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DOCTORAL THESIS

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

Author:
Dénes KISS

Supervisor:
Dr. Zsolt Tibor KOSZTYÁN

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Declaration of Authorship

I, Dénes KISS, declare that this thesis titled, "Reservoir Nodes - Identifying Drivers and Structural Change in Trade and Mobility Networks" and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
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- I have acknowledged all main sources of help.
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"Turbam vita. Cum his vive qui te meliorem facere possunt; illos admitte quos tu potes facere meliores."

Seneca

UNIVERSITY OF PANNONIA

Abstract

Faculty of Quantitative Research
Department of Management

Doctor of Philosophy

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

by Dénes KISS

This dissertation explores globalization as a series of interconnected crises unfolding through networked systems. By comparing trade and academic mobility networks, it shows that the same structural principles, centralization, assortativity, and resilience, govern both material and social exchange. Trade networks, shaped by geopolitical tensions and technological innovation, exhibit cycles of diversification and reconcentration, while Erasmus mobility reveals how culture, crime, and collaboration (3Cs) drive academic interdependence. Causality mapping exposes the pathways through which shocks spread, whether through product dependencies or institutional ties. The findings demonstrate that crises reveal, rather than distort, the architecture of globalization: a system where resilience emerges not from isolation, but from the adaptive interlinkage of its parts.

Acknowledgements

In this dissertation, the term *Reservoir Nodes* refers to actors whose structural position enables them to accumulate and redistribute flows, dependencies, and shocks within a network. These nodes function as systemic reservoirs: they store influence, concentration, and risk, and release them through spillovers, causal pathways, or crisis propagation.

AI tools (GPT-4o mini) were used to help organize and digest the literature. All sources were independently verified by the author. During the initial search and screening steps of PRISMA, AI tools were not used. However, during the fact checking of the selected literature AI tools were employed to verify the used models and data sources.

Language editing assistance was provided by GPT-4o mini and the built in suggestion tool of Overleaf to improve readability and grammar.

While employing these tools, all scientific content remains the sole responsibility of me, the author.

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forever grateful to Zsolt for introducing me to science

Chapter 1

Introduction

1.1 Relevance of Network Science in Modern Systems

In 2025, the study of networks transcends disciplinary boundaries, establishing itself for understanding the complex systems that underpin the modern world Albert and Barabási (2002). Network science is critical because it offers an encompassing framework for analyzing diverse systems Turnbull et al. (2018), from the micro-scale of protein interactions in biology Stelzl and Wanker (2006) to the macro-scale of global trade and international relations Nemeth and Smith (1985). The 21st century has seen an unprecedented increase of interconnected systems fueled by rapid technological advancements, globalization, and datafication Huang and Mayer (2023). These developments have not only amplified the complexity of systems, but have also heightened the risks and opportunities associated with their dynamics. Network science is uniquely positioned to address these challenges by providing tools to uncover hidden structures, predict emerging behaviors, and design robust systems Havlin et al. (2012).

The growing interest in big data analytics, quantum computing, and artificial intelligence Dunjko and Briegel (2018) shows the significance of network science in our recent times. In order to maximize their functionality and reduce systematic risks, these technologies create and depend on increasingly complex networks, both abstract and physical Vassakis, Petrakis, and Kopanakis (2018). The modeling of epidemic spread Wang et al. (2024b) and the resilience of global supply chains Perera, Bell, and Bliemer (2017), for instance, both rely on knowledge gained from network science. Network science is becoming a practical necessity rather than a theoretical exercise as the world becomes even more complex Majhi, Perc, and Ghosh (2022). It is clear from examining network science's present relevance and difficulties that its real-world applications and intrinsic complexity are influencing the direction of numerous fields.

1.2 Current Relevance and Challenges of Network Science

Both descriptive and prescriptive insights are made possible by the structural capacity of network science to assist in deciphering the complexities of interconnected systems Lepenioti et al. (2020). Across industries and research domains, this field has now moved from theory to practical implementation Glegg, Jenkins, and Kothari (2019). Network science is an essential tool for comprehending and influencing real-world systems, from mapping neural networks in the brain Kasabov (2014) to optimizing supply chains Eskandarpour et al. (2015) Costa et al. (2011). Its techniques, including machine learning integration Chen et al. (2019), dynamic modeling Kim et al. (2018), and graph theory Derrible and Kennedy (2011), offer a strong framework for analyzing and forecasting behaviors in systems where individual components show interdependence Kenett et al. (2014). Due to its importance, network science is now essential for addressing modern issues such as enhancing infrastructure resilience Wells et al. (2022) and encouraging international cooperation in scientific research Li et al. (2016).

Despite its immense potential, the application of network science is not without challenges. A primary issue lies in the scalability and complexity of real-world networks Cimini et al. (2019). As datasets grow exponentially in size and complexity, computational limits become a bottleneck Banf and Rhee (2017), requiring the development of more efficient algorithms and scalable technologies Hashim, Shuaib, and Zaki (2022). E.g., global trade networks Gosak et al. (2018) or social media ecosystems Rosen, Barnett, and Kim (2011) that often consist of millions of nodes and billions of edges, challenging existing analytical tools to provide timely and actionable insights. Capturing and modeling these dynamics often requires the integration of real-time data streams, which can be noisy, incomplete, or biased Verma et al. (2017). In this context, ensuring the accuracy and reliability of network models becomes a critical issue Cugola and Margara (2012).

As network science moves toward predictive and prescriptive applications, issues of transparency and interpretability emerge Shah and Konda (2021). Black-box models, while powerful, can obscure the mechanisms driving their predictions, making it difficult for stakeholders to trust and act on the results. Addressing this challenge requires advancing explainable algorithms that balance precision with interpretability Petch, Di, and Nelson (2022). Building on the current relevance and challenges of network science, various model-based approaches introduced and are applied across various disciplines and their significant connections to economics.

1.3 Model-Based Approaches Across Disciplines and Their Connections to Economics

Model-based approaches are foundational across a wide range of disciplines, serving as tools to conceptualize, simulate, and predict the behavior of complex systems. In network science, these approaches manifest through models like Erdős–Rényi graphs Lesne (2006), preferential attachment models Fang, Bi, and Li (2007), and agent-based simulations Abar et al. (2017). These frameworks help explain phenomena such as the emergence of hubs in social networks Borgatti et al. (2009), the diffusion of innovations Buskens (2020), and the cascading failures in interconnected systems Valdez et al. (2020). While network science is a natural home for such models, their influence extends deeply into other disciplines, with significant intersections in economics.

In biology, model-based approaches have revolutionized our understanding of systems on multiple levels. E.g., metabolic networks map the biochemical pathways Sweetlove and Fernie (2005) that sustain life, while ecological networks model species interactions within ecosystems Delmas et al. (2019). These frameworks offer insights into resilience, tipping points, and the impact of external shocks—concepts that align closely with economic systems, where markets and institutions are similarly structured as dynamic networks. The parallels between biological and economic systems, such as competition, cooperation, and resource allocation, highlight the universality of network-based models.

In sociology, network models describe patterns of human interaction, trust, and influence, shedding light on phenomena such as social capital Molina-Morales and Martínez-Fernández (2010), political polarization Ward, Stovel, and Sacks (2011), and the spread of cultural norms Gelfand and Jackson (2016). These models intersect with economics in studying markets as social constructs where trust, reputation, and informal networks influence economic outcomes Takács et al. (2021). For instance, the role of trust in financial transactions or the diffusion of financial innovations can be directly modeled using network science Cao, Yang, and Yu (2021). Dueñas and Mandel (2023) uses network inference to analyze the diffusion of popular music videos on YouTube, revealing that cultural diffusion is more influenced by geographic, cultural, and historical factors than by macroeconomic variables, and that musical influence tends to occur within modular groups rather than globally.

In physics, complex systems modeling, particularly through statistical mechanics, provides insights into phase transitions, criticality, and emergent behaviors Zeng et al. (2017). These concepts are increasingly applied in economics to understand market dynamics, such as financial crises, which can be likened to phase transitions in physical systems Bardoscia et al. (2021). E.g., models of percolation theory have been used to study the propagation of defaults in financial networks, illustrating the deep connections between these fields Havlin et al. (2015).

Economics itself has long relied on model-based approaches, ranging from general equilibrium models to game theory and agent-based modeling. These tools aim to simulate and predict the behavior of markets, firms, and consumers. Network science enhances this toolkit by introducing frameworks to analyze the interdependencies within economic systems, such as global trade networks, supply chains, and financial interconnectivity. The study of trade, exemplified by networks like BACI, illustrates how network analysis identifies structural imbalances Hung (2021), reveals key trading hubs Ducruet and Beauguitte (2014), and uncovers vulnerabilities in global commerce Cook, Liang, and Zhu (2010). In economics, these approaches have found a natural home, not only because markets and economies are inherently networks, but also because the methodologies developed in other fields provide fresh perspectives and tools for solving economic problems. Using these connections, we can achieve a deeper understanding of the systems that shape our world, fostering innovation and resilience in the face of global challenges.

The connections between disciplines are most evident in the shared challenges and methodologies they address. E.g., the concept of resilience is a common thread, whether in ecological networks recovering from biodiversity loss, supply chains adapting to disruptions, or financial systems weathering shocks. Similarly, concepts like clustering, centrality, and modularity, originating in network science Lee and Wilkinson (2019), are widely applied to study everything from neural connectivity in the brain to regional economic clusters in trade. Having established the foundational role of model-based approaches across various disciplines and their connections to economics, the critical critical role of networks in econometrics is explored.

1.4 Importance of Networks in Econometrics

Networks have emerged as a crucial framework in econometrics due to their ability to model and analyze the interdependencies that characterize economic systems. Traditional econometric models often assume independence among observations or homogeneity in relationships, which fails to capture the inherent interconnectedness of economic agents, markets, and institutions Spanos (1995). By integrating network structures into econometric analysis Sheng (2020), researchers can uncover complex dependencies, analyze systemic risks, and provide more accurate policy recommendations. Networks are instrumental in studying phenomena involving network effects and externalities Top, Dilek, and Çolakoğlu (2011), which are critical in many economic contexts. E.g., in adoption of technology, the value of a product or service often increases with the number of users Michel, Brown, and Gallan (2008), a dynamic best understood through network models Gregory et al. (2021). Econometric analysis of these effects enables policymakers and firms to design strategies that leverage positive externalities or mitigate negative ones, such as overconcentration of market power Moura Jr et al. (2024). Networks also play a pivotal role in advancing causal inference VanderWeele and An (2013), a central concern in econometrics. Traditional methods often rely on the assumption of no interference between units, but in networked systems, this assumption rarely holds. E.g., the impact of a policy intervention in one region might spill over into neighboring regions through trade or migration networks. By explicitly modeling these connections, network econometrics provides tools to disentangle direct, indirect, and total effects, enabling more precise causal estimates Chavira and Darwiche (2008).

Economic systems are inherently interconnected. Firms interact through supply chains, individuals through social networks, and countries through trade and financial systems. Networks provide a natural representation of these interdependencies Gao et al. (2012), enabling econometric models to capture spillover effects Leung (2020) and feedback loops Kwon and Cho (2007) that traditional approaches might overlook. For instance, trade networks reveal how shocks in one country can propagate through global supply chains, while financial networks can model the contagion effects of a banking crisis. Incorporating network structures allows econometricians to estimate not only the direct effects of economic policies but also their indirect effects as they diffuse through the network Guimaraes Jr et al. (2017).

A significant development in econometrics is the structural estimation of network models Platt (2022). These models allow researchers to infer the underlying mechanisms that generate the observed network structures, such as preferential attachment. In labor economics, for instance, network models can explain how job seekers leverage social connections Ebbes and Netzer (2022), while in industrial organization, they can reveal patterns of collaboration or competition among firms Álvarez, Marin, and Fonfría (2009). These insights are essential for understanding the microfoundations of economic behavior.

Networks are increasingly applied in various subfields of economics, enhancing the explanatory and predictive power of econometric models. Network analysis helps identify key players and bottlenecks in international trade Russo et al. (2023), evaluate the resilience of supply chains, and estimate the effects of trade agreements or disruptions. The study of Tajoli, Airoldi, and Piccardi (2021) reveals that the global network of trade in services is highly dense and resilient, with a small group of advanced countries dominating the flows, highlighting the crucial role of services in globalization and the importance of network structure in understanding countries' positions in service trade. Financial networks are critical for understanding systemic risk, interbank lending, and the spread of financial crises. Econometric models incorporating network data allow for better stress testing Galbusera and Giannopoulos (2019) and policy design. Social and professional networks shape labor market outcomes, such as employment opportunities and wage disparities Jabbar et al. (2020). Econometrics leverages network data to study how these connections influence economic mobility and inequality Chantarat and Barrett (2012). Collaborative networks between firms and researchers drive innovation Nieto and Santamaría (2007). Network econometrics can quantify the role of spillovers, clustering, and diversity in fostering technological advancements. Although networks offer immense potential for econometric analysis, their incorporation presents several challenges. First, the availability and quality of network data can be limited Karkouch et al. (2016), and the construction of accurate network representations often requires assumptions or approximations Zhang et al. (2018). Second, the complexity of network structures can strain traditional econometric methods, necessitating the development of new algorithms and computational tools. Third, interpreting results in the context of networks requires a nuanced understanding of both the economic and structural dynamics at play Kerr and Coviello (2020). Having established the significance of networks in econometrics, the focus now shifts to the critical role of open-access, full databases in advancing research and policy formulation in trade and mobility.

1.5 Importance of Open-Access, Full Databases in Trade and Mobility Research

Access to comprehensive and openly available databases are indispensable for advancing research and policy formulation in trade and mobility alike Arzberger et al. (2004). These databases provide the foundation for evidence-based analysis, fostering transparency, replicability, and collaboration. In the context of interconnected global systems, where trade Kurt and Kurt (2020) and human mobility Kwan and Schwanen (2016) are deeply intertwined with economic, social, and political dynamics, open-access, full databases enable a nuanced understanding of these complex phenomena while democratizing access to information.

Open-access, full databases ensure that analyses are built on robust and comprehensive datasets. For trade, this means capturing the full spectrum of import and export flows between nations, detailing the volume, value, and composition of goods and services exchanged. Similarly, for mobility, complete datasets include records of migration patterns, and various other economic, socioeconomic variables can be added. Such extensive data coverage allows researchers to observe macro- and micro-level patterns, identify anomalies, and assess systemic risks, or to model the network structure Marchiori and Possamai (2015). Partial or proprietary datasets, on the other hand, risk introducing biases, limiting the scope of analysis, and misrepresenting global dynamics Olteanu et al. (2019). Open-access databases democratize information, providing researchers and institutions worldwide with equal opportunities to analyze data. This is particularly important for scholars in low- and middle-income countries who may lack the resources to access proprietary datasets. By leveling the playing field, open data promotes inclusive research and ensures that diverse perspectives are represented in the analysis of e.g. trade and mobility.

Trade and mobility intersect with multiple disciplines, including economics, sociology, political science, and environmental studies. Open-access databases empower researchers from diverse fields to investigate questions that transcend disciplinary boundaries. E.g., the interaction between trade policies and labor migration Olteanu et al. (2019), or the environmental impact of trade-related transportation networks Dente and Tavasszy (2018), can only be fully explored when relevant data are available to all stakeholders. Shared access fosters interdisciplinary collaborations Petri (2010) that enrich our understanding of global systems. Effective policies require a holistic understanding of interconnected systems. E.g., trade agreements must account for their impact on labor mobility Lavenex and Jurje (2021) and supply chain resilience Li et al. (2020). Likewise, migration policies should consider the economic contributions of migrants, the push-pull factors driving movement, and the broader implications for social cohesion Rapoport and Docquier (2006). Open-access, full databases provide the granularity and breadth needed to design policies that address these multifaceted challenges.

In policymaking and academic research, transparency is crucial for credibility and trust Dando and Swift (2003). Open-access databases allow researchers to reproduce and validate findings, ensuring that results are robust and not influenced by selective data use or hidden methodologies. In trade, this transparency is critical for monitoring compliance with international agreements and identifying unfair practices Turnes and Ernst (2015). For mobility, open data facilitates the evaluation of migration policies and the management of transnational crises Schultz, Lutz, and Simon (2021). Governments, international organizations, and the public can all benefit from this openness, driving accountability and informed decision-making. Having highlighted the importance of open-access, full databases in trade and mobility research, it is essential to consider the broader implications of Erasmus and BACI network research.

1.6 Broader Implications of Erasmus and BACI Network Research

The Erasmus mobility program has been widely studied as a network of interconnected universities, institutions, and countries Gadár et al. (2022). Researchers have treated Erasmus mobility as a bipartite network, where nodes represent universities and countries, and edges represent the flow of students or faculty members between them Derzsi et al. (2011). Through network analysis, scholars have examined the degree centrality of major hubs, such as universities in countries like Germany, Spain, and France, which often attract the highest number of exchanges. Community detection methods, such as modularity maximization, have revealed clusters of closely connected institutions, often aligned with geographic or linguistic Bruggeman, Traag, and Uitermark (2012). Furthermore, time series network analysis has enabled scholars to track how Erasmus mobility flows evolve over time Teichler (1996) this dynamic perspective provides insights into the resilience and adaptability of the Erasmus network, helping policymakers identify potential vulnerabilities and opportunities for growth.

The BACI trade network, built on detailed trade flow data between countries, has been instrumental in understanding the global trade system. Scholars have analyzed BACI data as a weighted, directed network, where nodes represent countries and edges represent the volume and direction of trade flows. Key network metrics such as in-degree, out-degree, and betweenness centrality have identified major trading hubs such as China, the United States, and Germany, which dominate global trade dynamics De Benedictis et al. (2014). Community detection in the BACI network has uncovered regional trading blocs, such as those formed by EU member states or ASEAN countries Liang et al. (2019). These blocks reflect both geographic proximity and trade agreements that facilitate stronger connections. Scholars have also explored the evolution of these communities over time Wauchope et al. (2021), identifying how globalization and shifting economic power centers shape the structure of global trade.

Both Erasmus mobility and BACI trade networks share commonalities in their structural properties. Researchers have observed that these networks exhibit features of scale-free and small-world networks, characterized by a few highly connected hubs and a majority of nodes with lower connectivity. This structure has significant implications for resilience and vulnerability. E.g., disruptions to highly central nodes, such as key universities in the Erasmus network or major exporting nations in the BACI network can have cascading effects on the entire system. Having explored the broader implications of Erasmus and BACI network research, it is crucial to address the current gaps in these networks to advance our understanding and application of these systems.

1.7 Current Gaps in Erasmus and BACI Networks

The BACI trade network and Erasmus mobility network represent two critical systems of global interconnectivity, educational exchange and trade flows, that have been extensively analyzed but still present significant gaps in understanding.

The BACI trade network has been thoroughly explored in terms of trade volumes, directions, and the role of key hubs in global trade flows. Researchers have identified trading blocs, power shifts (e.g., the rise of Asia), and disruptions caused by geopolitical events, such as trade wars or pandemics. However, there is still a gap in understanding the temporal and causal dynamics of trade indicators, especially at the product and product group levels. Existing studies often treated trade networks as static or did not take into account of the compounding effects of shocks, crises, or technological advancements in trade flows.

For Erasmus mobility, current research has predominantly focused on descriptive and structural analyses of student and faculty exchanges. Studies have revealed the network's small-world and scale-free characteristics, its reliance on key institutional hubs, and its clustering based on geography, language. Temporal analyses have been less developed, with limited attention paid to how patterns evolve over time or how external drivers, such as crime rates, collaboration opportunities, or cultural factors, influence mobility flows. Furthermore, most studies are constrained by their focus on national or institutional levels, with limited insights at finer spatial scales such as NUTS3 regions or on individual participants.

Despite these advancements, several critical gaps persist in both networks:

- *Temporal Patterns and Evolution:* While both Erasmus and BACI networks are inherently dynamic, there is limited understanding of their temporal evolution. For Erasmus, questions remain about how mobility flows change over time, particularly in response to drivers like economic, socioeconomic, collaboration, and cultural aspects. Similarly, for BACI, the temporal dynamics of trade network flows at the product level—how they respond to crises or technological innovations—are not well studied.

- *Causal Relationships:* Few studies explore causal links between network indicators and external drivers. For instance, in the Erasmus network, the causal impact of crime or collaboration on mobility patterns is not fully understood. In the BACI network, the transmission mechanisms of shocks (e.g., financial crises or pandemics) and their impact on trade indicators at the product level remain underexplored.

- *Unit of Analysis:* Much of the research on Erasmus is limited to national or institutional levels, overlooking analyses at the NUTS3 and NUTS2 level or the individual level. Similarly, trade studies in BACI often aggregate data at the country level, missing insights at the product or product group level.

- *Comparative Approaches:* In both networks, comparative analyses of different models, independent variables, and units of interest are sparse. E.g., how do different econometric models perform in predicting Erasmus mobility flows when considering cultural versus economic factors? Or how do trade indicators for different product groups respond differently to crises?
- *Shock and Crisis Response:* Limited work has been done on the ability of the global trade networks to detect and respond to shocks. How do crises such as the COVID-19 pandemic propagate through trade networks, and how do they affect specific products or countries?
- *Integration of New Drivers:* Emerging drivers such as technological changes, crime rates, and cultural factors are often analyzed in isolation. It needs to understood how these drivers interact and influence the network dynamics over time.

Having identified the current gaps in the Erasmus and BACI networks, this dissertation aims to address these issues by providing novel insights and establishing expanded models to enhance our understanding and application of these systems.

1.8 Research Objectives, Contributions and Research Questions

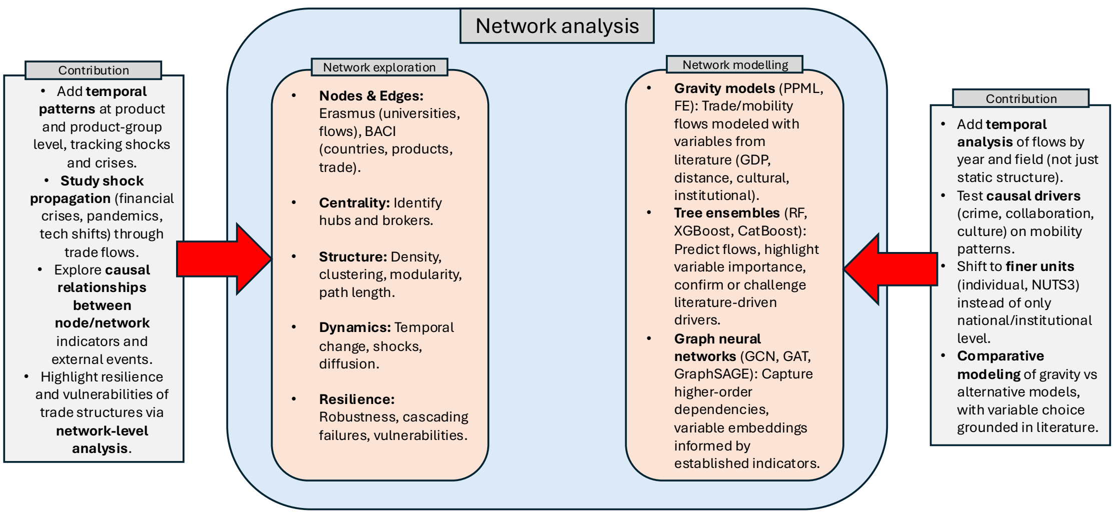

FIGURE 1.1: Research outcomes and enrichment of existing literature

This dissertation aims to address these gaps by providing novel insights into the temporal patterns and causal relationships within the BACI network and to establish an expanded gravitational model for the Erasmus model, vide supra in Fig. 1.1.

BACI Trade Network Contributions:

- *Temporal Patterns and Crisis Analysis:* By focusing on trade network indicators for different products and product groups, this study identifies temporal patterns that reveal how shocks (e.g., financial crises or pandemics) and technological changes affect trade flows. It further explores how these shocks propagate through the network, providing evidence of transmission mechanisms and their impacts.
- *Causal Relationships:* Using econometric methods, this research establishes causal links between network and node level indicators, enabling a better understanding of how and why specific changes occur in the network.

Erasmus Mobility Network Contributions:

- *Comparative Model Analysis:* This study compares models based on independent variables, such as crime, collaboration, and cultural factors, as well as units of analysis (individual and NUTS3-regional levels). By analyzing these drivers by year and scientific field, the study offers a more nuanced understanding of mobility flows.
- *Fine Grained Analysis:* By leveraging the entire Erasmus exchange network, this research provides evidence on four key areas of interest, focusing on individual and regional level analyses to uncover new patterns and insights.
- *Integration of Emerging Drivers:* This work evaluates the influence of existing and new drivers on mobility flows, providing a comparative analysis of their impacts across different contexts and time periods.
- *Policy Relevant Insights:* The findings contribute to designing targeted interventions for improving Erasmus mobility and trade policies, and optimizing collaboration and cultural exchange.

