasmus Research

Academic mobility has been extensively studied through the Erasmus program, which connects institutions, regions, and countries through exchange flows Derzsi et al. (2011). Network based analyses identify small world and scale free properties, with a limited number of highly connected institutions acting as hubs Bruggeman et al. (2012). Community detection reveals clustering shaped by geography, language, and institutional cooperation Gadár et al. (2022).

Temporal analyses document persistence and path dependence in mobility patterns across program cycles Teichler (1996). While these studies describe structural stability and gradual change, econometric modeling remains less developed. External drivers such as cultural distance, crime, and research collaboration are often analyzed separately, limiting understanding of their joint effects within a network context. Moreover, most studies focus on national or institutional levels, with limited attention to regional or individual level dynamics.

3.5 Data Availability and Open Access Networks

The study of large scale networks relies on comprehensive and transparent data sources Arzberger et al. (2004). Open access databases support reproducibility, cross country comparison, and interdisciplinary research. In trade analysis, full coverage is required to capture indirect dependencies and global spillovers Kurt and Kurt (2020). In mobility research, complete datasets enable analysis of institutional hierarchies, regional disparities, and micro level patterns Kwan and Schwanen (2016). Studies based on partial or proprietary data face limitations related to bias, aggregation, and comparability Olteanu et al. (2019).

3.6 Synthesis and Remaining Gaps

Despite extensive literature on both trade and mobility networks, several gaps persist. Temporal dynamics are often under modeled, particularly at the product and regional levels. Causal relationships between network indicators and external drivers remain insufficiently explored.

Aggregation obscures heterogeneity across units of analysis, while comparative evaluation of modeling strategies is limited. Finally, the propagation of shocks and crises through interconnected trade and mobility networks has not been systematically analyzed within a unified econometric framework. These gaps motivate approaches that integrate temporal network analysis, causal inference, and fine grained open access data to study structural change and interdependence in global systems.

4 Research Assumptions

The following assumptions specify the analytical premises under which the research questions are investigated.

RA$_1$ Trade networks are expected to show sequential structural shifts in response to technological change, geopolitical pressure, and crisis events, with early changes in assortativity followed by delayed responses in resilience and centralization.

RA$_2$ If cultural and institutional variables are structural drivers rather than dataset artefacts, the same determinants should remain significant across multiple scales, with collaboration acting as a stabilizing mechanism and crime as a selective constraint on destination choice.

RA$_3$ Both systems exhibit hierarchical organization and preferential attachment, implying that a small set of dominant actors should function as causal drivers whose behavior influences the adaptability and vulnerability of the overall network.

Results and Research Question Alignment

The empirical results reveal consistent structural patterns across trade and academic mobility networks. By combining temporal clustering, causality detection, and multivariate modeling, the analysis provides direct empirical answers to all three research questions. The following sections summarize these findings while explicitly linking them to the corresponding research questions and preserving the visual structure of the results.

RQ1: Structural evolution of global trade networks

The temporal evolution of structural indicators shows that global trade networks follow a limited number of synchronized trajectories across product groups. These trajectories are shaped by globalization, technological change, and geopolitical shocks.