While these contributions highlight significant advancements, it is also essential to contextualize the relative maturity of the networks being studied. The world trade network remains in an exploratory stage, where fundamental aspects, such as the comprehensive structural analysis of product groups over extended timeframes are still under-examined. This research seeks to bridge this gap by explaining temporal behaviors through network-wide and node-level indicators. Conversely, the Erasmus mobility network represents a more mature area of exploration, with gravitational models already in use. Building on that foundation by refining and expanding the existing framework to incorporate new variables and perspectives, advancing the understanding of mobility dynamics. In this way, the dissertation aligns its objectives with the dual aims of uncovering new insights in emerging areas and refining existing knowledge in more established domains, contributing to a comprehensive understanding of global networks in trade and mobility. As such I am formulating the following research questions that are explored and answered in the upcoming sections:

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?

The bulk of my figures and tables are sourced from Kosztyán, Kiss, and Obermayer (2023) and Kosztyán, Kiss, and Fehérvölgyi (2024). Having outlined the research objectives and contributions, it is important to reflect on the personal and academic journey that has led to this dissertation, highlighting the motivations and experiences that have shaped this research.

1.9 Personal and Academic Journey in Network Science

My journey into the study of networks began during my Bachelor's program, where I first encountered the Erasmus mobility network and its fascinating potential to reveal insights into global academic and cultural connections. In 2019, I participated in my first TDK (Scientific Students' Associations Conference) research project focused on the Erasmus network, exploring its structural characteristics and the patterns of student mobility across Europe. This research culminated in my participation in the OTDK (National Conference of Scientific Students' Associations) later that year, where I presented findings that highlighted the network's small-world properties, its clustering effects, and the influence of institutional hubs.

Encouraged by the positive reception of my work and intrigued by the open questions in this field, I continued to develop my expertise in Erasmus network research. In 2020, I authored a continuation TDK project that expanded the scope of analysis to include temporal patterns in mobility flows, investigating how external drivers such as regional disparities and cultural factors impacted exchange dynamics. My deepening focus on the Erasmus network provided an opportunity to present at the OTDK once more in 2021, where I refined my methodological approaches and began considering how to address the complex interplay of external drivers and network structure.

My Master's studies further solidified my commitment to understanding the Erasmus mobility network. In 2021, I wrote another TDK project focused on comparing models that analyzed mobility patterns with respect to independent variables such as collaboration opportunities, regional crime rates, and cultural affinities. This work aimed to explore the network at both individual and regional levels (e.g., NUTS3 regions) and to provide actionable insights into the drivers of mobility across disciplines and geographic areas. Once again, I had the privilege of presenting my findings at the OTDK in 2022, where my research was well-received for its focus on emerging drivers of mobility and its implications for educational policy.

These early academic endeavors reflect a clear trajectory of engagement with network science, grounded in my personal interest in uncovering the drivers and dynamics of global interconnectivity. While my research during my Bachelor's and Master's programs was focused exclusively on the Erasmus network, these experiences honed my skills in network analysis, econometric modeling, and the interpretation of complex datasets. They also fueled my determination to extend my work to broader, interconnected systems, such as the BACI trade network, which I now integrate into my dissertation.

My personal history with Erasmus network research has deeply shaped my academic trajectory and serves as the foundation for my doctoral work. This dissertation represents a culmination of my previous research while also broadening its scope to address critical questions about the temporal patterns, causal relationships, and impacts of external shocks in both the Erasmus mobility network and the BACI trade network. By addressing these issues, I aim to contribute meaningful insights to network science, demonstrating the value of interdisciplinary approaches to understanding the systems that connect and shape our world.

Chapter 2

Literature review

2.1 Networks in Economics

Networks can serve as a description of exchanges in economics, capturing the web of relationships and interactions that define modern economic systems Albert and Barabási (2002). Networks represent the interconnectedness between economic agents (individuals, firms, regions, or nations) and provide a structured framework for analyzing how these connections drive the flow of goods, services, information, and capital. This interconnectedness is not a static representation; it reflects dynamic processes that adapt and evolve, shaping decision-making, resource allocation, and outcomes in industries and markets Sherwood et al. (2017).

In economics, network theory offers a holistic look so that we can observe and analyze the structural and functional aspects of the relationships. By conceptualizing agents as nodes and their interactions as edges, networks allow for the modeling of complex systems with a high degree of sometimes hard to decipher granularity. The value added value comes from studying trade relationships, mobility, Louail et al. (2015) supply chain dependencies, financial transactions, where individual decisions make up the nodes within the network, creating feedback loops and effects observable on a temporal scale with enough available data. These effects underscore the nonlinearity and interdependence, attributes of economic networks.

Network theory sheds light on the mechanisms by which economic agents organize themselves, revealing patterns via clustering, centralization, and hierarchy. E.g., in global trade networks, certain nations or regions may emerge as central hubs due to their high connectivity and influence, while others occupy peripheral roles (outside of the "club") Colizza et al. (2006) with fewer connections. This centrality does not only show economic power but also systemic vulnerabilities, as disruptions to key nodes that can propagate rapidly across the network in mobility Gadár et al. (2022) and trade networks alike Kim, Chen, and Linderman (2015).

2.1.1 Key Models in Network Theory: Erdős–Rényi and Barabási–Albert Models

1. Erdős–Rényi Model (Random Networks) The Erdős–Rényi model describes random networks where nodes are formed independently and with equal probability. This model is one of the first of modern network theory. Its application in economics is limited due to its inability to capture the heterogeneity and formation of clusters commonly observed in real-world examples. It provides a baseline for understanding random interactions, such as initial trade linkages or the early stages of market formation Saveski et al. (2017).

2. Barabási–Albert Model (Scale-Free Networks) The Barabási–Albert model introduced the concept of scale-free networks, characterized by a power-law degree distribution Barabási and Albert (1999). These networks show highly connected nodes (hubs) and many other nodes within the network with fewer connections. In economics, scale-free networks are often emerge in sub-domains like trade, mobility, and social networks, where central hubs, such as countries, cities, institutions or multinational corporations. These hubs play a disproportionately large role in the system's overall functionality Ciriaco et al. (2025).

The Barabási–Albert model showcases the importance of preferential attachment, where new nodes are more likely to connect to established nodes in the networks Kanavos et al. (2024). This dynamic mirrors real-world phenomena such as the dominance of global trade hubs, the mobility concentration of students of highly ranked universities, and the emergence of leading firms in various industries.

2.1.2 Implications of Network Models in Economics

One of the industries where the wide spread application of network models proved to be a worthwhile effort in economics provides insights into several data rich areas Zheng et al. (2024) such as in market dynamics where understanding how information, innovation, and capital flow through the network. Resilience and vulnerability identification of critical nodes and links where the disruption could lead to systemic failures, such as financial crises or supply chain disruptions. Innovation diffusion explains how new technologies, practices, or products spread through networks of firms or consumers Mbatha (2024). These insights can only be gained via a systematic approach to economic networks through distinct stages of development, each characterized by unique dynamics and challenges:

1. Exploration Stage In the exploration stage, networks form organically as agents establish initial connections Tasselli and Kilduff (2021). This phase is marked by experimentation, uncertainty, and the gradual emergence of patterns. Examples include the establishment of early trade routes or the founding of start-up ecosystems or the formation of mobility networks.

2. Forecasting and Innovation Stage In advanced stages, networks might be used to leverage network derived and exogenous data as well to employ predictive models to anticipate future trends Berkani et al. (2023) and adapt proactively. This includes the use of artificial intelligence and machine learning to help optimize trade routes, forecast market demand, or detect systemic risks to mobility networks.

2.2 Review Approach

This section outlines the review process used to select and organize the studies presented in Tables 2.1 and 2.2. A structured filtering process based on the PRISMA framework was followed to narrow the initial pool of literature to a focused set of studies relevant for comparative and structural analysis. Full details on this process are provided in the Methods section.

The aim of this review is not to exhaustively catalogue all literature on trade and mobility networks, but to surface a representative set of papers that illustrate key methodological strategies, data sources, and structural insights within each domain. Studies were selected based on the specificity and transparency of their modeling approach, the relevance and granularity of the data used, and their contribution to advancing network-based perspectives on economic or academic exchange systems.

Across both tables, what emerges is a shared foundation of network thinking, despite differences in context. Both domains rely on core metrics centrality, clustering, path length to extract structure. Gravity models appear in both, but differ in the emphasis of included variables: economic fundamentals in trade, cultural and institutional factors in mobility. There is also a trend toward dynamic and machine-learning-based methods in both literatures, though more fully developed in trade studies to date.

The review sets the ground for the comparative synthesis that follows. The figures that follow this section position each study according to its contribution to network science either through method, application, or both / and help identify where existing literature leaves conceptual or empirical gaps. These approaches are outlined via the next sections and illustrated by Fig. 2.1, vide infra.

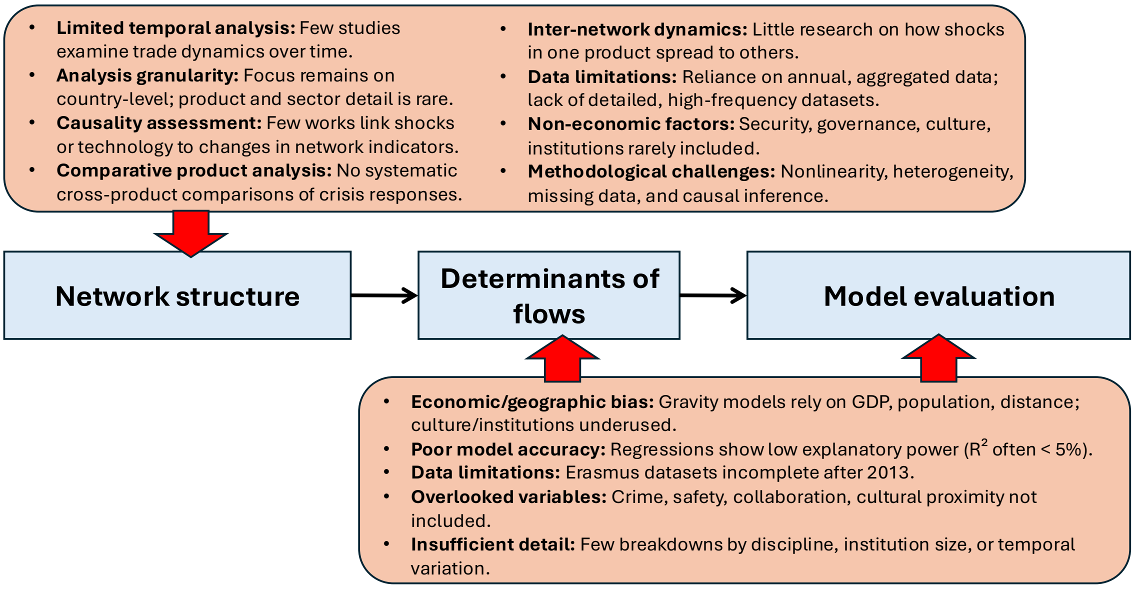

FIGURE 2.1: Explored literature gaps

2.2.1 Trade Networks

Trade is one of the most fundamental and pervasive human activities that shapes the world in which we live Fernandez-Mora (2023). Trade networks represent the connections and flows of goods and services between economic entities, such as countries, regions, or firms, and help understanding the structure and dynamics of global economies and societies Liu et al. (2025b).

Trade networks analysis provides an aspect research focus that reveal how companies, regions, and nations interact to benefit their communities as a whole De Benedictis and Tajoli (2011). They help identifying opportunities and challenges of trade integration and cooperation, providing insights into best practices and strategies to improve the benefits of trade while potentially mitigating its risks Shutters and Muneepeerakul (2012). Fagiolo, Squartini, and Garlaschelli (2013) demonstrates that while binary network models of the world trade network can effectively replicate observed topological properties using degree sequences, weighted network models reveal that higher-order properties cannot be deduced from local properties alone, highlighting the need for revised international trade models that account for these complexities. Trade networks are usually built up via nodes such as countries, regions, or firms and links e.g. flows of goods, services, or capital Garlaschelli and Loffredo (2005). The inherent complexity and multi-layered nature reflects the diversity of economic relationships across different scales. Fagiolo and Luzzati (2023) constructs a multi-layer network of international trade, migration, and finance to show that a country's global centrality in these networks significantly boosts its per-capita GDP, highlighting the importance of strategic international linkages for economic growth. Globalization has amplified these interactions, fostering deeper integration but also exposes vulnerabilities to external shocks such as crises, conflicts, and pandemics Gutiérrez-Moya, Lozano, and Adenso-Díaz (2023). Reino et al. (2017) demonstrates that detailed characterization of trade networks reveals the strong connection between global trade pressure and biological invasions, highlighting that the 2005 EU bird trade ban effectively reduced global bird invasion risks but also led to the emergence of alternative trade routes and increased invasion risks in other regions.

Key characteristics of trade networks include:

- *Density and Connectivity:* Reflecting the degree of trade integration, where some nations or regions emerge as central hubs while others remain on the periphery.
- *Trade Diversification:* Capturing the variety of products and services exchanged across networks, which influences economic resilience.
- *Network Asymmetries:* Highlighting the unequal distribution of trade benefits among participants, often mirroring broader inequalities Prell et al. (2015).

Analysis outcomes of trade networks influence various dimensions, such as economic growth where trade facilitates specialization, economies of scale, and access to new markets, driving innovation and productivity Teza, Caraglio, and Stella (2018). Poverty and inequality where trade integration can alleviate poverty, may also exacerbate inequality within and between nations, necessitating policies that promote equitable growth Higgins and Prowse (2010). Global trade agreements between underrepresented countries significantly reduce inequality in the international trade network, highlighting the importance of promoting such agreements beyond regional blocks to achieve a more balanced network Garcia-Algarra, Bengoechea, and Mouronte-López (2020). In the case of cultural exchange trade networks serve as a good baseline approximation for cultural diffusion, clearly helping understanding the collaboration among diversifying societies Shutters and Muneepeerakul (2012) that facilitate mobility. When it comes to environmental impacts trade can drive unsustainable resource use and pollution, highlighting the need for sustainable practices and governance frameworks Aller, Ductor, and Herrerias (2015).

Technological change is a key driver of trade network evolution. Innovations in transportation, communication, and digital infrastructure have significantly reduced trade costs and barriers, enabling greater participation in global markets Ferrier, Reyes, and Zhu (2016). Advanced analytics and automation are also reshaping supply chains, creating new efficiencies while disrupting traditional trade patterns.

Global Trade and Its Implications

Within these trade chain effect of patterns the global economies grow increasingly interdependent, the dual imperatives of economic development and environmental preservation come to the forefront. Sustainability, in this context, encompasses not only ecological considerations but also social and economic dimensions, all of which intersect with the mechanisms and outcomes of global trade AlGhasawneh et al. (2025).

One of the most critical dimensions of the sustainability and trade intersection is environmental impact, particularly concerning carbon emissions. Global trade, while fostering economic integration and development, has also contributed to rising CO2 emissions due to transportation and energy-intensive production processes Kander et al. (2015). Ji et al. (2016) provides the first comprehensive analysis of the global electricity trade network, highlighting the critical roles of nations like Germany, France, and the Czech Republic in Europe, and Russia, Ukraine, China, and Azerbaijan in the Eurasian sub-network, while also revealing the significant CO2 emissions associated with international electricity trade. Ostadzadeh et al. (2023) developed a modeling framework to characterize and project the global fossil fuel trade network, using trade predictive models and the matrix balancing method, revealing significant future changes and highlighting the importance of transparency and detailed data sharing for effective energy policy and research. Zhang et al. (2017) uses ecological network analysis to model global CO2 transfers in trade, revealing that competition and exploitation / control relationships dominate the network, and provides insights to clarify carbon reduction responsibilities and optimize the global CO2 transfer system. The inherent tension between economic growth and environmental sustainability urges policymakers to incorporate emission mitigation strategies into trade agreements. To address this, many researchers advocate for more stringent international regulations on carbon-intensive trade flows and the adoption of cleaner technologies across industries. Innovations such as green shipping corridors, renewable energy in manufacturing, and carbon border adjustment mechanisms could pave the way for more sustainable trade practices.

Beyond its environmental implications, global trade plays a pivotal role in advancing the sustainable development goals. International trade facilitates the redistribution of resources, knowledge, and technologies, creating pathways to reduce inequalities and promote inclusive growth Xiao et al. (2024). E.g., trade enhances access to medical supplies, clean energy technologies, and educational resources, all of which contribute to achieving specific sustainable development goals such as good health, quality education, and affordable clean energy. However, realizing the full potential of trade to support the sustainable development goals requires addressing structural imbalances within trade networks. Developing countries, for instance, often face barriers such as limited market access and unfavorable trade terms, which undermine their ability to benefit equitably from global trade systems. Ensuring that trade is inclusive and fair remains a critical challenge for sustainability-driven policies. Additionally, where these policies cannot be enforced or regulated, territories such as the EU can fall severely behind production capacities due to overregulation Seidl and Schmitz (2024). Countries with dominant positions in deep Regional Trade Agreements networks tend to perform better in fighting public sector corruption, highlighting the significant role of anti-corruption provisions and the benefits of international policy spillovers Zhang et al. (2023).

Trade also emerges as a key instrument in addressing global hunger and ensuring food security, particularly in the context of rising population growth and climate-induced disruptions. By enabling the redistribution of agricultural goods across regions, trade helps alleviate disparities in food availability and fosters resilience against local supply shocks Janssens et al. (2020). The integration of food systems into global trade networks is not without risks. Price volatility in international markets, often driven by speculative activities or geopolitical tensions, creates vulnerabilities for food importing nations Brander, Bernauer, and Huss (2023). To counteract these challenges, there is a self induced effort for international cooperation to stabilize food markets and develop adaptive trade policies that prioritize food security as a key element of the concept of sustainability Sukanya (2024).

The pursuit of sustainability within global trade necessitates long-term and diverse policy approaches. Effective strategies must integrate economic, social, and environmental considerations while fostering collaboration among nations which describes the following points.

1. *Sustainability-Driven Trade Agreements:* Embedding environmental and social standards into bilateral and multilateral trade frameworks to ensure that economic integration does not come at the expense of sustainability Leal-Arcas (2025).

2. *Careful Planning and Resource Management:* Promoting circular economy principles in trade, reducing resource depletion, and encouraging sustainable production practices Kandpal et al. (2024).

3. *Strengthening International Cooperation:* Facilitating knowledge sharing and technological transfers among countries to bridge gaps in sustainable trade capacity Rani et al. (2025).

These strategies underscore the importance of aligning trade policies with global sustainability goals, ensuring that economic benefits do not undermine environmental and social well-being. By addressing these interconnected challenges, global trade can serve not only as a mechanism for economic growth but also as a driver for sustainable development and the potential circumvention of crises.

Gap Exploration in Global Trade Networks

Crises such as financial downturns, geopolitical conflicts, and health emergencies reveal properties of trade networks. Crises often disrupt trade flows and highlight dependencies, they also force innovation and adaptation, leading to new patterns of economic interaction Gutiérrez-Moya, Lozano, and Adenso-Díaz (2023). Understanding these dynamics encourage that innovation and adaptation for building resilient trade systems capable of weathering the storm future challenges. The application of advanced econometric methods and network analysis tools have enabled scholars to explore the temporal and structural dynamics of trade networks Liu et al. (2025a). E.g. a study by Kulkarni et al. (2023) reveals that while agricultural trade networks in India are becoming more self-reliant and resilient to external shocks, non-agricultural trade networks are increasingly fragmented and dependent on leading exporter states, making them more vulnerable to disruptions.

Despite the increasing recognition of the importance and complexity of trade networks, numerous open research questions and challenges remain in the field. One of the key questions is how the structural characteristics of various products and product groups can be utilized to evaluate and categorize trade networks.

Network analysis is a valuable tool for understanding the structure and evolution of global value chains, revealing both stability and shifts in trade patterns across sectors and countries, and highlighting the adaptability of global value chains to changing global market conditions Piccardi, Tajoli, and Vitali (2024). Zamora Torres and González García (2019) concludes that while warehousing and time variables show satisfactory forecasts, customs administration needs significant improvement, highlighting the importance of government support to enhance the efficiency and competitiveness of the logistics chain in Mexico. Río-Chanona, Grujić, and Jeldtoft Jensen

(2017) analyzes the World Input Output Network (WIOD) to understand the dynamics of countries' and sectors' importance using PageRank and economic strength, revealing that secondary networks based on correlations and anti-correlations provide valuable insights into competitive relationships and market dynamics. Forecasting models provide insights into future trade patterns and the potential impacted elements of generated shocks, while causal models help in identifying underlying drivers of trade flows Kim and Shin (2002). Domazetoski et al. (2023) models the world economy as an interconnected network using the 2016 WIOD, defining a shock tensor to evaluate link sensitivity and shock propagation, revealing patterns that can assess trade relationships, risks, and making informed decisions. These approaches not only enhance our understanding of trade networks but also inform policy makers whose aim is to foster undisturbed stability and growth. Despite extensive research on trade networks in various forms.

Zhang and Zhang (2024) constructs and analyzes a global potassium salt trade network from 2000 to 2021, revealing trends of increasing prosperity, efficiency, and concentration, with significant roles played by major exporters and importers, and highlights the importance of diversifying trade partners and ensuring sustainable resource management. Asadabadi and Miller-Hooks (2020) presents stochastic optimization models to enhance the reliability and resilience of global port networks, emphasizing the importance of strategic investments to mitigate the impacts of potential future disaster scenarios. Buddenhagen et al. (2021) models the spread of quarantine weed contaminants through international ryegrass and clover seed trade networks, highlighting the importance of considering trade volume, network topology, and biosecurity measures to mitigate the risk of weed incursions. REZITIS, KARYTSAS, and ZANGELIDIS (2024) employs the gravity modeling framework and social network analysis to examine the impact of trade networks, non-tariff measures, and natural disasters on international beef trade flows from 2009 to 2019, highlighting the significant roles of network centrality and economic conditions in shaping trade relationships. By employing a multilayer analysis of the global trade network, we uncover intricate trade relationships and evolving mesoscale structures that are not detectable in aggregate mono-layer networks, highlighting the dynamic interplay of competition and cooperation among industries and nations over time Bartesaghi et al. (2022). Rosal (2024) demonstrates that network analysis is a valuable tool for understanding the structure and evolution of global value chains, revealing both stability and shifts in trade patterns across sectors and countries, and highlighting the adaptability of global value chains to changing global market conditions. Soyyigit, TOPUZ, and Ozeklcloglu (2020) concludes that the global coal trade network exhibits a complex, core-periphery structure with a few central exporter countries and many peripheral countries, highlighting the importance of high-degree statistics for a more reliable evaluation of the network's connectivity and the increasing significance of Asian countries as major coal importers. Dong et al. (2020) proposes an optimized crude oil trade network using a distributed bipartite model and Simulated Annealing Algorithm, significantly reducing trade costs and enhancing the robustness of trade relationships. Lo Re et al. (2023) concludes that the international network of Chinese firms is highly ramified but not very wide, characterized by a pronounced cluster structure and efficient communication, yet lacking strong mutual connections between subsidiaries, indicating a need for policy measures to enhance network synergies and strengthen ties with foreign countries. Shen et al. (2015) models international trade flows using open flow networks and flow distances, revealing the roles and positions of countries in global supply chains, and highlighting the effectiveness of these methods for understanding trade dynamics and economic risks. Chou, Teng, and Tung (2023) argues that political alliances significantly influence bilateral arms trade, with states in the same alliance network more likely to trade arms, highlighting the importance of both direct and indirect relationships in international arms trade dynamics. Jackson and Nei (2015) demonstrates that stable networks of military alliances are unlikely to exist without substantial trade considerations, highlighting how trade can prevent conflict by encouraging countries to defend their trade partners and discouraging them from turning against their allies. Shutters and Muneepeerakul (2012) extends triadic network analysis to global agricultural trade networks, revealing a unique triad significance profile that combines elements from biological regulatory and human social networks, and highlights how countries' roles in trade triads vary with their level of interconnectedness. It is demonstrated that the Fitness and Complexity algorithm effectively ranks countries and products by importance, revealing additional insights and serving as a useful predictor for economic outcomes, particularly in cases of country mergers and separations Liao and Vidmer (2018).

However significant gaps remain, such as the examination of the entire available network with all of the available product categories (summarized by Fig. 2.1 and Table 2.1 as items detailed). There is also a need for greater integration of temporal and causal analyses to understand the evolution of trade networks over time. As well as examination of the interplay between trade networks and non-economic factors such as security, governance, and cultural dimensions and improved up to date data availability and granularity to support robust, open-access research efforts, preferably on a monthly scale instead of the current yearly level.

Addressing this question necessitates exploring the extent to which structural changes in the trading patterns of individual product groups diverge from one another.

If the temporal patterns of these structural characteristics exhibit similarities across product groups, this could suggest that different product categories respond to crises or other external shocks in comparable ways. Conversely, if these characteristics are distinct, identifying which product groups form clusters based on shared structural traits could provide an intriguing avenue. This however raises further questions about the potential for temporal structural similarities and whether causal relationships exist between the patterns of different product groups. Investigating causality could provide valuable insights into how shocks propagate through trade networks and how technological advancements affect trade dynamics.