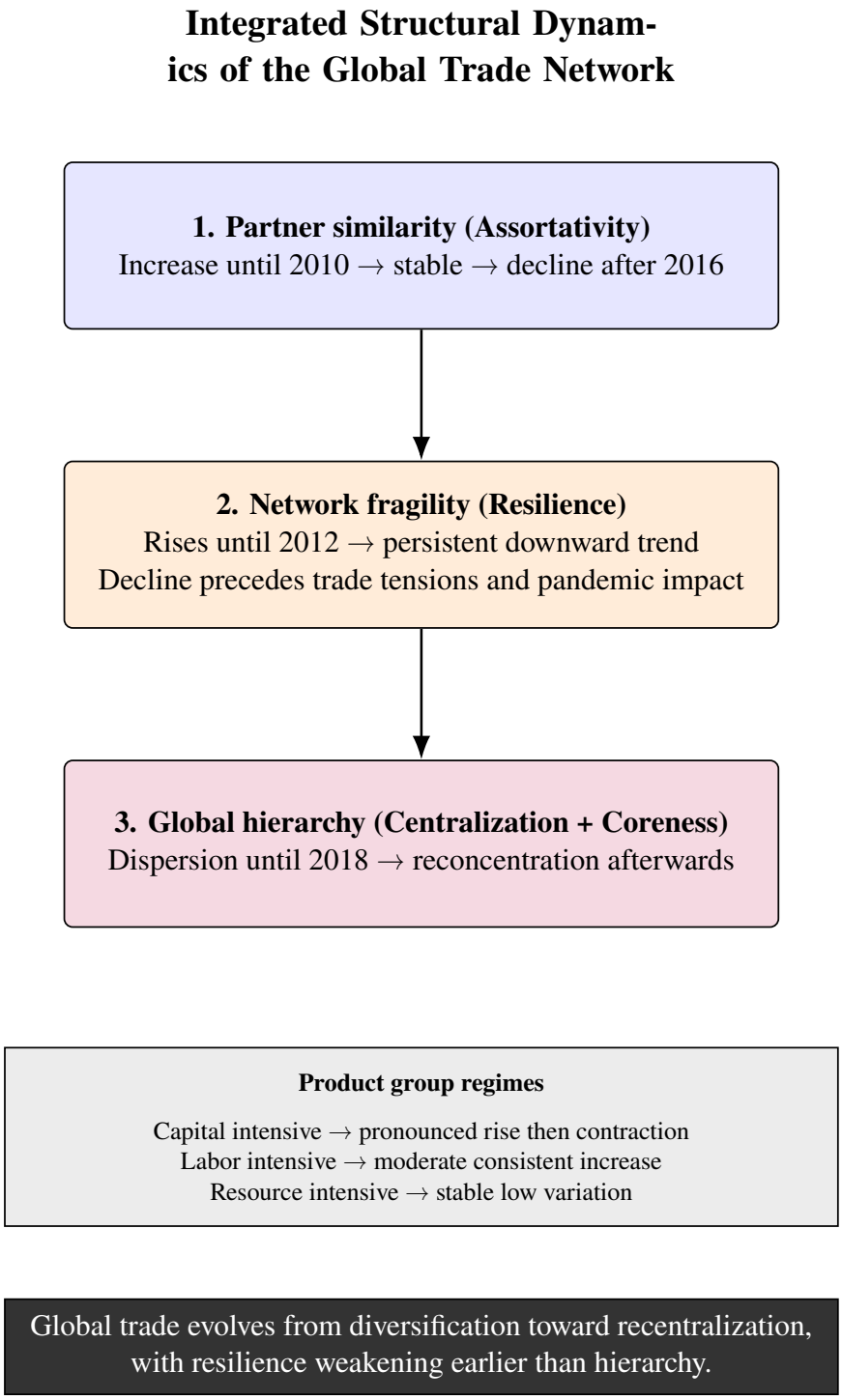

Figure 1: Integrated structural dynamics of the global trade network.

The figure above displays the cluster center of assortativity across all product groups.

A single dominant temporal pattern is identified. Assortativity increases steadily until approximately 2010, reflecting growing specialization among similar trading partners. After 2010, growth stagnates, followed by a pronounced decline after 2016. This reversal coincides with the slowdown of globalization and the escalation of trade conflicts, most notably the US-China trade war.

Centralization and coreness follow a similar trajectory, but with a delayed response. Decreasing eigenvector centralization and increasing coreness until 2018, indicating a gradual dispersion of trade dominance. After 2018, this trend reverses, signaling renewed concentration. The lag between assortativity and centralization indicates that partner similarity changes precede observable shifts in global hierarchy.