To understand how a shock, crisis, or technological change within one product's trade network might influence another, it is essential to examine the patterns and interconnections of node- and network-level indicators across product categories. Identifying the relationships between structural characteristics of different trade networks is crucial for determining whether certain products or product groups share common dynamics or whether the structural features of one trade network directly affect others. This exploration involves analyzing the temporal patterns of trade network indicators, assessing their interdependencies, and determining the degree to which they are interconnected. To the best of our knowledge, no prior studies have systematically examined the temporal patterns of trade network indicators across different products or investigated the causal relationships among these patterns. Such an analysis would provide a foundation for understanding the transmission of shocks, the spread of crises, and the impacts of technological changes on trade networks. In the discussed recent studies, in line with the results of the conducted systematic literature review, various databases that are structurally comparable have been analyzed, with a focus on trades between specific countries involving particular products.

Despite the numerous advantages of these methods, there are several important limitations that need to be considered. First, these approaches may not fully capture the dynamic and nonlinear nature of trade networks, which are subject to frequent temporal changes and external shocks. Second, the analysis might rely on simplifying assumptions or approximations that fail to reflect the true complexity of trade networks. E.g., the heterogeneity of products, countries, or trade links might be overlooked, reducing the accuracy of the models. Third, there are often data limitations or quality issues, such as missing values, measurement errors, or inconsistencies in trade data sources or classifications, that could compromise the reliability of the findings. Lastly, these methods may struggle to establish clear causal relationships or identify the direction of causality between trade network indicators and other related variables, such as economic, political, or technological factors. These challenges underscore the need for careful consideration and further refinement in trade network analysis methodologies.

Permanent Crisis Theory: From Stability to Instability

The Permanent Crisis Theory, as explained by Hont (1994), challenges the traditional economic assumption of equilibrium-driven markets. Instead of approaching toward a state of balance, economies are seen to oscillate between periods of relative stability and crises. This perspective re-frames the understanding of economic dynamics, suggesting that crises are not anomalies but rather an inherent part of the global markets.

Within the context of global trade network, this theory has significant implications. Trade networks, that are built by the movement of goods, services, and capital, often reflect these oscillations. When trade networks become centralized or brittle might amplify the effects of external shocks, leading to widespread disruptions in supply chains and economic activities Li, Chen, and Guo (2025). Thus, analyzing trade networks through the lens of Permanent Crisis Theory provides valuable insights into the structural vulnerabilities and systemic risks.

Trade Crisis

Figure 2.2 presents a timeline of significant shocks and crises that have influenced global trade between 1990 and 2025.

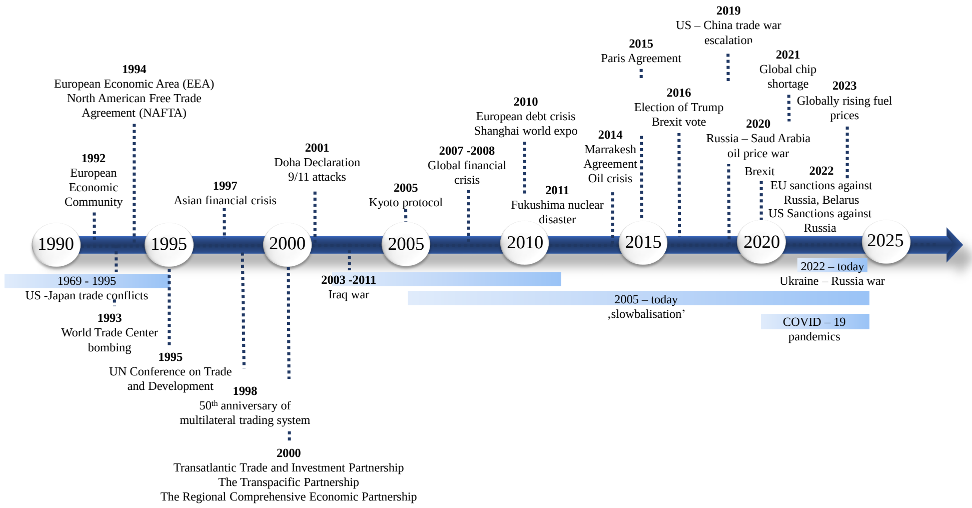

FIGURE 2.2: Shocks and crises related to trade (1990–2025).

The period from 1990 to 2025 has witnessed a multitude of crises and shocks that have reshaped the global trade landscape. Key events in the early 1990s, such as the formation of the European Economic Community and the North American Free Trade Agreement (NAFTA), laid the groundwork for enhanced economic integration. However, this progress was juxtaposed with security concerns highlighted by events like the World Trade Center bombing and discussions at the UN Conference on Trade and Development.

The turn of the millennium introduced further complexities. The Doha Declaration, launched in 2001, and the tragic 9/11 attacks marked a critical juncture, steering global trade toward heightened economic cooperation while emphasizing security concerns. Concurrently, sustainability began to influence trade through initiatives like the Kyoto Protocol and the emerging concept of 'slowbalisation,' which advocated for slower and more sustainable globalization Wickes (2021). Iapadre and Tajoli (2014) explores how emerging countries' internationalization often begins regionally through preferential trade agreements and evolves into global trade participation, driven by both regional linkages and autonomous economic development.

The global financial crisis of 2007–2008 emerged as a pivotal event with long-lasting effects, compelling a reexamination of trade agreements and economic policies Ahmed, Al-Gasaymeh, Mehmood, et al. (2017). This was followed by the European debt crisis, the Fukushima nuclear disaster Wang et al. (2022), and the Marrakesh Agreement, all of which tested the adaptability and resilience of global trade networks Smeets (2022). Distefano et al. (2018) highlights that real trade flows, rather than price variations alone, are crucial for evaluating food security, revealing that poorer countries suffer larger import drops after negative trade shocks, and emphasizing the need for international agreements to consider the resilience of these countries.

The 2010s brought new challenges and discussions. The Paris Agreement Wu, Zhou, and Qian (2022) elevated climate change as a critical issue for trade policies, while the election of Trump ushered in an era of protectionist policies that reshaped global trade dynamics Noland (2018). The escalation of the US–China trade war in 2019 further destabilized global supply chains, emphasizing the interconnected nature of the global economy Itakura (2020). Yazawa (2023) study further proves the evolving dynamics of international trade networks from 1992 to 2020, highlighting the shift in trade dominance from the U.S. to China, the impact of global events on trade structures, and the increasing reciprocity in trade relationships for most product categories. Proving this Zhou et al. (2018) proposes an analytical approach to calculate the robustness of the method of reflections and fitness-complexity method, demonstrating that fitness-complexity method is more resilient to perturbations and using it to simulate the trade conflict between the USA and China, revealing that China would lose competitiveness while the USA would gain slightly.

In the 2020s, the global trade landscape continues to face unprecedented challenges. Events such as the Russia–Saudi Arabia oil price war Ma, Xiong, and Bao (2021), the global semiconductor shortage Zhang and Zhu (2023), and the ongoing Russo–Ukrainian war underscore the vulnerabilities of international trade networks. These crises, compounded by the long-lasting impacts of the COVID-19 pandemic, have reinforced the need for resilience and adaptability in trade systems Steinbach (2023). The study of Antonietti et al. (2022) reveals that the World Trade Network's structure significantly influenced the initial diffusion and mortality of COVID-19, with country centrality playing a key role, while the network's mesoscale structure remained resilient to the pandemic's impact.

Significant changes in world trade have been the focus of numerous studies employing a variety of methods to address diverse research questions. These investigations have deepened our understanding of how trade networks evolve in response to crises, offering critical insights into the mechanisms driving global trade dynamics.

Trade Networks as Indicators of Structural Change

Structural changes in global trade networks are closely linked to broader shifts in globalization, technological advancements, and the emergence of crises. According to Xu, Ma, and Zeng (2019), the evolution of trade networks can serve as a barometer for understanding the ebb and flow of globalization or deglobalization. E.g., periods of increasing global interconnectedness often coincide with denser and more diversified trade networks, while phases of deglobalization result in fragmentation and regionalization of trade flows.

Similarly, trade networks can also reflect technological progress. As Shutters and Muneepeerakul (2012) argued, innovations in logistics, communication, and production have historically reshaped the topology of trade networks, enabling new patterns of interaction and efficiency. Conversely, the emergence of crises, as noted by Gutiérrez-Moya, Lozano, and Adenso-Díaz (2023), often disrupts these networks, creating bottlenecks and imbalances that hinder the flow of goods and services.

Temporal Patterns as Predictors of Crises and Shocks

Identification of temporal patterns in trade networks thus offers a promising avenue for predicting and understanding economic shocks. Several studies have highlighted the potential of trade network analysis to reveal early warning signals of impending crises. For instance, Gutiérrez-Moya, Lozano, and Adenso-Díaz (2023) demonstrated that disruptions in the structural indicators of trade networks, such as connectivity, centrality, and trade volumes, often precede major economic shocks. Kali and Reyes (2010) explored how financial crises ripple through interconnected trade systems, muscling their way into global markets. Luo et al. (2014) presents the GeoSocialApp, a visual analytics tool that integrates spatial and network analysis methods to explore the interaction between spatial and social relationships in the international trade network (ITN), demonstrating its potential to generate and validate hypotheses through combined visual-computational exploration and statistical analysis. Li et al. (2023) uses the Dynamic Time Warping (DTW) model to build correlation networks and analyze the connectedness of the international stock market at various levels, revealing that public events significantly increase market volatility and interconnectedness, which can signal the emergence of financial crises. The findings underscore the importance of examining not only the immediate effects of shocks but also their cascading consequences sequentially dripping down and showing their effects in the coming years, which can destabilize entire regions or sectors. This effect was shown by Papadopoulos et al. (2023), they demonstrated a deterioration in structural indicators, such as reduced diversity of trade partners, increased centralization, and / or declining network robustness. However Costa, Sallusti, and Vicarelli (2022) reveals that the Italian business system's trade network structure limits the transmission of foreign shocks, with a mismatch between sectors central to international and domestic trade, impacting Italy's ability to benefit from positive foreign spillovers and providing some protection against negative international shocks. The robustness analysis confirms that trade integration is strongly positively correlated with economic growth, and this result holds across different data sources, measures of network centrality, and model specifications Duernecker, Meyer, and Vega-Redondo (2022). E.g. highly centralized trade network, where a few countries dominate global trade flows, is more vulnerable to disruptions than a decentralized network with multiple redundancies. Cingolani, Panzarasa, and Tajoli (2017) introduces a novel three-faceted measure of centrality to evaluate countries' roles at different stages of global value chains, revealing that traditional trade statistics may overlook significant variations in countries' positions and market power within the international production process. This insight aligns with the Permanent Crisis Theory, which posits that systemic vulnerabilities are inherent in the structure of the global economy. When supply chains freeze or become overly dependent on a few critical nodes, the resilience of trade networks diminishes, increasing the likelihood of severe economic fallout during crises.

Resilience and Vulnerability in Trade Networks

The resilience of trade networks and their ability to withstand and recover from shocks is a critical factor in mitigating the impact of crises. As noted by Gutiérrez-Moya, Lozano, and Adenso-Díaz (2023), resilience is often undermined during periods of crisis when supply chains are disrupted, and trade networks become overly centralized. Centralization, might prove efficient on the short run, but very well can create bottlenecks that amplify the effects of disruptions, leading to cascading failures across the system. Enhancing the resilience of trade networks requires a bre-built focus on decentralization, diversification, and redundancy Zhuoming et al. (2024). Policies that promote these attributes can help mitigate the risks associated with systemic shocks and ensure the continued functioning of global trade systems during periods of instability. Thus, the exhibited resilience of trade networks is broadly defined as the capacity to withstand disruptions and recover effectively, ensuring the continued flow of goods, services, and economic stability even during crises Kharrazi, Rovenskaya, and Fath (2017). However several factors may influence the resilience of trade networks, ranging from structural to contextual:

- *Structural Factors:* The topology of the trade network, including its density, connectivity, and the distribution of central nodes, plays a critical role. Networks with diversified trade links and multiple hubs are generally more resilient to localized disruptions McDougall and Davis (2024).

- *Geographical and Cultural Factors:* The geographical positioning of countries and regional characteristics, including cultural similarities, can enhance or hinder resilience. For instance, cultural compatibility often fosters quicker recovery through cooperative policies and shared norms Karakoc and Konar (2021).
- *Policy and Institutional Factors:* Trade resilience is also shaped by governance mechanisms, international agreements, and the presence of institutions capable of coordinating responses during crises Chen et al. (2025).

The COVID-19 pandemic also underscored the vulnerabilities of global trade networks while highlighting the importance of resilience. The pandemic disrupted supply chains worldwide, exposing critical dependencies on specific regions and sectors. Countries with higher trade diversification and strong regional cooperation demonstrated greater resilience, recovering faster from supply chain disruptions Karakoc and Konar (2021). Key lessons include:

- *The Role of Redundancy:* Increasing inventories and creating alternative trade routes proved effective in mitigating disruptions Lücker, Timonina-Farkas, and Seifert (2025).
- *Emergency Preparedness:* Developing emergency response frameworks, such as strategic stockpiles and rapid policy coordination, significantly enhanced recovery capacities Son, Roscoe, and Sodhi (2025).
- *Public Sector Involvement:* Government interventions, such as subsidies and targeted support for critical industries, played a pivotal role in stabilizing economies Irianto et al. (2025).

Resilience operates across multiple levels of trade networks:

- *Micro-Level Resilience:* At the firm level, resilience involves flexibility in sourcing, production, and distribution Laari et al. (2024). Firms that leveraged digital tools and diversified suppliers were better able to weather disruptions.
- *Meso-Level Resilience:* Regional trade networks exhibited varied responses based on their internal connectivity and reliance on external partners. Regions with robust internal trade flows demonstrated higher adaptability Kosztyán, Kiss, and Fehérvölgyi (2024).
- *Macro-Level Resilience:* At the global level, trade systems demonstrated cascading effects, where disruptions in major hubs like East Asia impacted downstream supply chains worldwide Wang et al. (2024a). This highlighted the need for coordinated global responses to crises Obashi (2009).

Understanding these dynamics provides a comprehensive framework for enhancing resilience across all levels of trade networks. Trade networks are inherently complex systems, exhibiting nonlinear dynamics, feedback loops, boiling down to the aforementioned cascading effects. These characteristics influence how shocks propagate through the network and how the recovery unfolds Kostoska et al. (2020). Positive and negative feedback loops can amplify or dampen the effects of shocks. For instance, disruptions in one sector may trigger ripple effects across others, but timely policy interventions can mitigate such happenstances. Trade networks can experience abrupt changes or boiling points during crises, transitioning from stable states to disrupted ones. Identifying these thresholds is essential for preemptive action. By analyzing these dynamics, scholars can map the sources and pathways of trade shocks, providing insights into the mechanisms of resilience.

Examining Trade Networks: Overview and Scope

Researchers have adopted diverse approaches to analyze trade networks, often focusing on the trade flows of entire networks, such as those of countries De Andrade and Rêgo (2018) and Garlaschelli and Loffredo (2005). This perspective provides a comprehensive understanding of global trade by capturing aggregated interactions between nations. However, trade network studies are not limited to such holistic overviews; they frequently concentrate on specific products or product groups, offering more granular insights into particular economic dynamics Kostoska et al. (2020), Ren, Zeng, and Zhang (2020), and Gutiérrez-Moya, Lozano, and Adenso-Díaz (2023).

In rarer cases, the temporal development of trade networks is explored, revealing the evolution of trade relationships over time and their responsiveness to events like technological innovations or global crises Shutters and Muneepeerakul (2012) and Gutiérrez-Moya, Lozano, and Adenso-Díaz (2023). This temporal dimension adds depth to network studies, bridging the static analysis of trade structures with dynamic processes.

Aggregation and Product-Specific Analysis

Trade network research can be broadly categorized into two methodological approaches: analyzing networks of aggregated products versus those of individual product groups. Studies focusing on aggregated trade networks provide insights into macroeconomic patterns and global connectivity De Andrade and Rêgo (2018) and Garlaschelli and Loffredo (2005), while investigations into specific product groups uncover distinct trade behaviors and dependencies within specialized sectors Kostoska et al. (2020) and Ren, Zeng, and Zhang (2020).

Interestingly, these two perspectives are not mutually exclusive. The interrelationships between trade networks of different products and product groups underscore the interconnected nature of global trade systems. E.g., agricultural products might serve as inputs for manufacturing industries, linking seemingly distinct trade networks Shutters and Muneepeerakul (2012). Such interdependencies highlight the need for integrated approaches to studying trade networks.

Trade networks are typically represented as graphs where the vertices denote countries and the edges reflect the import or export volume or value of a given product or product group Sajedianfard et al. (2021). This graph-based representation enables the application of network science methodologies to assess trade relationships quantitatively. The weight of edges often signifies the intensity of trade interactions, providing a visual and mathematical means of identifying dominant trade routes, key players, and potential vulnerabilities in the network.

Trade Network Databases and Analytical Methods

To investigate world trade, several freely available databases provide comprehensive, country-level data on trade and other economic indicators. Prominent examples include the World Input-Output Database, the Atlas of Economic Complexity, the Food and Agriculture Organization of the United Nations Statistics Division, and the World Integrated Trade Solution World Bank (2022), Eurostat (2022), UN Comtrade Database (2022), and BACI-CEPII Database (2022). These databases contain crucial information on trade flows, such as export and import volumes, as well as macroeconomic indicators like gross domestic product (GDP), population trends, and public debt.

While such databases are integral to understanding global trade dynamics, numerous studies Hamdi and Hakimi (see, e.g., 2022) and Contractor et al. (2020) that rely on country-specific variables like GDP, private consumption, labor shortages, trade flows, or foreign direct investment (FDI) to analyze trade may not fully capture the complexity and diversity inherent in international trade systems. As Koopman, Wang, and Wei (2014) and De Benedictis et al. (2014) argue, it is insufficient to treat a country as a monolithic supplier or buyer of a particular product in the global market. Rather, it is more insightful to analyze export-import data at the product level, which allows for a more granular and accurate representation of trade relationships De Benedictis et al. (2014) and De Andrade and Rêgo (2018).

Several analytical methods have been developed to capture the intricacies of trade networks at this product level. These methods include the Convergence of Iterated Correlations (CONCOR) algorithm Smith and White (1992), the Heckscher-Ohlin model Baskaran et al. (2011), social network analysis Dong (2022), the Gravity Model Herman (2022), and complex network analysis techniques, such as Exponential Random Graph Models (ERGMs) and network probit models Fagiolo, Reyes, and Schiavo (2010) and Herman (2022). These approaches each offer different perspectives and insights into the structure and dynamics of international trade. E.g. applying machine learning techniques, particularly graph neural network models, to predict international trade flows offers superior accuracy and granularity compared to traditional models, as a downside it highlights the importance of addressing data drift through continuous monitoring and model retraining to maintain predictive performance Sellami et al. (2024). E.g. Xie, Wei, and Zhou (2023) integrates machine learning optimization algorithms with game theory and utility theory to construct a decision-making model for heterogeneous economies, using global oil trade data to simulate and evaluate the impact of trade frictions and external shocks on international energy cooperation.

In addition to these quantitative methods, qualitative network analysis (QNA) provides an alternative perspective by focusing on the micro-level, insider views of trade relations. Unlike traditional quantitative methods that emphasize macroperspectives, QNA emphasizes the lived experiences of actors within trade networks Ahrens (2018).

While all these methods are valuable tools for trade network analysis, the primary advantage of social network analysis is its ability to offer a holistic and relational perspective on trade. By measuring various network indicators and visualizing the different dimensions of trade relationships, social network analysis enables researchers to capture the full complexity of global trade dynamics, providing a more nuanced understanding of how countries and products are interconnected within the global trade network.

Recent Studies on Trade Networks Using social network analysis

Table 2.3 provides an overview of recent studies on trade networks that employ social network analysis. The table summarizes the key focus areas of these papers, highlighting the main findings, the analyzed periods or years, and the product groups involved in the studies. In some cases, the analysis includes each individual product (A), while in others, only pairs of production groups (PGs) or products (Ps) are considered.

Additionally, Table 2.3 indicates whether the studies conducted comparisons across products. Node-level analysis, which typically focuses on countries, is a prominent aspect of social network analysis, and the table specifies the number of countries involved in each comparison. The table also notes whether the studies included an examination of temporal patterns or explored causal relationships within the trade networks.

TABLE 2.3: Recent studies on trade networks using social network analysis

Author	Focus	Time period	Most findings	Prod. groups	By products	Node-level	Network-level	Temporal analysis	Causality analysis	Employed indicators	Database
Cingolani, Iapadre, and Tajoli (2018)	Textiles and electronic products	2007; 2014	High, but recently decreased regionalization.	PG(2)	+	-	+	+	-	Density, clustering, assortativity, centralization	BACI, COMTRADE
Amador et al. (2018)	All industries	1995-2011	Trade agreements have an impact on the network.	A	-	+(5)	+	+	-	Centralities, reciprocity, clustering	WIOD
Piccardi and Tajoli (2018)	High-tech and low-tech industries	2014	High-tech products exhibit high centralization. High centralization of complex products has a strong hierarchy in the trade network.	P(1242)	+	-	+	-	-	Complexities, centralizations, concentrations, vulnerability	BACI, ATLAS
Wang and Dai (2021)	Evolution of global food trade patterns	1992-2018	The complexity of food network is growing.	PG(2)	-	+(7)	+	+	-	Clustering, average path length, connectivity, centralities	FAOSTAT
Zhu et al. (2014)	Evolution of WTN in Asia and Oceania	1996-2019	The rise of China related in trades	A	-	+(2)	+	+	-	inter- and intra-communities	BACI
Hoang, Piccardi, and Tajoli (2023)	Concentrates on the structural changes.	1996-2019	Structural changes: more dense, reciprocal, compact but has not yet reached the full interconnectivity	A	-	+(12)	+	+	-	Centralities, density, assortativity, clustering coefficients	BACI
Nobi, Lee, and Lee (2020)	Structural changes of the trade networks	1995-2013	After the 2008 crisis the products' hierarchy increased. Role of China increased "next Giant hub"	A	-	+(2)	+	+	-	Hierarchical path	COMTRADE
Yazawa (2023)	Trade networks of 5 countries	1992-2020	Existence of imbalances. Detectable crisis, that influence the networks.	A	-	+(5)	+	+	-	Centralities	WITS

Node-Level and Network-Level Variables in Trade Network Studies

The studies outlined in Table 2.3 primarily focus on node-level and network-level variables within trade networks, examining key indicators such as centrality, assortativity, clustering coefficient, and resilience measures. In most cases, the analysis evaluates the complete structure of trade networks or compares a limited number of product categories. However, with the notable exception of Piccardi and Tajoli (2018), there has been little investigation into the similarity of structural parameters across different products in trade networks.

Although researchers have analyzed the temporal patterns of complete trade networks, they have not explored how these patterns emerge or how many distinct temporal patterns can be identified Yin et al. (2024). Furthermore, the influence of trade structures of one product on the trade dynamics of other products remains largely unexplored. This gap in research is particularly evident in studies that focus on either the entire trade network or just a small subset of products, leaving the examination of product-by-product temporal structural characteristics largely unaddressed. Summarized by Fig. 2.1.

A comprehensive comparison of all trading products is essential to determine the extent of differences in their network structures. Without conducting such an exhaustive comparison, the full diversity of temporal structural patterns across different products cannot be ascertained. Additionally, without causality testing, it is difficult to assess the extent to which structural changes in the trade of one product affect the trade dynamics of other products. These unanswered questions highlight the need for further research into the causal relationships and temporal structural characteristics that shape global trade networks.

Node and Network Level Indicators and Their Implications

Node-level indicators can be a tool for analyzing the significance and positioning of individual countries within trade networks. Metrics such as centrality, degree, and betweenness offer insights into the role of a country in facilitating trade flows and connecting disparate parts of the network. By examining these indicators over time, researchers can track changes of specific nations or products within the global economy Río-Chanona, Grujić, and Jeldtoft Jensen (2017). For instance, time-series analysis of node-level indicators can reveal how emerging economies integrate into global trade networks or how the roles of traditional trade hubs evolve in response to economic or geopolitical shifts. Such analyses are vital for understanding the dynamics of trade network power structures and their implications for policy and strategy. While node-level indicators offer insights into individual actors, network-level indicators describe the overall structure and behavior of trade networks. These metrics capture properties such as density, modularity, and clustering, which reveal the level of integration, the presence of trade blocs, and the resilience of networks to disruptions Xu, Ma, and Zeng (2019).

A time-series analysis of network-level properties sheds light on broader trends such as globalization, deglobalization, and the impact of crises. E.g., shifts in network density may indicate the rise of regional trade agreements or the fragmentation of global supply chains during geopolitical or economic shocks. Furthermore, these indicators are instrumental in assessing the resilience of trade networks, highlighting their ability to recover from disruptions and adapt to changing conditions Garlaschelli and Loffredo (2005). The resilience of trade networks is a critical area of study, particularly in the context of global crises such as pandemics, trade related crashes, or geopolitical conflicts Patrício, Ferreira, and Gerschewski (2025). Resilience reflects a network's capacity to withstand and recover from disruptions, ensuring the continuity of trade flows. This property is closely linked to network-level indicators such as connectivity, clustering, and redundancy Garlaschelli and Loffredo (2005). Reciprocities within trade networks, reflecting the mutual exchange of goods and services, provide another layer of complexity. Asymmetries, on the other hand, highlight inequalities in trade relationships, often mirroring broader economic disparities Wu et al. (2024). Understanding these properties bring forth developing strategies to enhance the robustness of global trade systems.