Resilience patterns reinforce this interpretation. The trade network was most resilient prior to 2012. After that point, resilience declines persistently, accelerating during the trade war period and preceding the COVID-19 shock. This demonstrates that structural fragility accumulated well before the pandemic.

Product-level heterogeneity is captured by global clustering patterns. Results identifies three distinct clustering regimes corresponding to capital-intensive, labor-intensive, and resource-intensive products. Capital-intensive products exhibit the strongest pre-2018 clustering growth followed by sharp decline, while labor-intensive products remain comparatively stable. Resource-intensive products show minimal structural change.

Together, these results show that global trade evolved from diversification toward recentralization, with resilience eroding prior to major crises. Structural change occurs sequentially: assortativity responds first, followed by resilience, and finally centralization.

RQ2: Cross-level consistency of cultural and institutional determinants

The gravity model results demonstrate that cultural, crime-related, and collaboration variables systematically influence Erasmus mobility across institutional and regional levels.

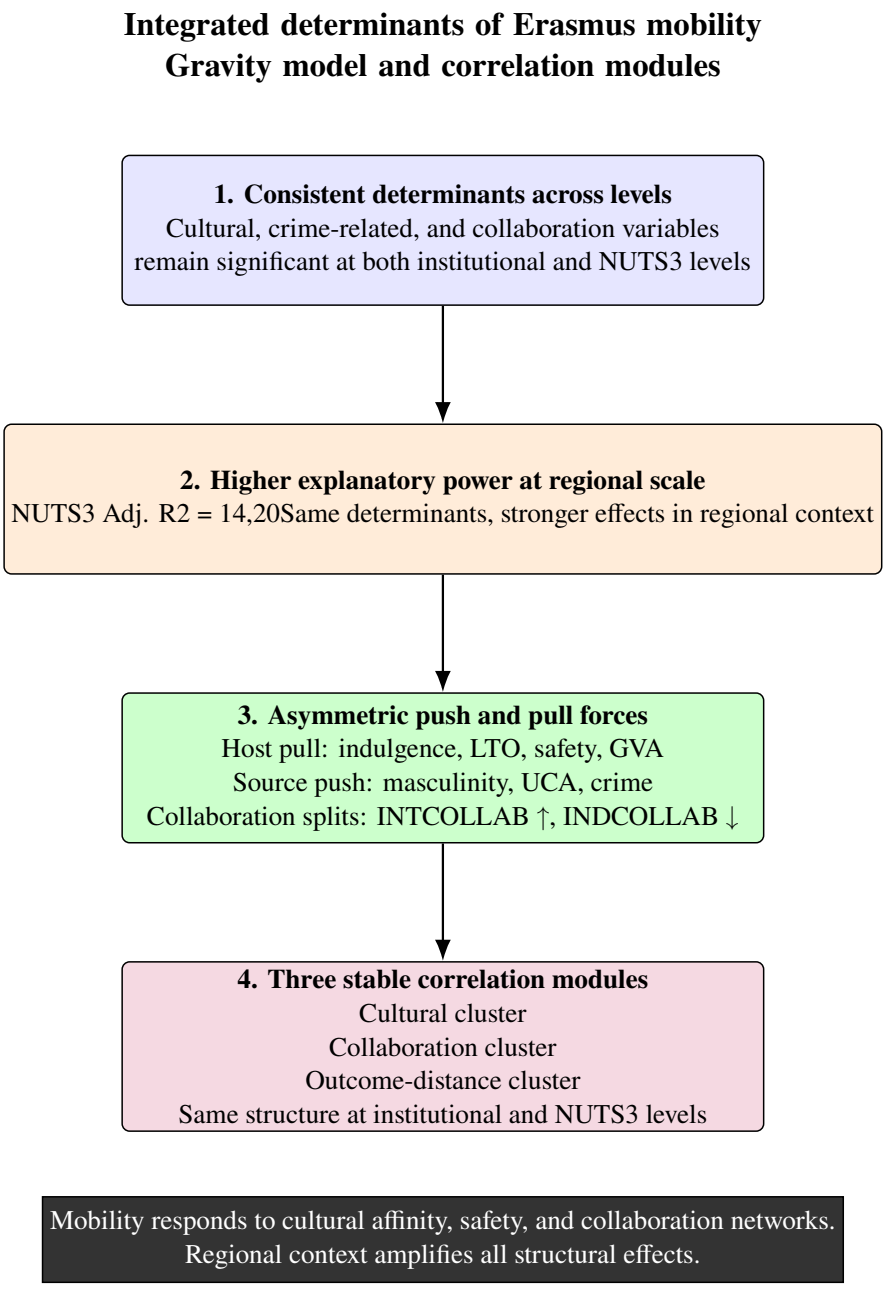

Figure 2: Integrated infographic summarizing gravity-model determinants of Erasmus mobility.

Results show that the NUTS3-level model achieve substantially higher explanatory power than the institutional model, indicating that regional context captures mobility behavior more effectively. Despite this difference in magnitude, the same determinants remain significant across levels.

At the institutional level, indulgence and long-term orientation of host institutions act as

dominant pull factors, while masculinity and uncertainty avoidance at the source function as push constraints. Collaboration variables show a dual role: international collaboration increases mobility, while excessive industrial collaboration reduces it.

At the NUTS3 level, crime indicators emerge as strong destination-side determinants, confirming that perceived safety matters more at the host location than at the source. Cultural indicators retain their explanatory power, with consistent signs across years and professions.

The clustered correlation graphs further confirm structural consistency. There are three stable modules at both levels: cultural variables, collaboration variables, and outcome-distance variables.

The stability of determinants across aggregation levels demonstrates that cultural and institutional effects are structural properties of the mobility system rather than artifacts of model specification.

RQ3: Structural and causal parallels between trade and mobility networks

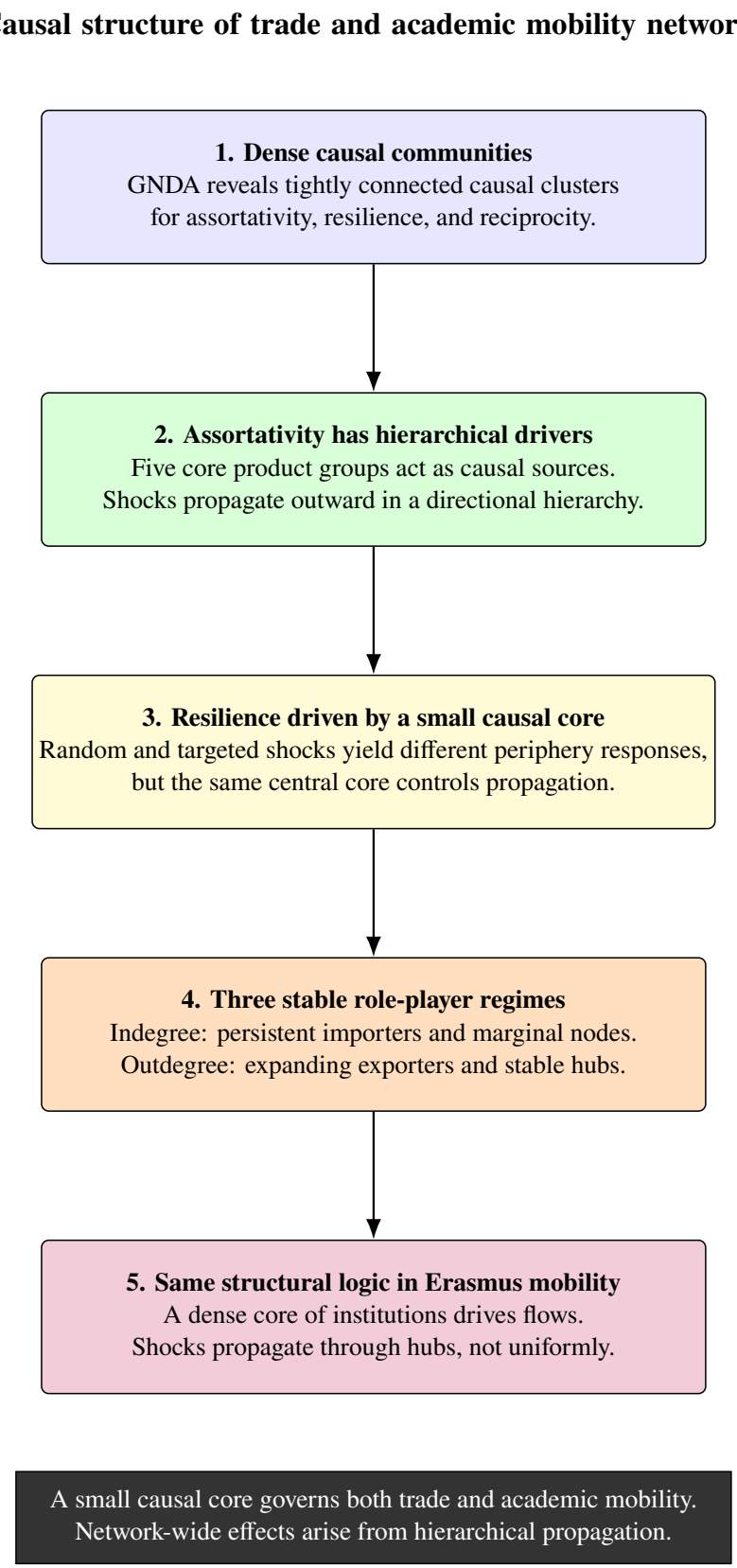

Figure 3: Integrated infographic summarizing causal dynamics of trade and mobility networks.

Causality analysis reveals that similar mechanisms govern both trade and academic mobility networks. GNDA applied to Granger causality networks identifies dense causal communities for assortativity, resilience, and reciprocity.

Five assortativity-driven causality groups, where a small number of product groups act as structural drivers. Changes in these groups propagate to others, indicating hierarchical dependency.

Resilience exhibits even stronger causal interdependence. Product groups respond differently to random versus targeted shocks, but in both cases a small core drives network-wide effects.

Role-player analysis reinforces these parallels. For product group 81, country-level indegree and outdegree centralities cluster into three stable regimes, revealing persistent importers, expanding exporters, and marginal participants.

The same hierarchical logic appears in Erasmus mobility, where a limited set of institutions and regions act as persistent hubs driven by collaboration intensity and cultural openness. In both systems, shocks propagate through densely connected cores rather than uniformly across the network.

Integrated interpretation

Across trade and academic mobility, networks evolve through synchronized structural cycles characterized by early diversification, delayed concentration, and declining resilience. Cultural, institutional, and collaborative factors act as structural drivers rather than contextual noise. A small number of central actors consistently shape system-wide outcomes, while crises amplify pre-existing vulnerabilities instead of creating new ones.

These results jointly confirm that global trade and Erasmus mobility networks are governed by shared principles of hierarchy, interdependence, and delayed shock propagation, providing unified empirical support for all three research questions.

5 Research theses

Three research theses were formulated in alignment with the research questions, carefully considering the results.