Contributions to the Literature

To address the methodological and research gaps in the existing literature, the following unique contributions were made:

C_1 A database of node- and network-level indicators was constructed for all products and product groups from 1995 to 2021 based on the BACI-CEPII trade network database;

C_2 The temporal patterns of trade network indicators were identified for different product groups using a recent nonparametric cluster analysis;

C_3 The causal relationships between the structural changes of different product groups were identified using Granger causality tests;

C_4 The intermediary roles of product groups and countries in transmitting structural changes were ranked using centrality measures.

The proposed database stores the calculations of node-level and network-level indicators for all countries and product groups (C_1). Analyzing structural changes in trade networks can help identify temporal and spatial patterns without the need to recalculate all variables for every country and product or product group. Based on the proposed database, temporal patterns are classified to identify how many temporal characteristics can be identified and how similar the temporal patterns of the structures of the trade networks are (C_2). In unexpected events and emergencies, similar responses will be observed for product groups with comparable temporal characteristics. Previous studies have demonstrated a connection between network indicators and crises Yazawa (2023). It is essential to identify the temporal aspects associated with this process and how they evolve over time. In this article, it is not suggested that crises can be detected through changes in network parameters, in contrast to Yazawa (2023). However, it is believed that the impact of these changes can be heightened in the presence of concentrated or vulnerable network indicators.

To determine which changes in a product contribute to structural changes in the trade of another product, defining the typical characteristics and grouping them is not a sufficient approach. Exploiting the opportunity given by the temporal pattern, it is also necessary to determine the precedential relationship between them with a causality analysis (C_3). Performing this task in pairs results in a causality graph. Clustering the graph creates causal groups that indicate the relationships between product changes in the trade networks. The sequence of products within causal groups based on embeddedness determines the leading products that influence changes in other product groups (C_4).

The contributions listed are distinct and original, with no comparable studies found during the literature review. The proposed methodological approach is based on social network analysis, with network-level indicators of the trade networks and the role of individual countries (i.e., node-level indicators) also computed. The evolution of these indicators over time, along with the identification of temporal patterns using nonparametric clustering procedures Kosztyán et al. (2024), which can group trade network characteristics, is examined. Moreover, the causal relationships between the changes in indicators over time are investigated to see how the structural change in the trade network of one product affects the trade network structure of other products. In this way, the temporal patterns of shocks and technological changes are not only characterized, but the interdependence of product trade networks is also examined, which can help model and better understand the shocks and technological changes.

2.2.2 Mobility

Historical Context of Mobility in Networks

The concept of mobility has long been a defining feature of human societies, serving as a medium for the exchange of ideas, cultures, and knowledge. In ancient times, the mobility of scholars, philosophers, and traders laid the foundation for intellectual and economic networks across regions Collins (2009). Institutions like Plato's Academy and the Library of Alexandria were early hubs for knowledge exchange, attracting learners and thinkers. In the Middle Ages, mobility within networks gained prominence through religious pilgrimages, trade routes, and the establishment of universities. The medieval university system, such as those in Bologna, Paris, and

Oxford, encouraged the movement of students and scholars, facilitating the development of transnational academic networks. The Renaissance further amplified academic mobility, driven by patronage systems and a growing emphasis on humanism and scientific discovery Kuuliala and Rantala (2020).

Modern academic mobility began to take shape in the 19th and 20th centuries, coinciding with the rise of nation-states and the industrial revolution Kim (2009). Governments recognized the value of international education in fostering innovation and diplomacy, leading to the establishment of scholarships and exchanges, such as the Rhodes Scholarship (1902) and the creation of the Institute of International Education (1919).

The Emergence of Institutionalized Mobility Programs

The institutionalization of mobility programs marked a significant turning point in the history of academic networks Gérard and Lebeau (2023). Early examples include bilateral exchange agreements between universities and government-funded scholarships, such as:

- Germany's Humboldt Scholarship,
- the U.S. Fulbright Program,

both established in the mid-20th century.

The post-World War II era saw a surge in the creation of international organizations and policies aimed at promoting mobility Gultekin (2025):

- UNESCO's establishment in 1945 emphasized cultural exchange and global understanding,
- Regional initiatives like the Erasmus program in Europe (founded in 1987) sought to create standardized frameworks for academic mobility.

Mobility as a Key Feature of Networked Systems

Mobility is a core feature of networked systems, enabling the flow of resources, information, and people across nodes Paiva et al. (2021). In academic and educational networks, mobility strengthens connections between institutions, promotes cross-border collaborations, and facilitates the dissemination of knowledge Nave and Franco (2024). Unlike static systems, networks with high mobility are dynamic, adaptive, and capable of responding to external changes.

The interplay between mobility and network dynamics can be seen in both physical and virtual spaces:

- Physical mobility involves the movement of individuals, such as students, faculty, and researchers, between institutions Teichler (2015).
- Virtual mobility leverages digital technologies to enable remote collaboration and knowledge sharing Nelson, Jarrahi, and Thomson (2017).

Key Drivers of Mobility in Educational Networks

Several factors have driven the growth and evolution of mobility in educational networks Glass and Cruz (2023):

- Globalization: The increasing interconnectedness of economies and cultures has amplified the demand for international education, as students seek to develop skills and competencies for a globalized workforce Hosen (2023).
- Technological Advancements: Innovations in transportation and communication have significantly reduced barriers to mobility, making it easier for individuals to study and work abroad Andrade et al. (2023).
- Policy Initiatives: Government and institutional policies, such as visa liberalization and scholarship programs, have incentivized mobility by reducing financial and bureaucratic obstacles Jacobs (2022).
- Institutional Partnerships: Collaborative agreements between universities have expanded opportunities for student exchanges, dual-degree programs, and joint research projects You et al. (2025).
- Cultural Exchange: Mobility is often driven by the desire to experience new cultures, languages, and perspectives, fostering mutual understanding and cooperation across borders Mariyono, Alifatul Kamila, and Alif Hidayatullah (2025).

Van Mol (2022) also highlights that maternal educational attainment significantly influences the likelihood of students studying abroad, with higher maternal education levels correlating with increased student mobility, particularly among female students.

The Evolution of Mobility Networks in the Digital Era

The digital era has transformed mobility networks, introducing new dimensions of connectivity and accessibility Odida (2024). Virtual mobility initiatives, such as online learning platforms and virtual exchange programs, have complemented traditional forms of mobility, enabling broader participation O'Dowd (2025). These developments have been particularly impactful during global disruptions, such as the COVID-19 pandemic, which highlighted the importance of hybrid and flexible mobility solutions Nikitas and Bakogiannis (2024). Digital technologies have also enhanced the efficiency of mobility networks by, streamlining application processes, facilitating virtual collaboration, improving access to information. However, challenges remain, including the digital divide, the need for robust cybersecurity measures to protect sensitive academic and personal data Huang (2024).

Challenges and Critiques of Mobility in Networks

While mobility networks offer significant benefits, they also face challenges and critiques:

- Unequal Access: Mobility opportunities are often limited by socioeconomic status, geographical location, and institutional capacity, perpetuating disparities in access to international education Hayvon (2024).
- Brain Drain: The outflow of talented individuals from developing regions to more developed countries can exacerbate inequalities and hinder local capacity-building efforts Jha et al. (2025).
- Environmental Impact: The carbon footprint of international travel raises concerns about the sustainability of traditional mobility practices Kanwal et al. (2024).

- Cultural Barriers: Differences in language, academic norms, and social practices can pose challenges for participants, potentially limiting the effectiveness of mobility programs Mellors and Vicencio (2025).

Addressing these challenges requires a multi-faceted approach, including targeted policies, increased funding, the promotion of inclusive and sustainable mobility practices Anthony Jnr (2025). Rostovskaya et al. (2020) reveals e.g. that a significant imbalance between the availability of academic mobility programs and the demand from Russian students, highlighting the need for better alignment to enhance international educational opportunities. The network of international student mobility tends to exhibit 'homophily' with respect to levels of democracy, indicating that the more dissimilar countries are in their democratic values, the lower the propensity to form or intensify student exchange ties Vögtle and Windzio (2020).

The Role of Mobility Programs

Internationalization in higher education has emerged as a cornerstone of global academic collaboration, with key elements including border-crossing, international cooperation, and research exchange receiving increasing scholarly attention. Within this landscape, international student mobility remains a critical mechanism for knowledge transfer, one that has evolved significantly in response to societal, technological, and policy changes Teichler (2017) and Sung (2022).

The prominence of mobility programs like Erasmus in Europe and global initiatives such as Fulbright and DAAD demonstrates their role in enabling the exchange of ideas, skills, and cultural understanding Cordie (2025). These programs not only foster academic enrichment but also enhance the employability of participants by exposing them to diverse learning environments and cross-cultural interactions You (2024).

Global Trends in Mobility: Leading Destinations and Shifting Patterns

Historically, countries like the United States, the United Kingdom, and Australia have dominated the international student exchange market Bai, Nam, and English (2024). These native English-speaking nations attract substantial numbers of students from across the globe due to their reputation for high-quality education, cultural appeal, and established academic infrastructures Nada and Legutko (2022). The strength of these countries' appeal has allowed them to maintain a diversified and competitive market, with significant growth potential Verbik and Lasanowski (2007). The subset of teacher exchange programs not only enhance the quality of teaching, research, and academic networking but also offer opportunities for professional growth and exposure to diverse working conditions, highlighting the need for further comparative studies between teachers and researchers to better understand the determinants influencing academic mobility Turnea et al. (2022). However, global trends in student mobility have begun to shift. Emerging economies, particularly in Asia, have started to challenge traditional mobility patterns by investing heavily in their higher education systems and internationalization efforts Zhuang, Oh, and Kimura (2025). Countries like China and Singapore, for instance, are increasingly viewed as competitive destinations for international students, especially from neighboring regions Beech (2018). Lee and Stewart (2022) highlights that experiential motivations are the most significant pull factor for short-term exchange students in Korea, particularly influencing female students, suggesting the need for universities to develop or enhance cultural activities and experiential programs to attract and support international students. This shift highlights the growing multipolarity of global academic exchanges, with mobility programs evolving to reflect changing geopolitical and economic realities.

Types of Mobility and Their Implications for Knowledge Transfer

Student mobility is broadly categorized into two types: degree mobility and credit mobility Granja and Visentin (2024). Degree-mobile students seek to complete an entire program abroad, often aiming to gain expertise in a distinctly different academic culture Khlgatian (2024). In contrast, credit-mobile students typically participate in short-term exchanges to complement their studies at their home institutions Souto-Otero et al. (2013).

These different mobility types underscore the dual nature of knowledge transfer. Degree mobility facilitates profound academic and cultural immersion Pherali (2012), while credit mobility enables comparative learning experiences and fosters collaboration between institutions Junor and Usher (2008). Both forms contribute to the development of globally competent graduates, capable of navigating increasingly interconnected professional landscapes Demianiuk et al. (2024). Şahin, Şahin, and Söylemez (2024) highlights significant geographical and structural differences between Erasmus+ and degree-seeking mobility networks in Europe, revealing the need for policy-makers to address regional inequalities and enhance the equity of student mobility programs.

Gadár et al. (2022) analysis of the ERASMUS student exchange network reveals that while the program effectively mitigates geographical distance barriers, the network structure is significantly influenced by subject areas, cultural and economic factors, highlighting the need for subject-based multilayer network models to better understand and optimize international academic mobility. Analysis of the Erasmus Program from 2008 to 2013 reveals a persistent gender bias favoring female students, with a denser network of connections and higher levels of reciprocity and homophily in the female Erasmus network, alongside a gradual trend towards gender parity, particularly in non-STEM disciplines and certain regions Benedictis and Leoni (2020).

Policy Frameworks and the Impact of the Bologna Process

In Europe, the Bologna Process has been instrumental in harmonizing higher education systems, creating a unified framework to enhance the comparability and compatibility of degrees. This initiative has also prioritized the mobility of students and academic staff, making European higher education more accessible and attractive to a global audience Senci, Hendrickson, and Debevc (2022). Hofhuis, Jongerling, and Jansz (2024) demonstrates that local students, especially those without prior international experience, benefit significantly from international classrooms, highlighting the importance of internationalization at home for enhancing intercultural competence

The Erasmus program, a flagship initiative under the Bologna framework, exemplifies this commitment to mobility. By providing financial support and institutional partnerships, Erasmus has enabled millions of students to participate in short-term exchanges, fostering academic collaboration and cultural exchange across borders. For students from Central and Eastern Europe, in particular, Erasmus has been a transformative opportunity, addressing historical imbalances in mobility opportunities Rivza and Teichler (2007). Another subset of international mobility is that it enhances climate justice in European student mobility requiring the addressing of the environmental impacts of mobility programs like Erasmus while also considering the colonial entanglements and asymmetries in global higher education, advocating for sustainable practices that balance educational benefits with broader issues of environmental and social justice Shields and Lu (2023).

Challenges in Data Collection and the Need for Comprehensive Datasets

Despite the success of mobility programs, significant challenges persist in accurately capturing their full impact. Data collection on outgoing and incoming student mobility often remains fragmented and incomplete, limiting researchers' ability to conduct comprehensive analyses Mellors and Vicencio (2025). E.g., while the Erasmus program boasts extensive participation, publicly available datasets fail to fully account for its multifaceted effects.

The dataset used in this study, covering the period from 2008 to 2013, illustrates this limitation. Since 2013, mobility opportunities have undergone substantial changes, influenced by factors such as political shifts, funding constraints, and policy revisions. The exclusion of Switzerland and the United Kingdom from Erasmus funding frameworks has notably reduced mobility flows to these countries, underscoring the importance of contextualizing data within broader political and economic developments Glass and Cruz (2023) and Kabanbayeva et al. (2019).

Additionally Väisänen et al. (2025) present a geolocated Erasmus+ mobility dataset covering 2014-2022, enriching raw EU mobility data with spatial coordinates at the LAU and NUTS 3 levels using Photon and Nominatim geocoding. The study focuses on producing a validated, open-access data product rather than theory building. It enables spatial analyses of student flows, regional brain gain/drain, and the impact of COVID-19 on European mobility patterns. The dataset achieves 96-99% geocoding accuracy and is accompanied by open Python scripts for reproducibility. Beyond technical validation, the authors demonstrate exploratory use cases such as mapping regional inequalities, academic cross-pollination, and flow visualization through edge-bundling techniques, offering a high-resolution empirical foundation for future mobility and policy research. However, they did not take into consideration the modeling advancements of the literature.

Gravity Models in Mobility

Economic analyses of migration have long been grounded in labor market theories, which emphasize the role of wage differentials and employment opportunities as primary drivers of workforce movement between countries Nosova (2024). However, migration decisions extend beyond these economic determinants, encompassing a complex interplay of social, cultural, and geographic factors. The gravity model of trade, adapted from its original application in international trade, provides a robust framework for understanding these dynamics Tiits et al. (2024). It conceptualizes migration as an exchange between individuals and the respective home and host countries, where the propensity to migrate is influenced by the "pull" of attractive factors in the destination and the "push" of barriers such as distance and cost Lewer and Berg (2008).

In its application to academic mobility, particularly within structured programs like Erasmus, the gravity model offers a nuanced understanding of how and why individuals participate in international exchanges. Traditional gravity models incorporate variables such as economic size (often represented by GDP), demographic characteristics, and geographic proximity to quantify the attractiveness of a host country and the obstacles posed by physical or logistical separation Caballero Reina et al. (2024). These variables effectively capture the foundational elements of migration but may overlook factors uniquely relevant to academic and cultural exchanges.

Student mobility under programs like Erasmus introduces additional layers of complexity. Unlike general labor migration, the decision to study abroad often hinges on cultural compatibility, academic prestige, and the availability of supportive institutional frameworks Eusafzai (2024). Cultural factors, in particular, have emerged as critical determinants in this context Gutema, Pant, and Nikou (2024). The shared linguistic or historical ties between countries, e.g., can significantly lower the perceived "distance" in gravity models Coimbra Vieira, Lohmann, and Zagheni (2024). Empirical studies on student mobility consistently highlight how familiarity with cultural norms, traditions, or languages of the host country enhances the attractiveness of the destination, even when economic variables like income differentials are less pronounced Camiciottoli (2010) and Sigalas (2010a). Paradowski et al. (2022) highlights the critical role of mutual out-of-class communication in second language acquisition among student sojourners, emphasizing that the proportion of outgoing to incoming target language interactions significantly influences interlanguage restructuring and overall language development, aligning with Swain's output hypothesis. Despite the recognized importance of student exchange programs in educational policy, empirical evidence on their effectiveness in primary and secondary education remains limited and methodologically fragmented, highlighting the need for more rigorous, large-scale, and longitudinal research to better understand their impact on language competence, intercultural competence, and language learning motivation Heinzmann et al. (2024). Németh et al. (2024) demonstrates that a multicultural and multilingual classroom environment significantly enhances Hungarian medical students' English language proficiency and intercultural competence, providing a quasi-Study Abroad at Home experience that prepares them for global medical practice.

The importance of cultural variables has been increasingly recognized in modifications of the gravity model for academic mobility. Hofstede's cultural dimensions, which quantify aspects such as individualism, uncertainty avoidance, and power distance, provide a structured means of incorporating culture into the model Lin and Lou (2024). These dimensions help explain variations in mobility flows that cannot be attributed solely to economic or geographic factors. For instance, students from countries with high uncertainty avoidance may prefer destinations with stable and predictable academic environments Donohue et al. (2024), while those from more individualistic societies might prioritize opportunities for self-expression and independence abroad Sherefetdinova (2024).

Incorporating these cultural elements into gravity models aligns with survey-based findings that underscore the role of cultural adaptation in successful mobility experiences Table **??**. E.g., studies within the Erasmus framework have revealed that students often prioritize destinations where they perceive cultural alignment Karimova et al. (2024) or the opportunity to explore cultural diversity without feeling alienated Merah et al. (2025). Beyond personal preferences, institutions also play a role in shaping mobility patterns Ye et al. (2025) by offering culturally tailored support services, which in turn influence the perceived attractiveness of a destination.

The application of gravity models in this domain not only enhances the predictive accuracy of migration patterns but also provides policymakers with actionable insights. Understanding the interplay between economic, cultural, and institutional factors enables the design of more inclusive and effective mobility programs. E.g., countries aiming to increase their attractiveness as academic destinations can invest in cultural exchange initiatives Staroseltseva (2024), language support programs, and bilateral agreements that strengthen historical or linguistic ties. Similarly, addressing barriers such as visa restrictions or recognition of academic credits can mitigate the "distance" effects in the gravity model Yotov (2024).

The Erasmus program offers a compelling case study for the application of gravity models, as it encapsulates the multidimensional nature of academic mobility. By integrating variables such as GDP, cultural proximity, and linguistic ties, researchers can better understand how student flows are distributed across the network and identify areas for policy intervention. Such insights are particularly valuable in addressing disparities in participation rates, ensuring that mobility opportunities are accessible to students from diverse backgrounds and regions. Shen, Xu, and Wang (2022) reconceptualizes international academic mobility by defining both students and academics as knowledge agents, highlighting their crucial role in the global knowledge system and emphasizing the need for more systematic and geographically diverse research to fully understand the implications of mobility on knowledge acquisition, circulation, and production.

The gravity model's adaptability makes it a powerful tool for analyzing mobility patterns not only in academic contexts but also in broader migration studies. By moving beyond a narrow focus on economic variables and embracing a holistic perspective that includes culture, geography, and institutional factors, researchers can capture the full spectrum of influences driving mobility. This approach fosters a deeper understanding of the interconnected nature of global academic networks and the factors that sustain their growth and resilience. A gravity model based study by Di Pietro and Perez-Encinas (2025) reveals that the Covid-19 pandemic caused a significant decline in international student mobility by 62-63% during the 2020-2021 academic year, with a notable recovery to pre-pandemic levels in 2021-2022, highlighting the resilience and adaptability of mobility networks in higher education.

Table **??** provides a summary of related studies and the independent variables considered in the gravity model. Variables related to both culture and collaboration were either not studied or were infrequently included in regression models. Furthermore, all models that analyzed the entire exchange network exhibited low determinant values, with R^2 values less than 5 percentage points. The studies considered in this table demonstrate considerable diversity in terms of both the unit of interest (such as students, institutions, or regions) and the research focus, which varied across the entire network, specific scientific fields, or limited survey samples.

The Identified Gaps in Student Mobility

While the Erasmus network has been widely studied using gravity and regression models, several core gaps remain. Most studies continue to rely heavily on economic and geographic variables like GDP, distance, and population, while giving limited attention to cultural and institutional factors. Cultural proximity, shared language, and the strength of institutional ties are treated inconsistently, even though they are regularly reported by students and institutions as decisive factors in mobility decisions (Camiciottoli, 2010; Jansen and Schuwer, 2015; Llanes, Tragant, and Serrano, 2012). Public safety, although acknowledged in qualitative research, is rarely included in quantitative models, despite evidence that crime rates shape perceptions of potential destinations (Hua, Li, and Zhang, 2020; Biagi and Detotto, 2014).

The performance of existing models reflects this narrow focus. Studies applying gravity models to the full Erasmus network often show low explanatory power, with R^2 values below five percent (Barrioluengo and Flisi, 2017; Savić et al., 2017). Part of the issue is the data. Comprehensive Erasmus datasets have been incomplete since 2013, making it difficult to trace structural or temporal patterns with confidence (Mellors and Vicencio, 2025; Glass and Cruz, 2023). Even when disciplinary or institutional variation is acknowledged, few studies actually model student flows by field of study or account for participation gaps between larger and smaller institutions (Rivza and Teichler, 2007; Chou, Huisman, and Lorenzo, 2024).

Taken together, this shows that key variables crime, culture, and collaboration are still largely missing from mainstream mobility modeling. These are not marginal concerns. Surveys repeatedly show they influence both individual choices and institutional outcomes (Llanes, Tragant, and Serrano, 2012; Neckerman, Carter, and Lee, 1999; Jansen and Schuwer, 2015). Without them, models fail to capture the actual structure and dynamics of student mobility. Summarized by Fig. 2.1 and Table 2.2 as items detailed.

The 3Cs in Mobility

Studies of the entire Erasmus network have largely overlooked factors such as public safety (measured by proxy indicators like crime rates) Bernasco, Lammers, and Beek (2016), institutional collaboration Jansen and Schuwer (2015), and, particularly, cultural drivers Neckerman, Carter, and Lee (1999). These variables, referred to as the 3Cs in this study, hold significant importance in mobility surveys Llanes, Tragant, and Serrano (2012).

Public safety plays a foundational role in shaping mobility decisions. Crime levels in a host country can act as a deterrent, discouraging prospective students from choosing certain destinations. Fear of victimization, whether based on real or perceived threats, introduces psychological and practical barriers to mobility. Higher crime rates correlate with lower levels of tourism and migration Biagi and Detotto (2014), with similar effects observed in student mobility Hua, Li, and Zhang (2020). E.g., students may prioritize destinations perceived as safe, even if such choices limit access to academic opportunities.

Institutional collaboration is another pivotal driver of mobility Nordt et al. (2024). Stronger partnerships between universities facilitate smoother student exchanges by reducing bureaucratic hurdles, improving credit transfer systems, and fostering long-term relationships. Collaborative agreements, joint programs, and exchange initiatives provide tangible benefits to participants by ensuring academic continuity and cultural immersion Jansen and Schuwer (2015).

While the Erasmus network exemplifies one of the most robust frameworks for institutional cooperation, disparities remain in the extent to which institutions participate Chou, Huisman, and Lorenzo (2024). Smaller or less resource-rich universities may struggle to maintain active partnerships Mulyati et al. (2025).

Cultural drivers play a nuanced yet critical role in mobility decisions. Cultural differences, such as varying degrees of uncertainty avoidance, shape how students perceive the risks and benefits of studying abroad Baluku et al. (2021). E.g., students from cultures with high uncertainty avoidance may be less likely to embrace opportunities in countries perceived as unpredictable or unfamiliar. Hofstede's six cultural dimensions Hofstede (2011) provide a robust framework for analyzing these dynamics. Highlights how hierarchical structures in home and host countries impact students' willingness to engage in new environments. Emphasizes how stress related to ambiguous or unfamiliar situations deters mobility. Underscores the trade-off between personal aspirations and group priorities. Addresses how cultural attitudes toward gender roles affect participation in mobility programs. Reveals how societies' focus on future planning influences their commitment to cross-border education. Explores the extent to which cultural norms encourage life satisfaction and enjoyment, factors closely tied to mobility aspirations Minkov and Hofstede (2011).

Crime, as an element of student mobility research, has been addressed in the systematic literature review presented in Table **??**. However, its role remains underexplored compared to other factors like economic and academic variables. While public safety concerns are widely recognized in tourism research, their implications for student mobility require further investigation.

The contributions of the literature are summarized as follows:

C_5 The PRISMA method is applied to collect gravity and regression models for describing Erasmus exchange networks.

C_6 These models are compared based on the independent variables, the unit of interest, and the research focus.

C_7 The influence of both existing and new drivers, such as crime, collaboration, and cultural aspects, are analyzed and compared by year and scientific field, focusing on two units of interest:

- Individual level.
- NUTS3-regional level.

- By employing econometric methods on the entire Erasmus exchange network, this study provides evidence in four key areas of interest:

  Q_1 Unit of interest established?

  Q_2 Should static or temporal methods be used in gravity and regression models?

  Q_3 Should the entire network be analyzed, or should it be divided by scientific field?

  Q_4 What are the primary variables influencing Erasmus exchange, and are these influences temporally stable and consistent across scientific fields?

Public safety, cultural compatibility, and institutional collaboration serve as vital components in understanding mobility patterns and decision-making processes. By integrating these factors, this research advances the field by not only addressing existing knowledge gaps but also providing actionable insights for improving student experiences and participation rates across diverse regions.

2.2.3 Shared Methodologies and Structural Parallels Between Trade and Mobility Networks

Trade and mobility networks are built and analyzed using the same set of network science tools. Both are modeled as graphs, with nodes representing countries, firms, or institutions, and edges capturing flows and goods and capital in trade, people and interactions in mobility. Bipartite and tripartite representations are applied in both cases to account for layered structures such as countries-products or institutions-fields (Dong et al., 2020; Cingolani, Panzarasa, and Tajoli, 2017; Savić et al., 2017; Benedictis and Leoni, 2020).

Social network analysis is standard in both fields. Centrality, clustering, assortativity, and degree distributions are used to assess structure and actor roles (Fagiolo, Squartini, and Garlaschelli, 2013; Cingolani, Iapadre, and Tajoli, 2018; Shutters and Muneepeerakul, 2012). Node-level indicators capture the influence or embeddedness of countries or universities, while network-level metrics evaluate integration, density, or fragmentation. These are calculated in both static and time-series settings. Gravity models are used in parallel. Trade models rely on GDP, distance, and tariffs (REZITIS, KARYTSAS, and ZANGELIDIS, 2024), while mobility models extend this with cultural distance, institutional collaboration, and regional variables (Di Pietro and Perez-Encinas, 2025; Rodríguez González, Bustillo Mesanza, and Mariel, 2011; Camiciottoli, 2010; Sigalas, 2010a). PPML estimators and fixed effects are applied in both, with similar issues around zero flows and unobserved heterogeneity. Temporal dynamics are central in both areas. Trade studies track shifts in network topology due to crises or shocks (Gutiérrez-Moya, Lozano, and Adenso-Díaz, 2023; Yazawa, 2023), while mobility studies use time-series data to observe program expansions, disruptions, or regional shifts (Derzsi et al., 2011). Structural resilience is assessed using redundancy, modularity, and decentralization whether in supply chains or institutional partnerships (Karakoc and Konar, 2021; Gutiérrez-Moya, Lozano, and Adenso-Díaz, 2023). Methodologically, both domains now include causal models, machine learning, and graph-based forecasting. Graph neural networks and clustering on causality graphs are used to detect lead-lag effects across trade products or between institutional networks (Sellami et al., 2024; Xie, Wei, and Zhou, 2023).

Data limitations are also similar. Trade data is often aggregated annually, and lacks cultural or governance variables. Erasmus mobility data is incomplete post-2013, and variables like public safety, collaboration density, and cultural proximity and the 3C's are rarely integrated into quantitative models, even though their importance is recognized in survey-based studies (Llanes, Tragant, and Serrano, 2012; Jansen and Schuwer, 2015; Camiciottoli, 2010; Mellors and Vicencio, 2025; Shutters and Muneepeerakul, 2012). The two domains are structurally and analytically aligned. They use the same techniques, share the same data problems, and increasingly converge in their application of temporal and causal methods.

Source	Model used	Data used
Garcia-Algarra, Bengoechea, and Mouronte-López (2020)	Bipartite network, Stochastic model	Trade volume, Degree, Strength, Gini index
Zhang and Zhang (2024)	Network construction, Centrality	Import data, Degree, Strength, Betweenness
Asadabadi and Miller-Hooks (2020)	Stochastic optimization, EPEC	Port reliability, Disaster scenarios
Buddenhagen et al. (2021)	Stochastic modeling, Simulation	Trade volumes, Contamination events
REZITIS, KARYTSAS, and ZANGELIDIS (2024)	SNA, Gravity model, PPML	Beef exports, GDP, Distance, Tariff rates
Duernecker, Meyer, and Vega-Redondo (2022)	Linear projection, BMA	Trade flows, GDP, Globalization index
Rosal (2024)	Gravity model, PPML	Trade flows, LSCI, Gravity variables
Piccardi, Tajoli, and Vitali (2024)	Network theory, Shortest path	WIOT, TiVA data
Semanur, Hüseyin, and Halil (2020)	Network theory, Graph theory	Coal trade values, Degree, Centrality
Sellami et al. (2024)	Graph theory, GATs	Trade flows, GDP, Population
Dong et al. (2020)	Bipartite network, Simulated annealing	Trade flows, GDP, Population
Lo Re et al. (2023)	Network construction, Centrality	Chinese firms, Subsidiaries
Chou, Teng, and Tung (2023)	SNA, Betweenness centrality	Arms trade, Alliances
Zhang et al. (2023)	Network analysis, Centrality	RTAs, Anti-corruption
Ostadzadeh et al. (2023)	Network construction, GLMs	Energy trade, GDP, Population
Bartesaghi et al. (2022)	Graph theory, Econometric models	WIOD, Orbis, Trade data
Domazetoski et al. (2023)	Fixed disturbance analysis, Volatility analysis	WIOD, Total Economy Database
Yazawa (2023)	Network analysis, Time-series analysis	WITS, Trade data, HS codes
Fagiolo and Luzzati (2023)	MMN, Fixed-effects regression	COMTRADE, Migration data, Finance data
Tajoli, Airoldi, and Piccardi (2021)	Network analysis, PPML	BaTis data, Service trade flows
Antonietti et al. (2022)	Centrality measures, Community detection	UN COMTRADE, ECDC COVID-19 data
Costa, Sallusti, and Vicarelli (2022)	SNA, Negative binomial regression	WIOD, UN COMTRADE, ECDC COVID-19 data
Kulkarni et al. (2023)	Network construction, Centrality	DGCI&S, Trade data, Prices
Xie, Wei, and Zhou (2023)	Decision-making model, ML optimization	Global oil trade data
Li et al. (2023)	DTW, MST	Stock market indices
Liao and Vidmer (2018)	RCA, Fitness metrics	International trade data
Distefano et al. (2018)	NFSS definition, Econometric analysis	FAOSTAT, Trade data
Cingolani, Panzarasa, and Tajoli (2017)	Tripartite graph, Centrality measures	Bilateral trade data
Luo et al. (2014)	GeoSocialApp, CONCOR algorithm	COW, Trade data
Reino et al. (2017)	Trade network metrics, Bayesian analysis	CITES, Bird trade data
Río-Chanona, Grujić, and Jeldtoft Jensen (2017)	Network analysis, Community detection	WIOD, Trade data
Fagiolo, Squartini, and Garlaschelli (2013)	Network construction, Null model	International trade flow data
Zhou et al. (2018)	Method of reflections, FCM	Country-product networks
Zhang et al. (2017)	Ecological network analysis	WIOD
Zamora Torres and González García (2019)	ANNs, Variable selection	Survey data
Iapadre and Tajoli (2014)	Bilateral trade indices, Network analysis	DOTS, IMF
Ji et al. (2016)	Network analysis, Community structure	UN Comtrade, Electricity trade data
Jackson and Nei (2015)	Network analysis, War and trade analysis	Alliance Treaty Obligation and Provisions Project data
Shutters and Muneepeerakul (2012)	Network analysis, Triad analysis	FAO, Agricultural trade data
Shen et al. (2015)	Open flow networks, Flow distances	NBER-UN trade data
Cingolani, Iapadre, and Tajoli (2018)	Density, clustering, assortativity, centralization	BACI, COMTRADE
Amador et al. (2018)	Centralities, reciprocity, clustering	WIOD
Piccardi and Tajoli (2018)	Complexities, centralizations, concentrations, vulnerability	BACI, ATLAS
Wang and Dai (2021)	Clustering, average path length, connectivity, centralities	FAOSTAT
Zhu et al. (2014)	Inter- and intra-communities	BACI
Hoang, Piccardi, and Tajoli (2023)	Centralities, density, assortativity, clustering coefficients	BACI
Nobi, Lee, and Lee (2020)	Hierarchical path	COMTRADE
Yazawa (2023)	Centralities	WITS

TABLE 2.1: Summary of Data and Models Used in World Trade

Links	Model used	Data used
Paradowski et al. (2022)	social network analysis (SNA) with complexity science to assess peer impact.	Interviews, certificates, evaluations, self-assessments, and interaction data from 39 students.
Heinzmann et al. (2024)	MAXQDA for qualitative and quantitative coding.	139 empirical studies on European school exchanges.
Shen, Xu, and Wang (2022)	Conceptual framework for knowledge and mobility.	Studies on international knowledge transfer and mobility.
Shields and Lu (2023)	Qualitative analysis of European student mobility and climate justice.	Analysis of student mobility, climate change, and education policies.
Turnea et al. (2022)	Descriptive analysis using SPSS for mobility determinants.	Data from 234 teachers and researchers from 12 universities.
Gadár et al. (2022)	Network Science Tools: Degree Distribution, Rich Club, and Spatial Constraint.	ERASMUS Network, HEIs' geocoordinates, ETER, GRID, EU Data, ERASMUS Network Data.
Di Pietro and Perez-Encinas (2025)	PPML estimator, Fixed Effects.	Total students, Covid-19 variables, GDP, population, distance, colonial ties.
Şahin, Şahin, and Söylemez (2024)	social network analysis, Modularity, Pearson Test.	Mobility Balance Factor, Geographical Subnetworks.
Hofhuis, Jongerling, and Jansz (2024)	CFA, Latent Growth Models, FIML.	MPQ-SF, Perceived Stress, Life Satisfaction, Cultural Background, GPA.
Németh et al. (2024)	Action Research, Project-Based Learning, Thematic Analysis.	Hungarian medical students, Semi-structured focus group interviews.
Rostovskaya et al. (2020)	Statistical Analysis: Mean, Standard Deviation, t-Test.	291 students, demographic info, academic mobility awareness, language proficiency.
Benedictis and Leoni (2020)	Network Models: One-Mode, Binary Matrix, Centrality Measures.	Universities as nodes, characteristics, student flows, centrality measures.
Van Mol (2022)	Descriptive statistics, Logistic regression, MANOVA.	Dutch Student Monitor data (2006–2015), study abroad participation.
Vögtle and Windzio (2020)	Exponential Random Graph Models (ERGMs).	Diploma mobility data, GDP, democracy, language, proximity.
Lee and Stewart (2022)	Explored pull factors influencing exchange students in Korea.	Surveyed 611 students from Fall 2019 to Spring 2020.
Golubeva, Gómez Parra, and Espejo Mohedano (2018)	Statistical analysis.	Survey responses from 174 Erasmus students.
Teichler (1991)	Survey analysis.	Responses from 3,212 Erasmus students.
Souto-Otero et al. (2013)	Comparative analysis.	Data set on Erasmus and non-Erasmus students in seven countries.
Lesjak et al. (2015)	Motivational analysis.	Survey responses from 360 Erasmus students.
Rodríguez González, Bustillo Mesanza, and Mariel (2011)	Panel data econometric specification.	ESM bilateral outflows data from 1995-2006 for 29 countries.
Maggioni and Uberti (2009)	Network analysis and gravity equation model.	Internet hyperlinks, EPO co-patent applications, Erasmus student mobility, and European research networks.
Rodríguez, Martínez-Roget, and Pawlowska (2012)	Dynamic panel data model (GMM).	Academic tourism demand data in Galicia.
Savić et al. (2017)	social network analysis.	ERASMUS staff and student exchange agreements in FETCH project.
Breznik, Gologranc, et al. (2014)	Network analysis (island approach).	Erasmus student exchanges at institutional level.
Derzsi et al. (2011)	Network analysis and random network models.	Erasmus student mobilities network data from 2003.
Engel (2010)	Evaluation study.	VALERA Study on Erasmus mobility.
Sigalas (2010a)	Longitudinal survey and regression analysis.	Two-wave survey on Erasmus students in continental Europe and England.
Verbik and Lasanowski (2007)	Analysis of national data.	National data on international student mobility.
Barrioluengo and Flisi (2017)	Comparative analysis.	Student mobility data in the EU from 2011-2014.
Van Mol and Michielsen (2015)	Research project analysis.	Interaction patterns of students in Austria, Belgium, Italy, Norway, Poland, and the UK.
Llanes, Tragant, and Serrano (2012)	Statistical analysis.	Written and oral data from 24 Spanish undergraduates.
Sigalas (2010b)	Longitudinal survey and data analysis.	Erasmus students' attitudes towards the EU.
Camiciottoli (2010)	Corpus-based research and questionnaire analysis.	Lecture comprehension course data and post-course questionnaire responses.
Otero (2008)	Comparative survey analysis.	Survey responses from over 15,000 Erasmus students in 2004/05 and 1998.
Orr, Gwosc, and Netz (2011)	Survey analysis.	Survey responses from over 200,000 students in 25 countries (2008-2011).

TABLE 2.2: Summary of Data and Models Used in Mobility Studies

Chapter 3

Methods

3.1 Systematic literature review techniques

To ensure the use of current research and to identify existing gaps, a structured and reproducible literature review method must be applied. The use of systematic literature reviews has become increasingly important for producing transparent, replicable, and theory-informed insights. Following the typologies of review methods summarized by Paré et al. (2015), systematic reviews with or without meta-analysis are best suited for quantitative, structured, and model-based domains such as trade and academic mobility networks. Meta-analytical approaches extract and integrate results across studies using statistical procedures. This provides a solid empirical foundation for theoretical and methodological refinements. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework has been widely adopted in the social sciences and beyond. It relies on clear research questions, structured data identification, and strict eligibility criteria for inclusion and exclusion (Liberati et al., 2009). The process begins with defining the guiding questions. For this work, the main questions were concerned with the units of analysis used in previous studies (individuals, institutions, regions, or countries), the structure of the models applied (gravity or regression), and the scope of variables included (economic, demographic, cultural, institutional, or social). The PRISMA protocol was used for both trade and Erasmus network mobility studies, each representing large-scale relational systems modeled using comparable techniques.

In the case of trade networks, the review process focused on studies modeling international trade as complex weighted networks or applying gravity-based frameworks. Databases such as Web of Science and Scopus were used to retrieve peer-reviewed articles published in English. Keywords included combinations of "trade network," "gravity model," "economic complexity," and "bilateral trade." Over 1700 records were initially retrieved. After the removal of duplicates and irrelevant publications, 63 papers were assessed in detail. Studies were selected for inclusion based on the presence of quantitative modeling, network-level analysis, and consideration of structural variables beyond GDP and distance. Key works applied network science tools such as centrality and assortativity measures (Fagiolo, Squartini, and Garlaschelli, 2013; Cingolani, Panzarasa, and Tajoli, 2017), bipartite network approaches (Dong et al., 2020), and gravity models extended to include institutional quality, policy alignment, and structural similarity (REZITIS, KARYTSAS, and ZANGELIDIS, 2024; Tiits et al., 2024).

The systematic review of trade literature revealed a growing emphasis on causal modeling, the use of fixed effects and Poisson pseudo-maximum likelihood estimators, and the integration of network topology indicators. However, most models still relied heavily on economic fundamentals and lacked systematic inclusion of social, political, or cultural drivers. Studies rarely addressed institutional learning, intergovernmental collaboration, or resilience mechanisms in trade structures. The methodological overlap with mobility research was clear, but the two fields remained largely disconnected in empirical practice.

The systematic review of mobility studies focused on Erasmus exchange network modeling. The identification phase relied on keywords such as "Erasmus," "mobility," "gravity model," and "student," leading to an initial pool of 2120 English-language studies. Following the PRISMA procedure, duplicate and unrelated entries were removed, narrowing the pool to 81. Further filtering based on full-text eligibility reduced the list to 19 studies that met the inclusion criteria. These included gravity and regression models using either institutional or country-level mobility flows and incorporated variables such as GDP, distance, demographic indicators, and in a few cases, cultural or institutional factors (Golubeva, Gómez Parra, and Espejo Mohedano, 2018; Rodríguez González, Bustillo Mesanza, and Mariel, 2011; Barrioluengo and Flisi, 2017). The PRISMA screening also identified survey-based studies and large-scale database analyses using ERASMUS, OECD, EUROSTAT, and UNESCO data (Lesjak et al., 2015; Savić et al., 2017; Verbik and Lasanowski, 2007). These studies highlighted financial constraints, institutional prestige, student motivations, and linguistic or cultural familiarity as core mobility drivers (Camiciottoli, 2010; Sigalas, 2010a; Llanes, Tragant, and Serrano, 2012). Cultural distance and psychic distance emerged as important but underrepresented concepts in most regression frameworks. While surveys consistently reported the significance of language support, perceived safety, and cultural adaptation, these variables were often omitted from quantitative models.

Both reviews confirmed a shared methodological foundation across trade and mobility research. Network science tools, gravity models, and econometric estimators are used in both domains. Yet, both fields tend to treat structural variables as secondary and often rely on a narrow range of indicators. Particularly in Erasmus mobility studies, most regression models have low explanatory power, with R^2 values frequently below five percent (Mellors and Vicencio, 2025; Savić et al., 2017). Additionally, the lack of post-2013 Erasmus data introduces a barrier to understanding the evolving dynamics of mobility programs.

Fig. 3.1 summarizes the PRISMA process for identifying the relevant literature across both domains (v.i.). The table of literature results further illustrates which independent variables have been applied and where structural or cultural dimensions remain missing 2.2 and 2.1.

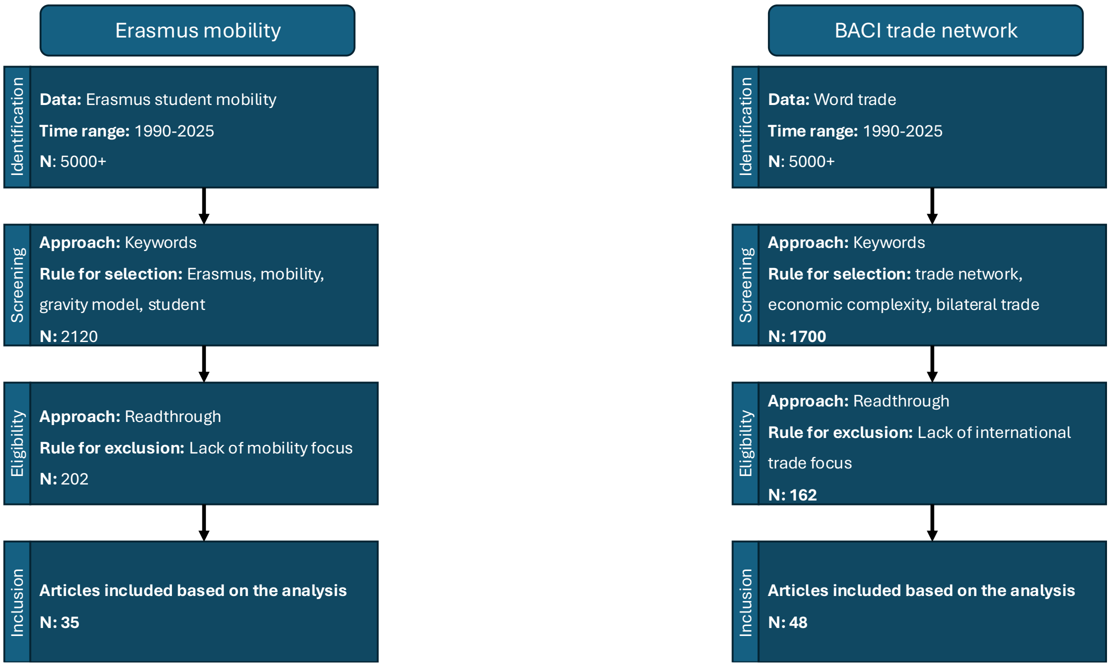

FIGURE 3.1: PRISMA Outcomes of Erasmus and BACI-CEPII

3.2 Data sources and employed data

Multiple data sources are employed and integrated to address the research questions. These sources include:

1. The BACI CEPII database, an international trade database with a high level of product disaggregation. BACI covers more than 200 countries from 1995 to 2020 and reconciles the data reported by the countries to the United Nations Statistics Division using a statistical procedure that ensures consistency and reliability Gaulier and Zignago (2010). The product classification is based on the harmonized system, which consists of 6 digits and includes 5,012 products. The BACI database fills in the missing values of bilateral trade flows by using the information reported by at least one partner country Mayer and Zignago (2011).

2. ERASMUS data, containing data on exchanges for both students and teachers from 2008 to 2014.

3. ETER (European Tertiary Register), which includes the organizational and financial data of HEIs.

4. EUROSTAT, which provides economic indicators.

5. Hoftade's database of national cultures.

These data sources, although freely available, required significant integration and refinement to achieve a connected database structure. The ERASMUS and ETER databases were integrated and cleaned by Gadár et al. (2020). The higher education institutions (HEIs) were geocoded, and NUTS3 levels were added. Based on NUTS1-3 levels, Hofstede's national culture database was connected to the country level (NUTS1), while economic indicators from EUROSTAT were connected to the NUTS2 and NUTS3 levels.

3.2.1 Data employed BACI-CEPII

All data are obtained from the BACI database (see Fig. 3.2). Two databases are constructed for network-level analysis and for node-level analysis: 3D (BACINET3D) (see Fig. 3.2 (b)) and 4D (BACINODE4D) (see Fig. 3.2(c)).

In this study, the BACI database, which is an international trade database with a high level of product disaggregation, is employed as the data source for the analysis. BACI covers more than 200 countries from 1995 to 2020 and reconciles the data reported by the countries to the United Nations Statistics Division using a statistical procedure that ensures consistency and reliability Gaulier and Zignago (2010). BACI has several advantages over other similar databases, such as product detail, geographical coverage Disdier et al. (2010), and unit values De Benedictis et al. (2014). The product classification is based on the harmonized system, which consists of 6 digits and includes 5,012 products. The harmonized system has been in use since 1989. However, some countries still report using the previous classification, i.e., the standard international trade classification, which only covers approximately 1,241 products at a 4-5-digit level. The BACI database fills in the missing values of bilateral trade flows by using the information reported by at least one partner country Mayer and Zignago (2011).

Products can be classified as follows: free main clusters, such as *capital-intensive products*, including chemical substances/products such as organic chemicals and pharmaceuticals as well as electrical machinery, vehicles and nuclear reactors Rothaermel (2016); *labor-intensive products*, including small and large commercial goods such as clothing made of wool, cotton, silk and animal skin, and goods made of wood and metals Hanson (2021); and resource-intensive products, including agricultural, mining, energy products and basic metals Vaillant and Gilles (2017).

The data in the BACI-CEPII database are available free of charge from the official CEPII website. The database contains the annual trade flow, exporter and importer countries, and the products with the 6-digit code from the HS system ("product level"). The structure of a record is as follows: `t | i | j | k | v | q`, where `t` is the time (1995–2020), `i` is the exporter (ISO3 country code), `j` is the importer (ISO3 country code), `k` is the product (6 digit), `v` is the value (in USD), and `q` is the quantity. `2018 | AFG | AGO | 845420 | 114.676 | 26.000` is an example. The product is the "ingot molds and ladles", which includes 8454 products (converters, ladles, ingot molds, and casting machines of a kind used in metallurgy or in metal foundries), while the product group is 85 (nuclear reactors, boilers, machinery and mechanical appliances, parts thereof). The exporter is Afghanistan (AFG), and the importer is Angola (AGO). Based on these edge lists, trade networks are calculated for each product group in each year. Based on these networks, the studied network and node-level indicators are calculated.