RT$_1$ Overall, the global trade network has transitioned from a resilient, diversified structure into a polarized and dependency driven system, where technological acceleration and recurrent crises jointly amplify instability. Kosztyán et al. (2024)

RT$_2$ Cultural determinants such as indulgence, long-term orientation, masculinity, and uncertainty avoidance consistently influence mobility across institutional, regional, and national levels, demonstrating that cultural effects are structural rather than context-specific. Kosztyán et al. (2023)

RT$_3$ Global trade and academic mobility networks share fundamentally similar structural logics, characterized by hierarchical organization, preferential attachment, and the dominance of a small number of central actors. Kosztyán et al. (2023, 2024)

6 Summary and Conclusion

6.1 Contribution to the literature

This dissertation contributes to the literature by examining global trade networks and academic mobility systems as structurally comparable networked environments, where crises, technological change, and institutional characteristics produce measurable impacts on connectivity, centralization, assortativity, and resilience. The work bridges two domains that are rarely analyzed together: the evolution of structural indicators in product-level world trade (using BACI data) and the determinants of Erasmus mobility across institutional and regional scales. By doing so, the dissertation demonstrates that both systems are shaped by similar mechanisms of interdependence, vulnerability, and adaptation, despite operating in different practical contexts.

The first contribution is the identification and reconstruction of temporal patterns in global trade networks. The results show synchronized cycles in assortativity, centralization, coreness, and resilience, with clear turning points linked to events such as the 2008 financial crisis, the US–China trade war, and the COVID-19 pandemic. These structural changes do not appear randomly; they unfold sequentially across indicators, providing evidence of lagged systemic responses. The empirical results show that assortativity declines first, resilience follows with a delay of two to six years, and centralization reverses only after fragmentation has already begun. This exposes a process in which global networks move from diversification toward renewed dependency.

The second contribution addresses the determinants of academic mobility. Through multi-level modeling at institutional, regional (NUTS3), and national scales, the analysis demonstrates that cultural, crime, and collaboration variables retain explanatory power across all aggregation levels. Indulgence and long-term orientation act as pull factors; masculinity and uncertainty avoidance operate as push constraints. Crime matters predominantly on the host side, while collaboration expands participation. The same variables reappear with consistent direction and significance, indicating structural rather than context-specific effects.

The third contribution concerns the integration of causality analysis. By applying Granger causality and GNDA, the dissertation identifies product groups that act as structural drivers in the evolution of trade networks. These groups form causal communities, and shocks propagate within them before extending to other sectors. A comparable dynamic appears in academic mobility, where highly collaborative and culturally open institutions anchor cross-border exchanges. This parallel demonstrates that hierarchical influence and preferential attachment operate in both systems. A small number of central actors drive change, and their behavior affects the adaptability of the entire network.

1. The thesis provides evidence that global trade networks evolved from a diversified structure into a more dependency-driven system. This transformation is visible in sequential changes to assortativity, resilience, and centralization, which align with historical crises and technological acceleration.

2. The thesis demonstrates that cultural and institutional determinants of mobility retain consistency across institutional, regional, and national models, confirming that these variables operate as structural drivers rather than dataset-specific artefacts.

3. The thesis shows that trade and academic mobility networks share comparable systemic mechanisms. Both systems concentrate influence within a limited set of actors, react to shocks through lagged structural adjustment, and stabilize through diversification rather than centralization.

6.2 Implications

The findings show that global interconnected systems whether based on the exchange of goods or individuals operate under similar structural constraints. In both environments, efficiency and resilience do not develop simultaneously. Increases in efficiency tend to be associated with concentration, while resilience improves through redistribution and diversification. From a policy and analytical standpoint, this implies that interventions prioritizing growth, specialization, or central control will likely increase vulnerability, while measures supporting redundancy, alternative pathways, or distributed collaboration strengthen stability.

6.3 Practical Implication

The results show that improving system performance requires recognizing the trade-off between efficiency and resilience. Policies that encourage specialization, concentration of flows, or reliance on a few dominant hubs may increase short-term efficiency but create structural fragility. In contrast, resilience emerges when networks diversify partners, distribute connectivity, and maintain alternative pathways. Therefore, policymakers and institutional managers should design interventions that deliberately balance efficiency goals with redundancy measures. For trade, this means developing secondary supply routes, monitoring concentration risk, and supporting regional diversification. For mobility programs, it implies expanding partnerships beyond traditional hubs, strengthening collaboration networks, and reducing dependency on a small set of hosting institutions.

6.4 Limitations

A limitation of the empirical work is the reliance on available data structures: BACI remains the most complete dataset for trade, but its sectoral resolution restricts the investigation of sub-product technological shifts; Erasmus data allow institutional and regional modeling, but do not capture decision-making or risk perception at the individual level. Furthermore, causal inference is constrained by observable indicators and cannot fully account for non-recorded informal flows or political decision-making that precedes measurable effects.

These limitations do not undermine the results; they define the analytical boundaries. Within those boundaries, the study shows consistent patterns: shocks propagate unevenly, concentration increases fragility, and cultural–institutional factors affect mobility independent of economic distance. Extensions of the work may evaluate post-2020 stabilization patterns, digital mobility programs, and restructuring of supply chains after the Red Sea disruptions, as well as modeling parallel network adaptation under simultaneous geopolitical and technological pressure.

6.5 Research Summary Table

I have summarized my research questions, research assumptions, and research theses in Table 1, aligned with the empirical results of the global trade network analysis and the Erasmus mobility models.

Table 1: Research summary

Item	Statement
RQ1:	How do temporal dynamics and causal relationships in trade network indicators vary across products, and what do these patterns reveal about the transmission and impact of shocks, crises, and technological change?
RA1:	Trade networks are expected to show sequential structural shifts in response to technological change, geopolitical pressure, and crisis events, with early changes in assortativity followed by delayed responses in resilience and centralization.
RT1:	Overall, the global trade network has transitioned from a resilient, diversified structure into a polarized and dependency driven system, where technological acceleration and recurrent crises jointly amplify instability.
RQ2:	What do cross-level analyses (institutional, NUTS3, and national) reveal about the consistency of cultural and institutional determinants of mobility?
RA2:	If cultural and institutional variables are structural drivers rather than dataset artefacts, the same determinants should remain significant across multiple scales, with collaboration acting as a stabilizing mechanism and crime as a selective constraint on destination choice.
RT2:	Cultural determinants such as indulgence, long-term orientation, masculinity, and uncertainty avoidance consistently influence mobility across institutional, regional, and national levels, demonstrating that cultural effects are structural rather than context-specific.
RQ3:	What structural and causal parallels exist between trade and academic mobility networks, and how do they jointly affirm global patterns of interdependence, adaptation, and resilience?
RA3:	Both systems exhibit hierarchical organization and preferential attachment, implying that a small set of dominant actors should function as causal drivers whose behavior influences the adaptability and vulnerability of the overall network.
RT3:	Global trade and academic mobility networks share fundamentally similar structural logics, characterized by hierarchical organization, preferential attachment, and the dominance of a small number of central actors.

7 The author's publications related to the topics

Journal Articles

1. Kosztyán, Z. T., Kiss, D., & Obermayer, N. (2023). Investigating Erasmus mobility exchange networks with gravity models. *Cogent Social Sciences*, 9(2), 2253612. DOI: https://doi.org/10.1080/23311886.2023.2253612

2. Kosztyán, Z. T., Kiss, D., & Fehérvölgyi, B. (2024). Trade network dynamics in a globalized environment and on the edge of crises. *Journal of Cleaner Production*, 465, 142699. DOI: https://doi.org/10.1016/j.jclepro.2024.142699

Conferences

1. Kosztyán Z. T. & Kiss, D. (2025). OGIK 2025, Debrecen, Debreceni Egyetem, Hungary.

2. Kiss, D., & Kosztyán Z. T. & Király T. & Fehérvölgyi B. (2025). Trade Network Dynamics in a Globalized Environment and on the Edge of Crises. Presentation. EcoNet NetWorkShop, Pécs, Hungary.

3. Kiss, D., & Kosztyán Z. T. & Obermayer N. (2022). A személyiségtípusok szerepe a szoftver projektek tervezésében. Poster. OGIK 2022, Salgótarján, Somoskő, Hungary.

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