3.2.2 Data employed Erasmus

In this study, four main data sources are integrated: (1) ERASMUS, (2) ETER, (3) EUROSTAT, and (4) Hoftade's database of national cultures. All these data sources are freely available; however, most of them are not integrated. The ERASMUS data source contains data on exchanges for both students and teachers from 2008 to 2014. ETER (European Tertiary Register) contains the organizational and financial data of HEIs. The first two data sources were integrated and cleaned by Gadár et al. (2020). These authors integrated other data sources that were not used in the current study, such as the global research identifier database GRID and the point of interest

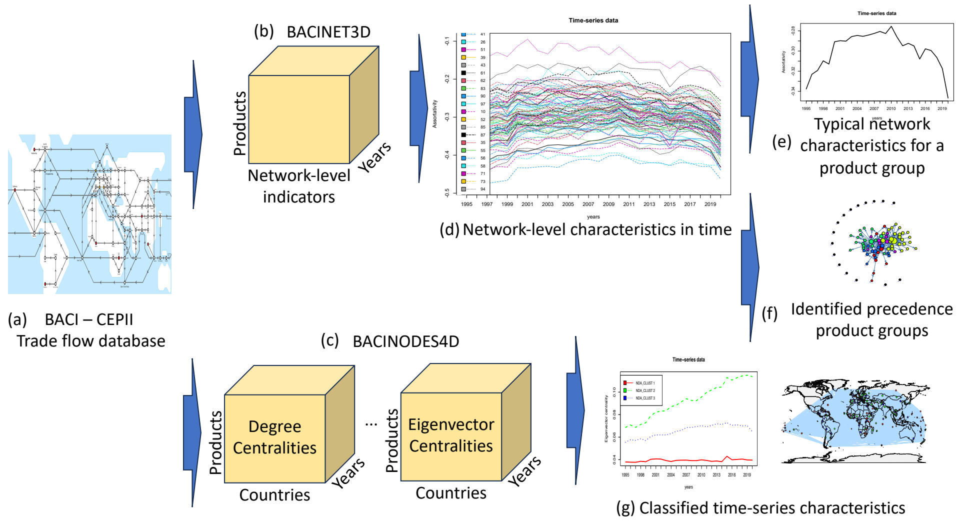

FIGURE 3.2: Applied data sources, BACI

database POI by Google. HEIs are geocoded, and NUTS3 levels are added by Gadár et al. (2020). Based on NUTS1-3 levels, Hofstade's national culture database is connected to the country level (NUTS1), while economic indicators from EUROSTAT are connected to the NUTS2 and NUTS3 levels (see Figure 3.3).

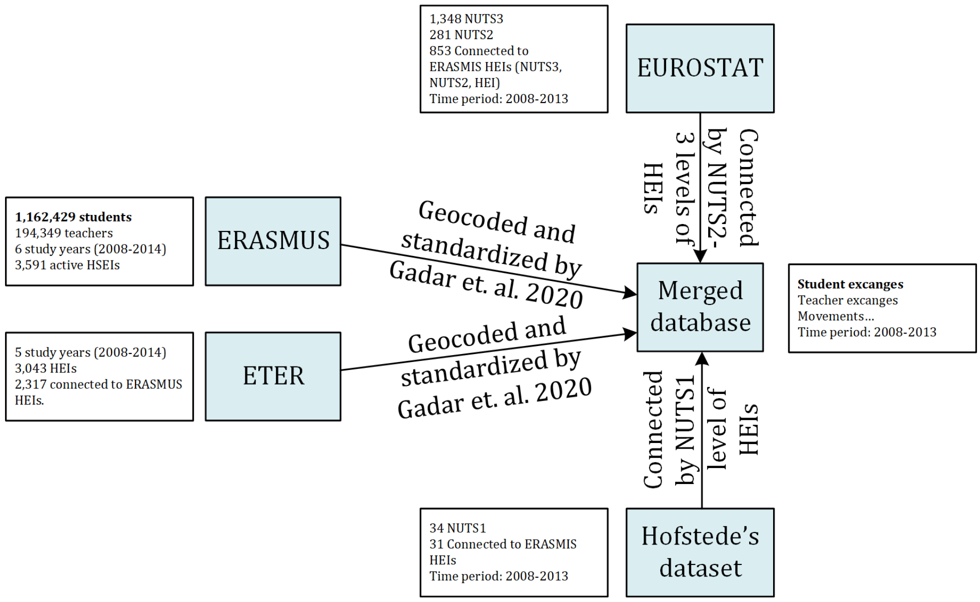

FIGURE 3.3: Applied data sources Erasmus

The data collected from ERASMUS, EUROSTAT and Hofstede's had to be refined to achieve a connected database structure, and the chosen common key was the NUTS3 location of the higher education institutions. The ERASMUS and ETER databases that were geocoded and standardized by Gadár et al. (2020) provided the main data frame with the 1, 162, 429 mobile students and the 194, 349 mobile teachers from 3, 591 HEIs from 2008 to 2014. All of the mobility data of students and teachers could be used, since the 'EUROSTAT and Hofstede databases included more NUTS2-3 and NUTS1 data, respectively, than needed for the merging process. There were active HEIs in 853 out of the existing 1348 NUTS3 regions within the investigated time period. The NUTS1 regions were similar to the 34 regions present in Hofstede's database 31 and were thus connected in the merged database. Although the data would also have made it possible to examine teachers' mobility, their driving factors are completely different from those of the students, so we will analyze this in detail in later research.

3.3 Models employed

3.3.1 Proposed Framework for Analyzing Trade Network Dynamics

To tackle these challenges, this study proposes a novel and comprehensive framework for analyzing the dynamics and interdependencies of trade networks at the product level. This framework is built on a robust and detailed dataset of international trade flows, offering a rich resource for investigating trade network indicators across products and product groups.

The methodology includes the use of cluster analysis to identify variations and implications of trade network indicators for different products and to compare their network characteristics against external factors such as technological advancements and trade agreements. Causality tests and centrality measures are further employed to explore the effects of shocks, crises, and technological changes within trade networks. These analytical tools enable the identification of key drivers and recipients of structural changes, offering insights into the mechanisms that shape the evolution of trade networks.

By integrating these approaches, this study aims to provide a systematic understanding of the temporal patterns and interdependencies within trade networks, contributing to both theoretical advancements and practical applications in the field.

3.3.2 Indicators

The structural (i.e., network-level) indicators for each product group from 1995-2020 are computed. In addition, role changes, characterized by node-level indicators, for each country over the same period are calculated. Afterward, the temporal patterns of the indicators are classified using a recently introduced nonparametric clustering method. Then, Granger causality tests are applied to analyze and identify the causal relationships between the structural changes of different product groups, allowing scholars to detect the effects of technological changes, shocks, and crises on trade networks. Fig. 3.2 shows the data preparation and analysis process.

Network-level indicators characterize an entire trade network for a specific year and product, while node-level indicators characterize each country in the network. The network-level indicators and the distribution of node-level indicators within trade networks enable different types of analysis that can provide insights into the structure, dynamics, and impacts of trade flows. Additionally, network-level indicators can capture the global properties and features of a trade network, such as its density Hoang, Piccardi, and Tajoli (2023), centrality Piccardi and Tajoli (2018), clustering Grant and Yung (2021), resilience (the size of the largest component/size of the total network after deleting an edge or vertex) Sun et al. (2023), assortativity Dueñas and Fagiolo (2014), asymmetry Meshcheryakova (2020), and reciprocity Amador et al. (2018). Furthermore, these indicators can reveal how the trade network evolves over time and how it responds to technological changes, shocks, or crises. The network-level indicators in this study have already been examined before in the case of trade network networks. At the same time, the interaction of their product-by-product temporal characteristics has not yet been investigated. The distribution of node-level indicators on trade networks can reflect the local properties and roles of individual countries or regions in the trade network, such as their centrality Cingolani, Iapadre, and Tajoli (2018), node coreness Hoang, Piccardi, and Tajoli (2023), and inequality Dueñas and Fagiolo (2014). The indicators utilized in this study are commonly employed for the examination of trade networks. However, it should be noted that the temporal patterns have not been categorized, and the correlation between them has not yet been studied. Nevertheless, these indicators can demonstrate the disparities between countries or areas, or they can be utilized to assess and contrast their trading patterns and behaviors, as well as the reciprocal influence or interdependence they exert on one another. In addition, by integrating network-level and node-level indicators and conducting timely analysis, a comprehensive understanding of the trade network and its impact on trade policy and development is achieved (refer to contribution C_2).

The following node- and network-level indicators are employed (see Table 3.1 & Table 3.2).

TABLE 3.1: Node-level indicators of trade networks and their applications

Group of node-level indicators	**Short description**	**Typical questions to be answered**	**Analyzed indicators**
Asymmetry, inequality	Measures the balance and reciprocity of trade flows between countries or regions.	How fair or reciprocal is the trade between two countries?	Net asymmetry
Centrality, coreness	Measures the importance and influence of countries or regions in a trade network based on their connections and positions.	How central or influential is a country in the trade network?	Betweenness centrality, Harmonic centrality, Eigenvector centrality, Node coreness

TABLE 3.2: Network-level indicators of trade networks and their applications

Group of network-level indicators	Short description	Typical questions to be answered	Analyzed indicators
Scale-free property, assortativity	Measures the degree distribution and attribute similarity of nodes in a trade network.	How similar are the nodes in terms of their degree or other attributes?	Gamma, Assortativity coefficient
Centralization, coreness	Measures the concentration of power and cohesion of structure in a trade network.	How unequal is the distribution of power or influence in a network? How cohesive is the network structure?	Betweenness centralization, Eigenvector centralization, Network redundancy
Connectivity, clustering, resilience, robustness	Measures the connectivity, clustering, resilience, and robustness of the trade network.	How easy is it to reach one country from another? How strong are the ties? How stable is the network to shocks or failures?	Giant component size, Random and targeted resilience
Asymmetry, reciprocity	Measures the asymmetry and reciprocity of trade flows between pairs of countries or regions.	How asymmetric or reciprocal is trade among countries?	Binary asymmetry, Mean asymmetry, Reciprocity variance

3.3.3 Causality and forecasting

A time series of trade networks from 1995 to 2020 is applied to examine whether the network-level or node-level indicators of a product or country, such as its centrality or centralization, have a causal effect on the indicators of another product or country. To test for causality, the Granger causality test Granger (1969) is applied. This test measures whether the past values of one time series can help predict the current or future values of another time series.

Let X and Y be two time series with observations $X_1, X_2, \ldots, X_t$ and $Y_1, Y_2, \ldots, Y_t$, respectively. The null hypothesis of the Granger causality test is that X does not Granger cause Y, while the alternative hypothesis is that X Granger causes Y. A time series regression model for both Y and X is constructed, the model for Y includes its own past values and the past values of X, and the model for X includes only its own past values. The F statistic is applied to compare the explained variance to the unexplained variance in the regression models, and the null hypothesis is rejected if the F statistic exceeds a critical value based on the degrees of freedom and the significance level. Various lags k are tested via Granger causality tests, where k is always a positive integer. Because of the relatively short time series data, to find the best data, lag information criteria (ICs), such as the Akaike information criterion (AIC) or the Bayesian information criterion (BIC), are applied to compare different models with different lag orders. For these tests, the lag is generally one year, which is consistent with the similar characteristics of the temporal patterns of the product groups.

$\mathcal{G}k^p(\mathcal{V}, \mathcal{E}_k^p)$ is denoted as a directed binary causality graph, where $\mathcal{V}$ is a set of nodes (countries or products), and $eij \in \mathcal{E}_k^p$ if and only if node i Granger causes node j with lag k at significance level p. The directed binary causality graph shows the direction of causal relationships between the time series indicators and can provide information on how a shock propagates through a trade network (see C3).

3.3.4 Network-based time-series clustering and analysis

Kosztyán, Kurbucz, and Katona (2022) proposed the network-based dimensionality reduction analysis method for nonparametric dimensional reduction. Compared to the principal component analysis and principal factor analysis, the network-based dimensionality reduction analysis has several advantages: it does not require pre-defining the number of groups of variables or the number of latent variables, and it can handle high dimension, low sample size datasets, where the number of variables exceeds the number of observations. Kosztyán et al. (2024) extended the method to the generalized network-based dimensionality analysis, which allows for arbitrary symmetric or asymmetric similarity functions between variables, such as correlation, partial correlation, or causality functions. In the generalized network-based dimensionality analysis, a similarity graph of the variables is constructed, and the modules or communities represent groups of variables with dense connections. The number of communities determines the number of latent variables, which are defined as linear combinations of the standardized variables and eigenector centrality. The network-based dimensionality reduction analysis and generalized network-based dimensionality analysis can specify factor loadings and drop variables that do not fit the latent variables or are peripheral in a community.

The method can be applied to cluster or reduce dimensions in causal networks or short time series. By applying generalized network-based dimensionality analysis to a directed binary causality graph network, groups of products and countries with dense causality relations and cluster centers that represent fictive products or countries can be identified. The distance from the cluster center indicates the degree of dependence on other products or countries. By applying generalized network-based dimensionality analysis to the time series of indicators, groups of products or countries with similar time-series characteristics and typical patterns over time can be identified. The distance from the typical pattern indicates the degree of deviation from the group; therefore, countries and products can be ranked according to dependencies (see C4).

3.4 Multivariate analysis

In this study, multivariate analysis, such as the gravity model and random forest regression models, was used with the following variables (see Table 3.3).

Denote the set of independent variables of location i in year t as $\mathcal{I}_{it}$, where $\mathcal{I}_{it} = \{HOTELS_{it}, GDP_{it}, ..., INDUL_{it}\}$.

The following time-series fixed-effect gravity model was used for all subjects within the time period.

$$Y_{ijt} = \beta_0 d_{ij}^{\beta_1} \prod_{\mathcal{V}_{it} \in \mathcal{I}_{it}} \mathcal{V}_{it}^{\beta_{\mathcal{V}_{it}}} \prod_{\mathcal{V}_{jt} \in \mathcal{I}_{jt}} \mathcal{V}_{jt}^{\beta_{\mathcal{V}_{jt}}} + u_{ijt}, \tag{3.1}$$

where Y_{jt} is the number of Erasmus students travelling from location i to location j in year t, $\beta_0, \beta_1, \beta_{\mathcal{V}_{it}}, \beta_{\mathcal{V}_{jt}}$ are regression parameters, $\mathcal{V}_{it} \in \mathcal{I}_{it}$ is the independent variable for location i in year t, and u_{ijt} is the residual.

TABLE 3.3: List of variables in gravity-like model

Variable description	Variable name	Data table	Time period
Location of source institution	i	ERASMUS	2008-2014
Location of host institution	j	ERASMUS	2008-2014
Year of travel	t	ERASMUS	2008-2014
Number of travelers between institutions in the year t	Y_{ijt}	ERASMUS	2008-2014
Distance between specific locations	d_{ij}	ERASMUS	2008-2014
Number of accommodations	*HOTELS*	EUROSTAT	2013
Gross domestic product	*GDP*	EUROSTAT	2008-2013
Number of collaborations between the institutions	*COLLAB*	ETER	2008-2014
Number of international collaborations of the institutions	*INTCOLLAB*	ETER	2008-2014
Number of industry collaborations of the institutions	*INDCOLLAB*	ETER	2008-2014
Live births	*LIVEBI*	EUROSTAT	2012
Gross value added	*GVA*	EUROSTAT	2012
Crimes committed	*CRIMES*	EUROSTAT	2012
Inhabitants per square kilometers	*INHABSQK*	EUROSTAT	2008-2013
Population	*POPUBYAGE*	Hofstede	2010
Power distance	*POWERDI*	Hofstede	2010
Individualism	*INDIVID*	Hofstede	2010
Masculinity	*MASCU*	Hofstede	2010
Uncertainty avoidance	*UNCAVO*	Hofstede	2010
Long term orientation	*LOTEORI*	Hofstede	2010
Indulgence	*INDUL*	Hofstede	2010

This gravity model was used for all subjects, all time periods, and each year. Since there were no zero values, the logarithmic version of Eq. (3.1) was used in a regression model **??**.

$$\log Y_{ijt} = \log(\beta_0) + \beta_1 \log d_{ij} + \sum_{\mathcal{V}_{it} \in \mathcal{I}_{it}} \beta_{\mathcal{V}_{it}} \log \mathcal{V}_{it} \sum_{\mathcal{V}_{jt} \in \mathcal{I}_{jt}} \beta_{\mathcal{V}_{jt}} \log \mathcal{V}_{jt} + \epsilon_{ijt}, \tag{3.2}$$

where ϵ_{ijt} is the residual of the linear regression model.

The linearized regression models have conditions, such as residuals should follow a normal distribution, and there is no heteroscedasticity or multicollinearity. In the case of a large dataset, where there are a large number of indicators, the main concern is multicollinearity Panduro and Thorsen (2014), which means that the "independent variables" are not truly independent from each other. More precisely, there are significant relationships among independent variables, which can distort the regression model. Multicollinearity is measured by a variance inflation factor (VIF) Mansfield and Helms (1982), which should be lower than 2.5. There are three main ways to handle multicollinearity: (1) Variables with high VIF coefficients should be dropped, but in this case, the information about these variables' importance is also dropped. (2) Variables should be grouped via principal component analysis or a factor analysis; however, in this case, the reduced model also loses information. (3) We followed the third method, where in addition to regression models, robust methods, such as the random forest regression method Sun et al. (2021), are used Segal (2004), as they are much less sensitive to multicollinearity than linear regression methods are Sun et al. (2021).

In addition to the regression analyses, we used correlation-based network analyses to explore the relationships among the indicators. First, a correlation graph of the indicators is specified. In this correlation graph, the nodes represent the indicators, and the arcs represent the strength of the correlation between nodes (i.e., indicators). By the Leiden method Traag, Waltman, and Eck (2019), the modules are specified such that the nodes within a module have a stronger connection than do the nodes between two different modules. In addition, with a Force Atlas II algorithm Jacomy et al. (2014), each node is arranged so the nodes with the greatest degree centrality were in the center of the modules. This situation allows us to analyze which indicators are related to most other variables.

Chapter 4

Results

4.1 Indicators

Two databases are proposed (see C_1) to identify the temporal patterns of structural network-level indicators (see C_2 and Section 4.1.1). Spearman's correlation is applied as a similarity function between time series to capture different types of product trends. The results of the causality analysis are presented (see C_3) in Section 4.1.2, and the role-playing countries in a product and their changes over time (see C_4) are presented in Section 4.1.3.

4.1.1 Temporal patterns of structural network-level indicators

Fig. Figures 4.1 and 4.2 shows the temporal changes in assortativity (a), eigenvector centralization, and mean coreness (b) in trade networks. Assortativity refers to the quantification of the degree of similarity between trading partners based on their traits or specialties. The phenomenon of assortativity can be understood as a measure of the degree of specialization and trading with comparable partners. An increase in assortativity signifies a greater level of specialization and trade with partners who possess similar characteristics. Conversely, a decrease in assortativity suggests a greater level of diversification and trade with partners with differing characteristics. Eigenvector centralization and mean coreness are two interconnected metrics that assess the level of concentration and cohesion within a network's structure. The phenomenon of growing centralization, also known as decreasing coreness, signifies the emergence of a few highly linked nodes or a more integrated community. Conversely, decreasing centralization or increasing coreness suggests a more equitable distribution of centrality or a network that is more fractured. The aforementioned variables may be influenced by a range of factors, including technical advancements, trade policies, comparative advantages, demand trends, geopolitical shifts, market dynamics, competitive forces, political instability, and supply chain disruptions.

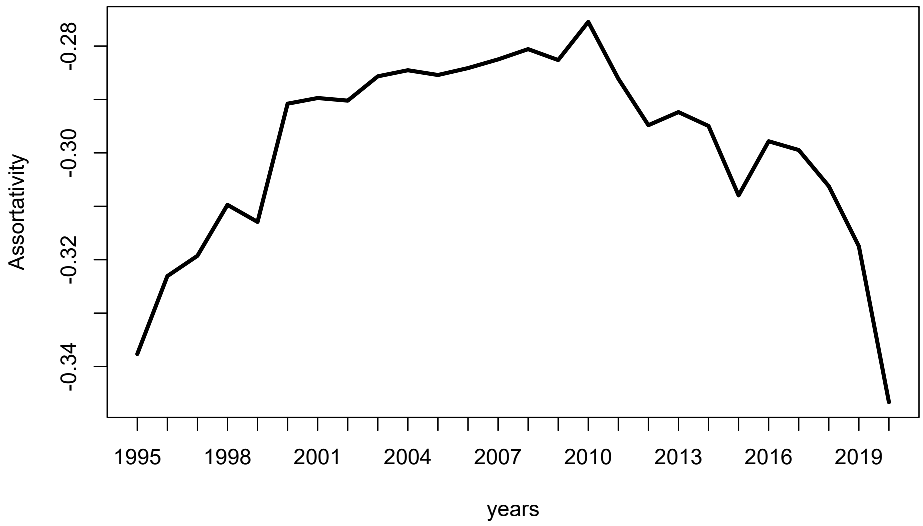

FIGURE 4.1: Cluster centers of temporal patterns of assortativity over time. The dissimilarity (1-similarity) measure is the Euclidean distance of the time series. The number of clusters found is 1.

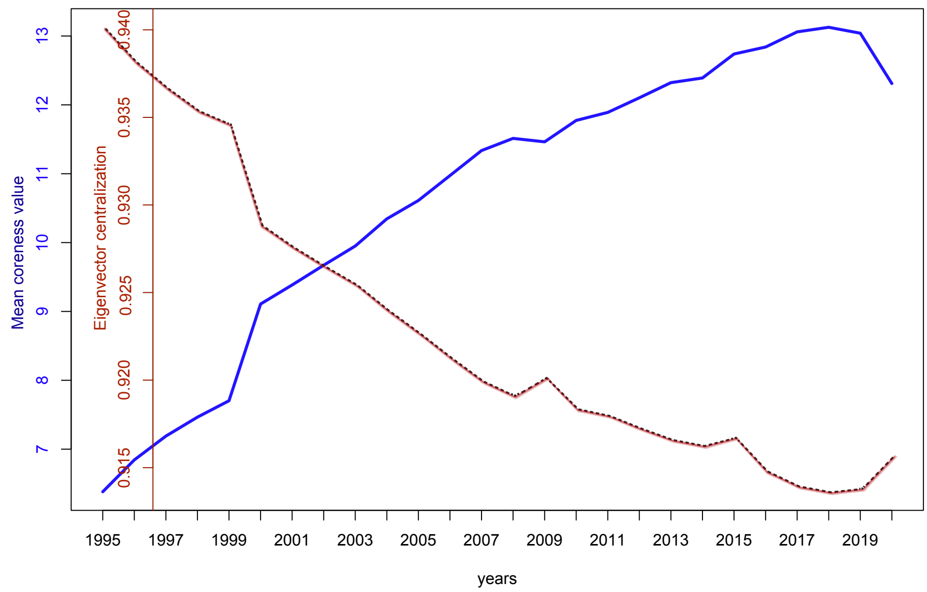

FIGURE 4.2: Cluster centers of temporal patterns of eigenvector centralization and mean coreness over time. The dissimilarity (1-similarity) measure is the Euclidean distance of the time series. The number of clusters found is 1.

Fig. 4.1 shows that based on the Euclidean distances, only one type of characteristic can be identified for all product groups. Fig. 4.2 shows the annual cluster centers (i.e., factor scores) of the product groups as typical assortativity, centralizations, and coreness characteristics. Fig. 4.1 shows that assortativity increases until 2010, and coreness also increases (centralization decreases) until 2018. Afterward, the trend reverses.

Global clustering (see Fig. 4.3) and resilience (see Fig. 4.4) measure the connectivity and robustness of trade networks. Additionally, global clustering measures how well the nodes form clusters or communities based on their trade patterns. Increasing global clustering indicates more specialization and cohesion within the network, while decreasing global clustering indicates more diversification and fragmentation within the network. Resilience (the size of the largest component/size of the total network) refers to the capacity of the network to effectively adapt to and recover from diverse disruptions, including events such as economic shocks, natural disasters, or political instability. Increasing resilience indicates a more robust and adaptable network, while decreasing resilience indicates a more vulnerable or unstable network.

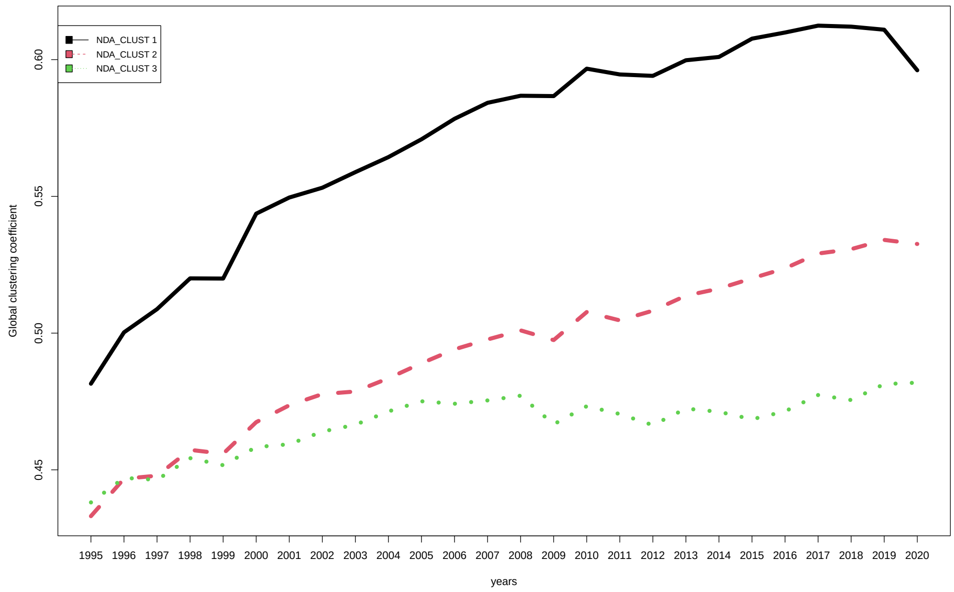

FIGURE 4.3: Temporal patterns of global clustering coefficients of product clusters over time. The similarity measure is Spearman's correlation. There are 3 clusters in global clustering.

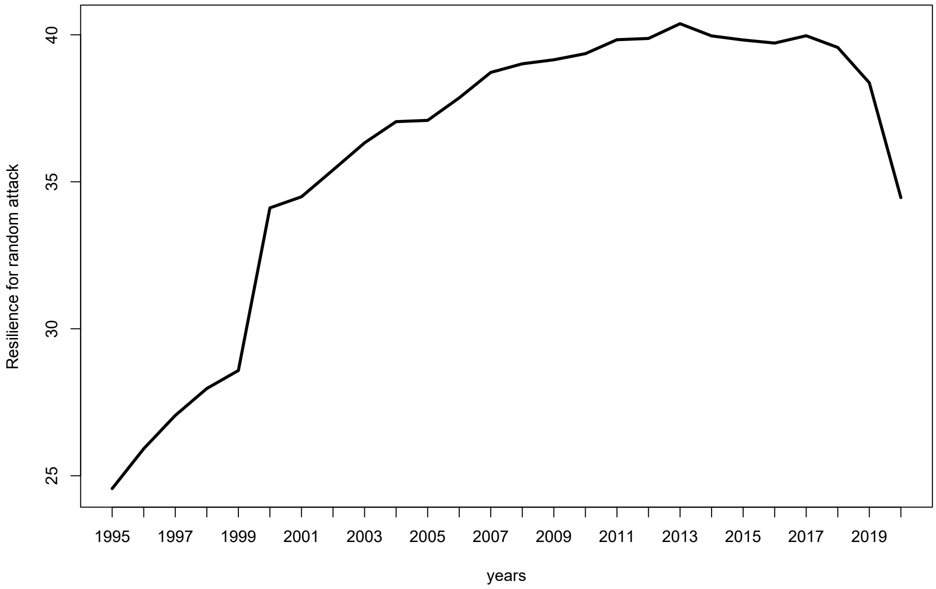

FIGURE 4.4: Temporal patterns of resilience values for random attack. The similarity measure is Spearman's correlation. There is 1 cluster in resilience.

The three identified product patterns exhibit different clustering characteristics, as shown in Fig. 4.3. The first cluster consists of so-called capital-intensive (high-tech) products. For this cluster, trade increases until 2018. However, before the COVID-19 pandemic in 2020, it is observed that clustering growth halts. The second group contains so-called labor-intensive products. For this group, there is an increase in clustering. However, this group is less affected by the US–China trade war after 2018. The third cluster contains so-called resource-intensive products, and there is insignificant clustering growth. Fig. 4.4 reveals that the network is more resilient before 2012, meaning that it could withstand shocks and disruptions better. However, the network's resilience declines after 2012. During the US–China trade war, but before the pandemic, the decline in resilience is accelerated, suggesting a reduced ability to recover from adverse events and maintain efficiency and stability.

The annual changes in reciprocity and bilateral/multilateral asymmetry in a trade network show how balanced and equitable bilateral and multilateral trade relationships are within the network. Reciprocity refers to the idea that trade between two countries or entities is roughly equal in terms of the value and volume of goods or services exchanged. A positive change in reciprocity (negative change in asymmetry) over time suggests that trade relationships within the network are becoming more balanced and mutually beneficial, with each country receiving a fair share of the benefits from trade. On the other hand, a negative change in reciprocity (increasing asymmetry) may indicate that some countries or entities benefit more from trade than others, leading to potential imbalances and inequities within the network.

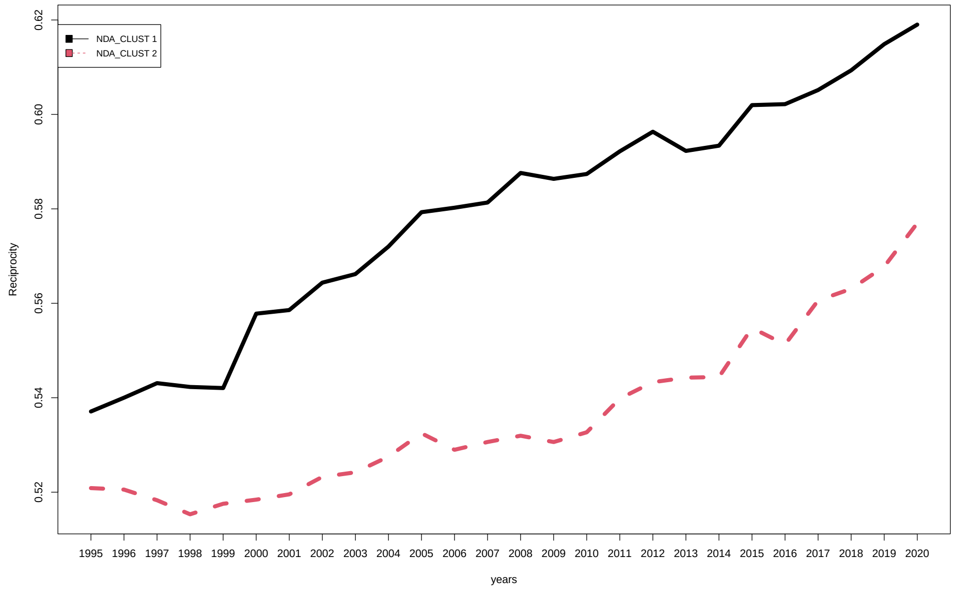

FIGURE 4.5: Temporal patterns of reciprocity values over time. The similarity measure is Spearman's correlation. There are 2 clusters.

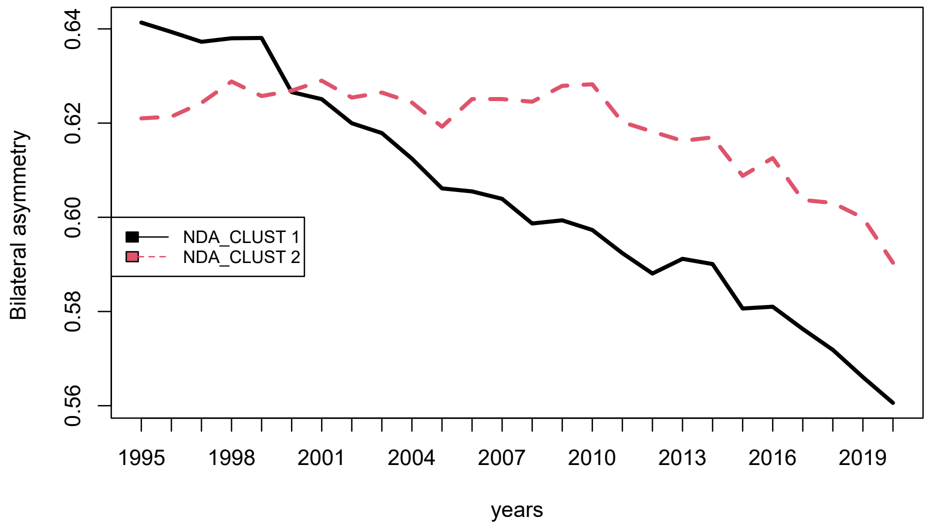

FIGURE 4.6: Cluster centers of bilateral asymmetry values over time. The similarity measure is Spearman's correlation. There are 2 clusters.

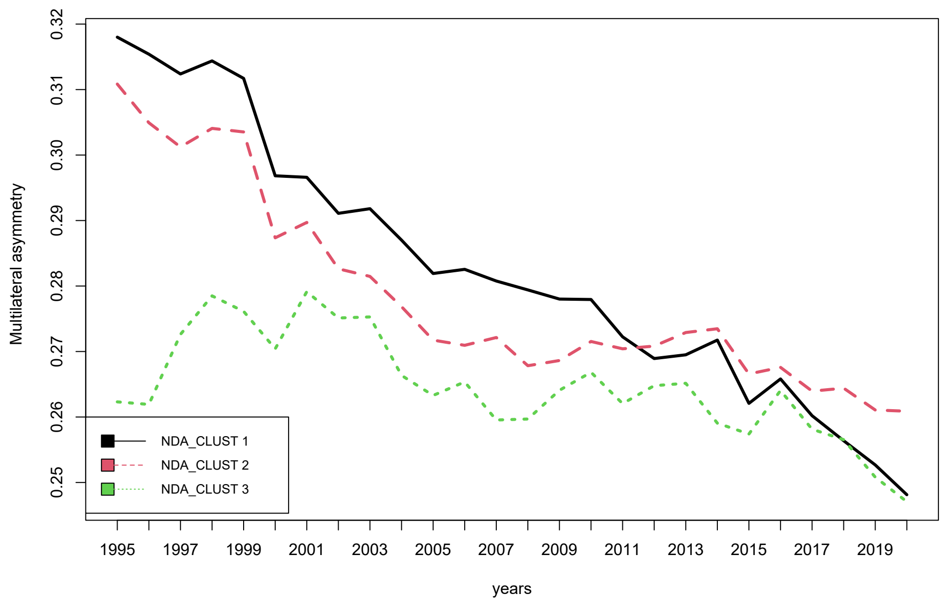

FIGURE 4.7: Cluster centers of multilateral asymmetry values over time. The similarity measure is Spearman's correlation. There are 3 clusters.

Fig. 4.5 shows that GNDA identifies two clusters of products when considering reciprocities in time. Cluster 1 consists of capital-intensive products, while cluster 2 consists of labor- and resource-intensive products. Fig. 4.6 shows that in the first, larger cluster, the reciprocity increases, while in the second cluster, the increase in reciprocity is more moderate. The characteristics of the identified temporal patterns of bilateral and multilateral asymmetries are in line with the reciprocity results (see Fig. 4.6). The multilateral asymmetry follows the clusters identified in the global clustering coefficients (see Fig. 4.7), while in the case of reciprocity, the two smaller groups are combined.

4.1.2 Causalities of structural indicators

In the cases of eigenvector centralization, betweenness centralization, global clustering, and multilateral asymmetry, there are very few causalities between products.

However, changes in assortativity (Fig. 4.8), resilience (Fig. 4.9, 4.10) and reciprocity (Fig. 4.11, 4.12) are indicated by causality groups of different colors. In part, because the relationship is few years, the smallest information criterion proved to be a one-year delay. This delay is considered for causality.

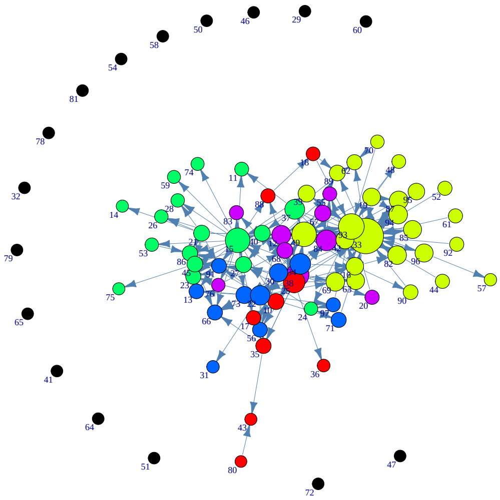

FIGURE 4.8: Granger causality network of assortativity indicators. The significance level is $p = 0.001$.

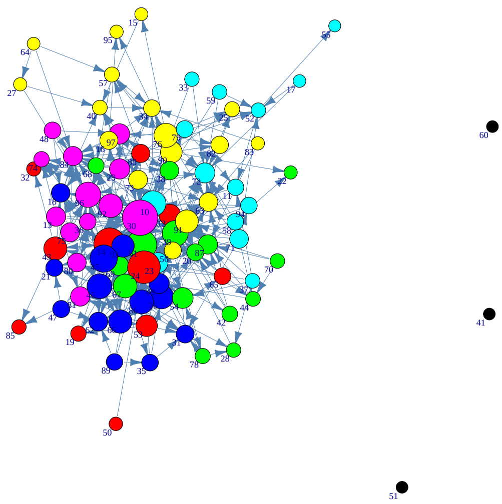

FIGURE 4.9: Causalities of resilience for random attack. The significance level is $p = 0.001$.

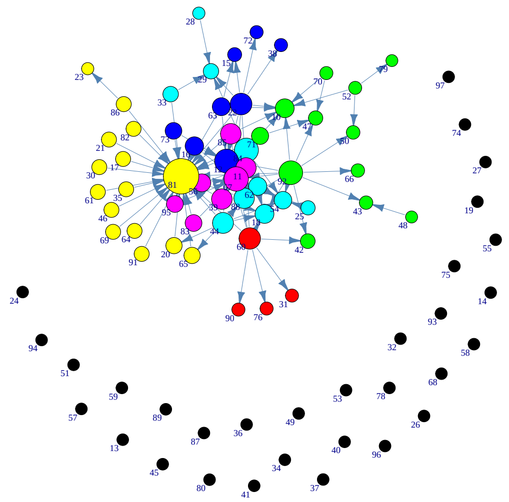

FIGURE 4.10: Causalities of resilience for systematic attack. The significance level is $p = 0.001$.

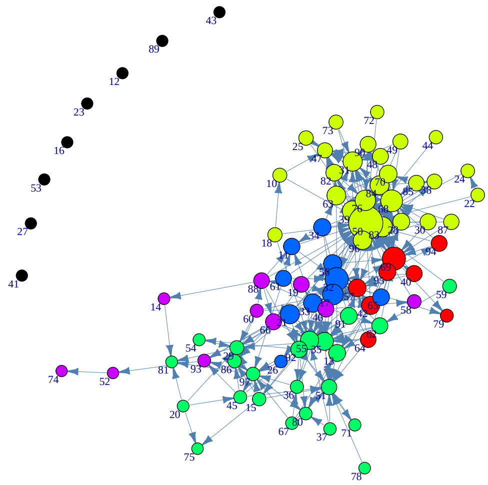

FIGURE 4.11: Causalities of bilateral asymmetries. The significance level is $p = 0.001$.

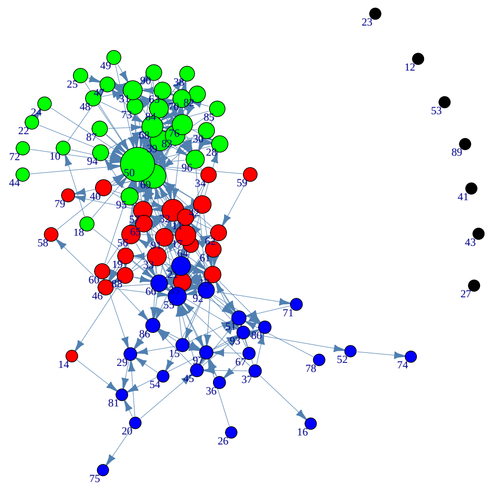

FIGURE 4.12: Causalities of reciprocity. The significance level is $p = 0.001$.

GNDA identifies five causality groups for assortativity (see Fig. 4.8) and reciprocity (see Fig. 4.11), six causality groups for resilience (Fig. 4.9, 4.10), and three groups for bilateral asymmetry of trading products.

Table 4.1 shows the most embedded products in clustered causality networks. In this case, the factor loading value gives the EC value of the product in a causality network. A higher value indicates greater embeddedness in a causality network. The greater the NDA score of a product in a precedence network is, the more sensitivity these product groups are to change.

TABLE 4.1: Eigenvector centralities (as factor loadings) of assortativity for the top five product groups (PR_i and NDA_i for cluster i). Products are sorted by descending loading.

Ord	PR_1	NDA_1	PR_2	NDA_2	PR_3	NDA_3	PR_4	NDA_4	PR_5	NDA_5
1	33	1.000	15	1.000	22	1.000	38	1.000	25	1.000
2	93	0.583	45	0.720	73	0.625	12	0.785	35	0.762
3	87	0.382	27	0.706	56	0.608	84	0.785	17	0.669
4	94	0.382	86	0.653	34	0.608	67	0.768	88	0.444
5	49	0.371	23	0.588	30	0.476	68	0.682	36	0.380

TABLE 4.2: Eigenvector centralities of resilience for random attack. Top six product clusters (PR_i and NDA_i). Products are listed by descending factor loading.

Ord	PR_1	NDA_1	PR_2	NDA_2	PR_3	NDA_3	PR_4	NDA_4	PR_5	NDA_5	PR_6	NDA_6
1	76	1.000	39	1.000	10	1.000	46	1.000	30	1.000	14	1.000
2	90	0.935	61	0.905	23	0.798	66	0.869	97	0.790	24	0.764
3	82	0.888	67	0.636	79	0.640	49	0.781	84	0.769	43	0.747
4	25	0.828	38	0.576	72	0.631	26	0.762	96	0.723	53	0.528
5	63	0.798	68	0.514	58	0.442	86	0.723	92	0.620	88	0.504

TABLE 4.3: Eigenvector centralities of resilience for systematic attack. Top six product clusters (PR_i and NDA_i). Products are listed by descending factor loading.

Ord	PR_1	NDA_1	PR_2	NDA_2	PR_3	NDA_3	PR_4	NDA_4	PR_5	NDA_5	PR_6	NDA_6
1	81	1.000	92	1.000	84	1.000	22	1.000	67	1.000	60	1.000
2	86	0.299	10	0.668	54	0.965	12	1.000	11	0.721	31	0.577
3	20	0.276	47	0.573	88	0.851	15	0.675	85	0.643	90	0.577
4	61	0.276	50	0.516	44	0.844	63	0.675	39	0.643	76	0.577
5	35	0.276	52	0.472	18	0.635	73	0.403	56	0.643		

TABLE 4.4: Eigenvector centralities of bilateral asymmetry for the top five product clusters. Products are listed in descending order by factor loading.

Ord	PR_1	NDA_1	PR_2	NDA_2	PR_3	NDA_3	PR_4	NDA_4	PR_5	NDA_5
1	50	1.000	55	1.000	32	1.000	88	1.000	69	1.000
2	31	0.611	92	0.953	17	0.860	46	0.834	57	0.852
3	68	0.588	51	0.895	11	0.596	19	0.784	95	0.695
4	76	0.541	15	0.835	34	0.572	66	0.638	64	0.547
5	83	0.502	97	0.826	61	0.572	60	0.581	40	0.547

TABLE 4.5: Eigenvector centralities of reciprocity for the top three product clusters. Products are listed in descending order by factor loading.

Ord	PR_1	NDA_1	PR_2	NDA_2	PR_3	NDA_3
1	50	1.000	97	1.000	32	1.000
2	68	0.621	55	0.971	35	0.876
3	69	0.547	45	0.847	33	0.869
4	31	0.539	15	0.801	17	0.811
5	76	0.534	86	0.753	57	0.771

4.1.3 Temporal patterns of role-players

This section focuses on product group 81, which consist of base metals, cermets, items that include tungsten and molybdenum, ferrous products obtained by the direct reduction of iron ore, and granules and powders of pig iron, spiegeleisen, iron, or steel. This group is highly influenced by changes in resilience of other products over time (Table 4.3). The products in this product group are often used as raw materials for many industrial products and are distributed across low-complexity networks. Therefore, these products are flexible against targeted attacks and do not affect the trade of high-tech products. The trade structure indicators (e.g., assortativity, clustering, γ parameter of fitted power-law distribution) of this group of products is not causally affected by other products (Tab. 4.1). Moreover, bilateral asymmetry and reciprocity changes in this group over time depend on only a few other product groups (Fig. 4.11, Table 4.4). Significant disturbances in the trade of this product group were observed, especially before the COVID-19 pandemic.

Fig. 4.13 shows (in/out) degree centralities over time for all countries. The applied GNDA identifies three classes. There is one cluster of highly increasing products, one of slowly increasing products, and one of stable products.

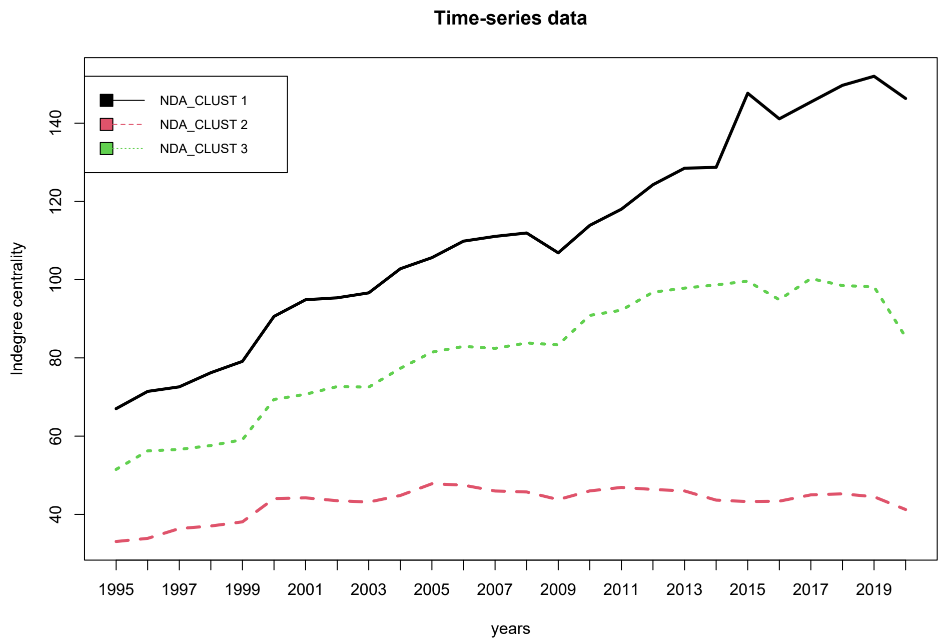

FIGURE 4.13: Typical characteristics of indegree centralities in the country–group trade network over time.

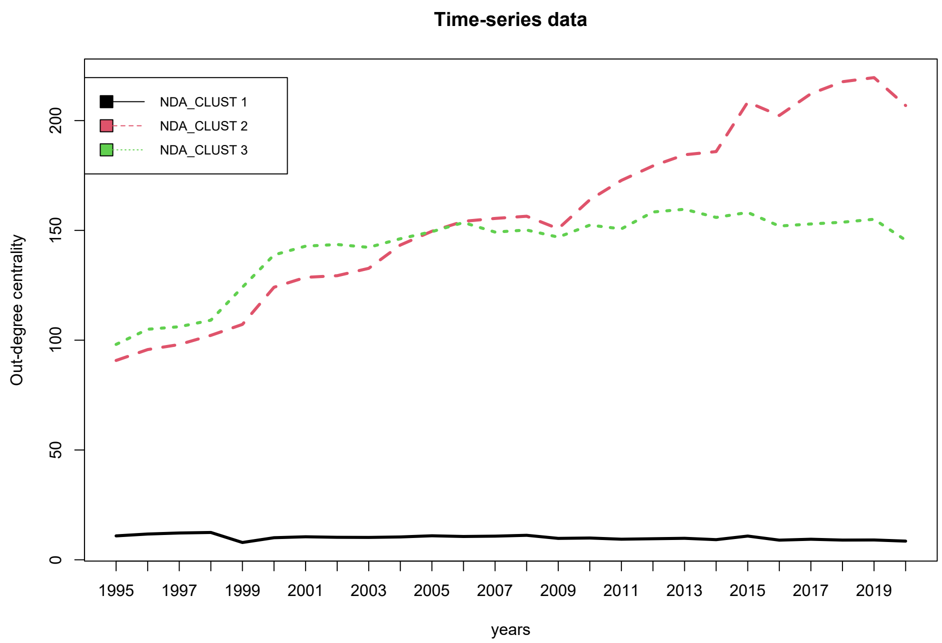

FIGURE 4.14: Typical characteristics of outdegree centralities in the country–group trade network over time.

Table 4.6 shows the factor loadings of the top four countries.

TABLE 4.6: Factor loadings of GNDA for the top four countries based on indegree centralities (CTY_i represents the i-th cluster of countries, and NDA_i the corresponding loading).

Ord	CTY_1	NDA_1	CTY_2	NDA_2	CTY_3	NDA_3
1	LVA	0.980	NCL	0.698	FRA	0.934
2	LTU	0.975	LCA	0.665	BLR	0.926
3	BGR	0.973	DZA	0.649	UKR	0.916
4	RUS	0.973	TTO	0.640	SLV	0.916

TABLE 4.7: Factor loadings of GNDA for the top four countries based on outdegree centralities (CTY_i represents the i-th cluster of countries, and NDA_i the corresponding loading).

Ord	CTY_1	NDA_1	CTY_2	NDA_2	CTY_3	NDA_3
1	COD	0.598	IND	0.970	BEL	0.847
2	MDA	0.579	KOR	0.967	CHE	0.841
3	PRK	0.553	CZE	0.958	ZAF	0.836
4	CXR	0.440	SVN	0.958	ITA	0.810

Table 4.6 and Fig. 4.13 show the diversification of imports characterized by the in-degree centrality. First, Cluster 1, consisting of countries such as Lithuania (LVA), Latvia (LTU), Bulgaria (BGR), and Russia (RUS), exhibits high factor loadings that are close to or equal to 1 in terms of the in-degree centrality. In addition, Cluster 2 comprises countries such as New Caledonia (NCL), Saint Lucia (LCA), Algeria (DZA), and Tobago (TTO). In the case of these countries, import diversification does not change. The import channels include the same countries. These countries exhibit moderate factor loadings ranging from 0.6 to 0.7 in terms of the in-degree centrality. Finally, Cluster 3, comprising countries such as France (FRA), Belarus (BLR), Ukraine (UKR), and El Salvador (SLV), exhibits high factor loadings above 0.9 in terms of the in-degree centrality, indicating strong inbound trade connections similar to those of Cluster 1. The results show that import diversification increases slightly here and then decreases before the pandemic.

Examining the diversification of exports (see Table **??**(b) and Figure **??**(b)), the first cluster includes Congo (COD), Moldova (MDA), North Korea (PRK) and the Christmas Islands (CXR). The countries in this cluster either do not have raw materials or participate only to a small extent in the trade of this product group, which is confirmed by the fact that the factor loadings are the smallest here. The countries belonging to the second cluster, namely, India (IND), South Korea (KOR), the Czech Republic (CZE), and Slovenia (SVN), have greatly increased their number of customers. In addition, the factor weights are also the largest here. The third cluster includes Belgium (BEL), Switzerland (CHE), the South African Republic (ZAF) and Italy (ITA), which only slightly increase their number of customers and strengthen their intermediary role. The factor loadings are between those of the first and second clusters.

4.2 Multivariate analysis

Table 4.8 shows the estimated coefficients (β) and the relative importance values of indicators ($R^2\%$) from the source (host) (i) to the target (j) locations.

TABLE 4.8: Results of overall time-series gravity model

Description, level of variable	VARIABLES	INSTITUTIONAL β	$R^2\%$	NUTS3 β	$R^2\%$
Number of accommodations, NUTS3	$HOTELS_i$	-2.91	3	-7.69	6
GDP, NUTS3	GDP_i	-	-	0.63	1
Number of collaborations, Institution	$COLLAB_i$	-	-	-	-
Number of international collaborations, Institution	$INTCOLLAB_i$	3.61	4	-	-
Number of industry collaborations, Institution	$INDCOLLAB_i$	-5.94	12	-3.43	3
Live births, NUTS3	$LIVEBI_i$	3.11	3	14.02	9
Gross value added, NUTS3	GVA_i	-3.64	2	6.46	7
Crimes committed, NUTS3	$CRIMES_i$	3.37	4	5.04	3
Inhabitants / km^2, NUTS3	$INHABSQK_i$	-	-	-	-
Population, NUTS3	$POPUBYAGE_i$	-	-	-	-
Hofstede, Power distance, NUTS1	$POWERDI_i$	-	-	-2.72	1
Hofstede, Individualism, NUTS1	$INDIVID_i$	-	-	-4.08	4
Hofstede, Masculinity, NUTS1	$MASCU_i$	3.38	6	5.47	2
Hofstede, Uncertainty avoidance, NUTS1	$UNCAVO_i$	1.68	6	2.54	1
Hofstede, Long-term orientation, NUTS1	$LOTEORI_i$	1.73	3	1.74	2
Hofstede, Indulgence, NUTS1	$INDUL_i$	-	-	-4.45	1
Number of accommodations, NUTS3	$HOTELS_j$	2.38	7	5.62	9
GDP, NUTS3	GDP_j	-	-	-2.85	3
Number of collaborations, NUTS1	$COLLAB_j$	-	-	-1.68	8
Number of international collaborations, NUTS1	$INTCOLLAB_j$	3.98	4	3.53	6
Number of industry collaborations, NUTS1	$INDCOLLAB_j$	-4.11	4	-6.38	1
Live births, NUTS3	$LIVEBI_j$	1.91	3	12.44	10
Gross value added, NUTS3	GVA_j	1.66	1	7.61	13
Crimes committed, NUTS3	$CRIMES_j$	-	-	8.55	6
Inhabitants / km^2, NUTS3	$INHABSQK_j$	-	-	-	-
Population, NUTS3	$POPUBYAGE_j$	-	-	-	-
Hofstede, Power distance, NUTS1	$POWERDI_j$	1.65	3	-3.33	3
Hofstede, Individualism, NUTS1	$INDIVID_j$	1.41	4	-	-
Hofstede, Masculinity, NUTS1	$MASCU_j$	-	-	-	-
Hofstede, Uncertainty avoidance, NUTS1	$UNCAVO_j$	-2.67	8	-	-
Hofstede, Long-term orientation, NUTS1	$LOTEORI_j$	-2.60	10	-	-
Hofstede, Indulgence, NUTS1	$INDUL_j$	4.04	13	1.78	1
Overall Adj. $R^2\%$ ($R^2\%$ by Random Forest Regression)			3.42 (7.80)		14.20 (33.90)

$R^2\%$: Relative adjusted R^2
$-$: insignificant indicator

The institutional level of the gravity model produces a low $R^2\% = 3.42$ value, while the NUTS3 level of the gravity model produces a greater $R^2\% = 14.20$ value. In this way, more significant indicators can be identified with the NUTS3 level of regression. The importance values of indicators in target and source regions show different patterns. All cultural indicators from the source location and all collaboration indicators to the target location are significant at the NUTS3 level. In addition, health and economic indicators, such as gross value added (GVA) and live births, are important and significant for both source and target regions.

Table 4.8 shows that all common significant dependent variables regarding the institutional and NUTS3 levels, except the gross value added of the home institution (GVA_i) and the power distance of the country of the host institution ($POWERDI_j$), have the same sign.

Figure 4.15 and 4.16 shows a clustered correlation graph, where nodes are variables, and arcs represent the strength of the correlation. Blue arcs represent positive correlations, while red arcs represent negative correlations. The thickness of the arcs is proportional to the strength of the correlation. The clusters are done with Traag, Waltman, and Eck (2019)'s community detection method, where variables (i.e., nodes) within a module are more correlated than variables between modules.

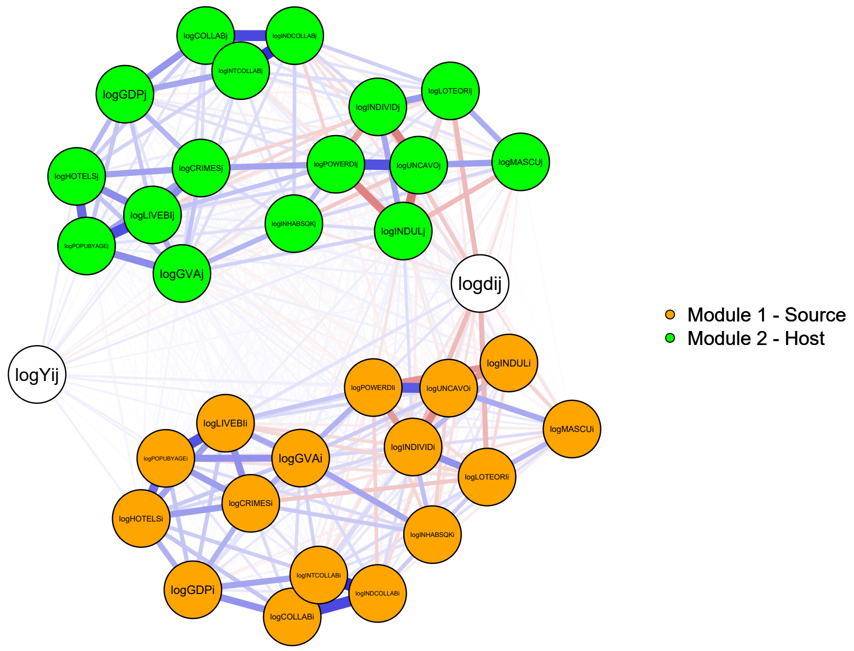

FIGURE 4.15: Clustered correlation graph at the institutional level.

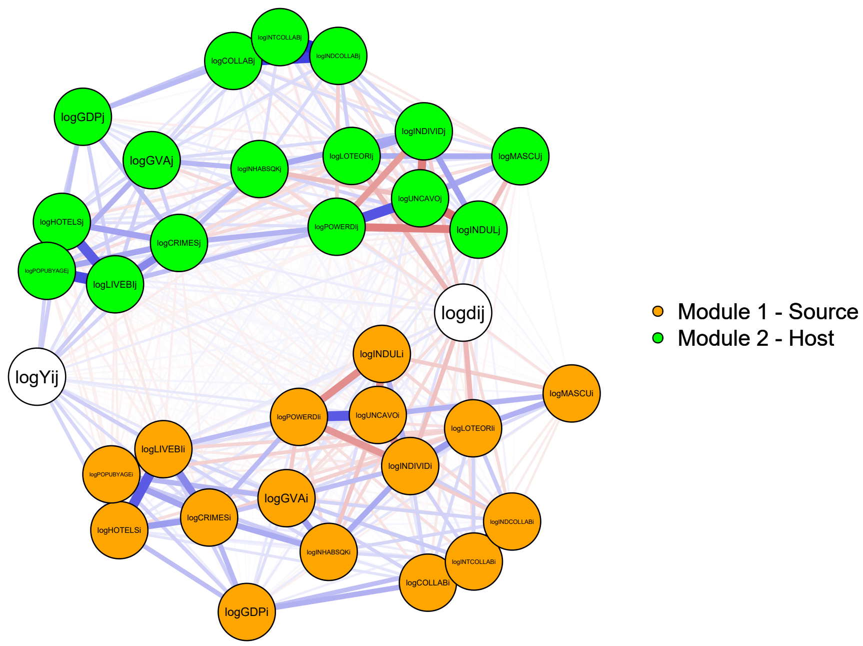

FIGURE 4.16: Clustered correlation graph at the NUTS 3 level.

The correlation graph shows that three modules can be identified. The first module collects the source indicators, while the second module collects only the host-related indicators. Module 3 collects the output (number of exchanges) and the distances between the host and the source regions.

High internal correlation among some variables, such as cultural variables, indicates multicollinearity; however, we do not want to omit these variables from the model. Therefore, a robust method, the random forest method, is used to examine the relationships between dependent (mobility exchange) and independent variables. The random forest method is applied after providing a higher adj. $R^2 = 0.339$. Table 4.10 shows the outcome of those calculations.

TABLE 4.9: Evaluation metrics at the institutional level

	Value
MSE	0.934
RMSE	0.966
MAE	0.798
MAPE	258.75%
R^2	0.078

TABLE 4.10: Evaluation metrics at the NUTS 3 level

	Value
MSE	0.664
RMSE	0.815
MAE	0.675
MAPE	129.36%
R^2	0.339

Tables 4.11-4.12 show the overall adjusted R^2 values by professions and years. Profession 9 is not specified; however, in this category, it is mainly the military institutes that are connected to each other.

TABLE 4.11: Overall R^2% by years and professions, institutional

Professions	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**All**
1. Education	1.80	3.10	3.23	3.33	2.45	2.71	4.99
2. Humanities and arts	0.72	1.04	1.18	1.25	1.16	1.67	4.43
3. Social sciences, business, and law	0.94	1.30	1.45	1.11	1.06	1.05	4.60
4. Science, math, and computing	0.86	2.24	1.87	1.11	1.66	1.23	5.65
5. Engineering, manufacturing, and construction	1.85	3.50	3.84	2.59	2.36	2.17	6.96
6. Agriculture and veterinary science	3.82	3.05	3.21	5.39	3.49	4.27	5.25
7. Health and welfare	3.67	2.49	4.40	3.45	2.03	1.75	6.23
8. Services (hotel, travel, hair, beauty)	2.56	5.14	1.67	3.5	0.83	2.31	5.64
9. Unknown/not specified	30.69	6.50	6.10	5.70	12.67	4.96	11.70
Overall Adj. R^2%	3.81	3.94	3.75	3.84	3.35	3.26	3.42
R^2% by Random Forest Regression	3.00	7.00	4.00	7.00	12.00	2.00	7.80

The highest overall R^2% is provided by profession 9, which fluctuates greatly over time. The lowest overall R^2% is in the humanities and arts professions. In terms of the institutional level, the adjusted R^2% is always greater if the data are separated by profession, while at the NUTS3 level, separation by professions does not increase the overall adjusted R^2%. The fluctuation of R^2% is characteristic of professionals; however, it is stable across time for all professions at both the institutional and NUTS3 levels. The results of Table 4.11 suggest that at the institutional level, the professions have to be separated; however, generally, the annual regression does not increase the explanatory power of the model, while the total annual R^2 is stable over time. The annual fluctuation in values by profession is explained by the small number of exchanges among institutions. Despite the institutional results of overall R^2, at the NUTS3 level, generally, the model fits better if exchanges are separated by both year and profession.

At the NUTS3 level, in addition to the unspecified profession (9), the social sciences (3), engineering (5), humanities (2), and computing sciences (4) have greater overall adjusted R^2%, while agriculture has a lower R^2%.

TABLE 4.12: Overall R^2% by year and profession at the NUTS3 level

Professions	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**All**
1. Education	4.10	3.39	3.00	3.32	4.11	3.57	6.48
2. Humanities and arts	9.91	14.07	13.52	9.18	9.04	8.77	11.35
3. Social sciences, business, and law	13.11	10.09	11.29	11.3	11.61	11.58	12.27
4. Science, math, and computing	9.90	8.08	7.95	8.94	8.41	7.43	11.83
5. Engineering, manufacturing, and construction	12.22	12.58	11.97	11.76	11.24	10.56	12.85
6. Agriculture and veterinary science	3.09	3.16	18.69	6.69	6.40	6.47	5.72
7. Health and welfare	9.15	8.65	10.98	8.19	7.59	6.64	9.37
8. Services (hotel, travel, hair, and beauty)	4.52	5.68	5.17	6.17	6.39	5.22	6.01
9. Unknown/not specified	19.37	10.77	30.13	16.07	13.23	16.08	9.44
Overall adjusted R^2%	13.24	13.42	14.08	13.97	13.98	13.32	14.20
R^2% by Random Forest Regression	27.90	26.10	28.40	30.60	31.50	31.10	33.90

Table 4.13 shows only the relative importance values (R^2%) and the estimated coefficients (β) of annual national cultural indicators at the institutional level.

TABLE 4.13: Impacts and coefficients of cultural indicators by year and by institution (2008-2013)

	R^2%							β						
Variables	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**All**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**All**
$POWERDI_i$	-	-	25	17	10	17	-	-	-	5.09	2.98	1.80	4.10	-
$POWERDI_j$	3	6	-	-	-	3	3	-1.66	-1.73	-	-	-	1.62	1.65
$INDIVID_i$	-	-	-	-	-	-	-	-	-	-	-	-	-	-
$INDIVID_j$	4	-	-	-	-	10	4	2.18	-	-	-	-	2.98	1.41
$MASCU_i$	10	8	-	8	-	18	6	2.95	1.53	-	2.57	-	4.46	3.38
$MASCU_j$	-	8	-	-	8	-	-	-	2.13	-	-	1.78	-	-
$UNCAVO_i$	15	17	-	-	-	-	6	2.31	2.70	-	-	-	-	1.68
$UNCAVO_j$	-	-	8	-	-	-	8	-	-	2.14	-	-	-	-2.67
$LOTEORI_i$	-	-	-	-	-	-	3	-	-	-	-	-	-	1.73
$LOTEORI_j$	5	-	5	-	-	3	10	-2.96	-	-1.53	-	-	-1.66	-2.60
$INDUL_i$	-	-	5	14	15	14	-	-	-	2.82	3.41	2.83	4.55	-
$INDUL_j$	15	-	-	7	5	-	13	-4.20	-	-	-1.92	-1.50	-	4.04
All cultural	52	39	43	46	38	65	53	-	-	-	-	-	-	-
$COLLAB_i$	3	2	5	-	-	-	-	2.00	1.45	2.95	-	-	-	-
$COLLAB_j$	-	-	-	-	-	-	-	-	-	-	-	-	-	-
$INTCOLLAB_i$	-	-	-	5	-	-	4	-	-	-	2.83	-	-	3.61
$INTCOLLAB_j$	-	-	-	2	-	-	4	-	-	-	-2.39	-	-	3.95
$INDCOLLAB_i$	7	13	12	12	7	-	12	-2.75	-2.92	-3.20	-3.52	-2.44	-	-5.94
$INDCOLLAB_j$	2	3	-	3	-	-	4	1.35	-1.42	-	2.28	-	-	-4.11
All collaborations	12	18	17	22	7	-	24	-	-	-	-	-	-	-
$CRIMES_i$	25	11	-	21	-	-	4	4.11	2.58	-	2.92	-	-	3.37
$CRIMES_j$	-	2	6	-	-	-	-	-	1.96	2.58	-	-	-	-
Remaining	11	30	34	11	55	35	19	-	-	-	-	-	-	-

Notably, Table 4.14 indicates the great total relative importance value of cultural indicators in every year, and both the relative importance value (R^2%) and the estimated coefficients change over time. In addition, these values are different for the host and target institution.

Table 8. Most of the signs of the β values are different for the 9 study categories and the overall values as well. The behaviors are mostly similar across each year

TABLE 4.14: Impacts and coefficients of cultural indicators by year and by NUTS3 region (2008-2013)

	R^2%							β						
Variables	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**All**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**All**
$POWERDI_i$	4	-	-	-	-	-	1	-2.63	-	-	-	-	-	-2.72
$POWERDI_j$	3	-	3	4	3	-	3	1.59	-	-1.47	-2.67	-2.24	-	-3.33
$INDIVID_i$	-	5	6	3	6	-	4	-	-3.61	-4.29	-1.45	-4.20	-	-4.08
$INDIVID_j$	-	4	2	-	-	4	-	-	-1.60	-1.92	-	-	-1.61	-
$MASCU_i$	-	5	4	-	4	-	2	-	3.46	2.06	-	1.75	-	5.47
$MASCU_j$	-	4	-	-	-	-	-	-	-1.72	-	-	-	-	-
$UNCAVO_i$	12	-	-	-	-	-	1	5.26	-	-	-	-	-	2.54
$UNCAVO_j$	5	-	5	-	-	-	-	-2.54	-	-1.88	-	-	-	-
$LOTEORI_i$	-	-	-	-	-	-	2	-1.57	-	-	-	-	-	1.74
$LOTEORI_j$	6	7	-	6	9	6	-	-1.77	-2.46	-	-2.78	-4.74	-2.14	-
$INDUL_i$	-	-	-	4	-	3	1	-	-	-	-2.23	-	-2.27	-5.54
$INDUL_j$	6	6	-	-	2	-	1	1.73	2.66	-	-	-1.41	-	1.78
All cultural	36	31	19	17	24	13	15	-	-	-	-	-	-	-
$COLLAB_i$	3	-	3	-	-	-	-	2.02	-	2.67	-	-	-	-
$COLLAB_j$	3	-	-	-	-	2	8	2.39	-	-	-	-	1.84	-1.68
$INTCOLLAB_i$	-	-	2	2	-	3	-	-	-	-2.30	2.15	-	3.20	-3.43
$INTCOLLAB_j$	-	-	5	2	-	-	6	-	-	3.52	-1.90	-	-	-3.53
$INDCOLLAB_i$	-	-	-	3	-	4	3	-	-	-	-2.68	-	-2.78	14.02
$INDCOLLAB_j$	5	-	3	-	-	6	1	-3.19	-	-3.37	-	-	-3.56	-6.38
All collaborations	11	-	13	7	-	15	18	-	-	-	-	-	-	-
$CRIMES_i$	16	6	8	13	5	8	3	13.00	11.97	13.39	12.42	11.19	10.68	5.04
$CRIMES_j$	9	7	11	18	3	21	6	10.96	13.34	15.06	14.26	15.33	15.62	8.55
Remaining	28	56	49	45	68	43	58	-	-	-	-	-	-	-

within these categories, with some notable exceptions. The exchanges in study category 2 (humanities and art) showed that the perceived threat of the unknown was similar between the institutions ($UNCAVO_i$, $UNCAVO_j$). Mobility within study category 5 (engineering, manufacturing, construction) showed that students came from institutions that allowed participation in decision making and went to institutions that offered a stricter, less participation-friendly environment ($POWERDI_i$, $POWERDI_j$). Study category 6 (agriculture, veterinary science) had a similar result to category 5 in terms of power distance. Category 7 (health, welfare) showed that students traveled from areas with similar long-term orientation prospects to their host region ($LOTEORI_j$). Study category 8 (services (hotel, travel, hair, beauty)) showed that students came from institutions that allowed limited participation in decision making and went to institutions that offered a similar environment ($POWERDI_i$, $POWERDI_j$). Category 9 (unspecified) showed that students traveled from relatively strict institutions, just like those in category 8 ($POWERDI_i$, $POWERDI_j$). The international collaboration ($INTCOLLAB$) data suggest that throughout the whole column, mobility was positively affected by such collaboration on both the host and home ends. However, the more collaboration projects an institution took part in ($INDCOLLAB$), the less likely students and teachers from that institution were to be mobile.

Tables 4.15-4.16 shows the relative importance values and the estimated coefficients (β) of national cultural and collaboration indicators by profession on the NUTS3 level. The cultural indicators provide the most explanation in the institutional model. Both relative importance values and the estimated coefficients of indicators are significantly different for both target and source institutions and for each profession.

The threat from the unknown ($UNCAVO_i$) chiefly affected the mobility in study category 1 (education), accounting for 45% of the relative (R^2). Study categories 3, 5, 6, and 8 showed similar results distinct from category 1. Exchanges within study category 2 (humanities and art) were mostly driven by ($MASCU_i$). The mobility of

TABLE 4.15: Impacts and coefficients of cultural indicators by profession and by institution

R^2%	1., education	2., humanities, art	3., social sciences, business, law	4., science, math, computing	5., engineering, manufacturing, construction	6., agriculture, veterinary science	7., health, welfare	8., services	9., not know / not specified	All
$POWERDI_i$	14	4	-	3	8	15	-	4	5	-
$POWERDI_j$	6	5	-	-	4	11	7	3	-	3
$INDIVID_i$	-	3	4	-	-	10	3	-	24	-
$INDIVID_j$	3	5	6	-	-	-	10	-	5	4
$MASCU_i$	5	28	12	6	-	-	11	-	-	6
$MASCU_j$	-	7	-	10	8	6	-	-	-	-
$UNCAVO_i$	17	2	8	5	12	12	9	25	13	6
$UNCAVO_j$	6	3	-	18	11	-	4	-	-	8
$LOTEORI_i$	3	-	-	2	-	6	4	3	-	3
$LOTEORI_j$	6	5	4	9	5	-	4	20	-	10
$INDUL_i$	-	3	-	-	2	-	3	2	-	-
$INDUL_j$	6	13	20	10	2	-	-	-	-	13
All cultural	66	78	54	63	52	60	55	57	47	53
$COLLAB_i$	2	1	-	1	-	5	3	-	3	-
$COLLAB_j$	1	2	-	3	-	-	-	-	3	-
$INTCOLLAB_i$	3	1	4	2	-	-	3	3	3	4
$INTCOLLAB_j$	-	3	7	-	2	-	3	4	2	4
$INDCOLLAB_i$	10	-	3	7	8	3	5	-	3	12
$INDCOLLAB_j$	6	8	3	4	4	-	5	7	10	4
All collaborations	22	15	17	17	14	8	19	14	24	24
$CRIMES_i$	-	-	-	7	11	-	6	8	3	4
$CRIMES_j$	-	-	6	-	-	-	-	-	-	-
Remaining	12	7	23	13	23	32	20	21	26	19
β	1.	2.	3.	4.	5.	6.	7.	8.	9.	All
$POWERDI_i$	3.87	3.37	-	1.97	2.03	3.58	-	-2.34	-2.37	-
$POWERDI_j$	4.86	4.35	-	-	-2.78	-2.97	3.43	-2.49	-	1.65
$INDIVID_i$	-	2.87	3.11	-	-	-3.87	3.58	-	-3.48	-
$INDIVID_j$	1.85	2.28	2.56	-	-	-	8.13	-	1.42	1.41
$MASCU_i$.	2.03	10.39	4.55	5.02	-	-	4.78	-	-	3.38
$MASCU_j$	-	5.45	-	-4.42	-5.30	3.02	-	-	-	-
$UNCAVO_i$	3.80	-1.47	4.20	2.49	6.57	2.61	4.08	6.73	2.93	1.68
$UNCAVO_j$	-3.32	-2.01	-	-7.40	-4.92	-	3.20	-	-	-2.67
$LOTEORI_i$	3.11	-	-	2.75	-	-	-3.60	2.84	-	1.73
$LOTEORI_j$	-1.81	-2.68	-1.60	-5.90	-3.84	-	-3.70	-4.99	-	-2.60
$INDUL_i$	-	-2.55	-	-	2.43	-	-2.30	1.53.	-	-
$INDUL_j$	3.20	7.59	8.12	3.25	-1.82	-	-	-	-	4.04
$COLLAB_i$	-2.62	-1.59	-	-1.52	-	3.19	-1.74	-	-1.93	-
$COLLAB_j$	2.37	-2.82	-	4.34	-	-	-	-	-1.54	-
$INTCOLLAB_i$	3.16	1.46	4.54	2.01	-	-	2.97	-2.86	2.08	3.61
$INTCOLLAB_j$	-	3.84	5.62	-	3.58	-	4.35	3.07	1.68	3.95
$INDCOLLAB_i$	-5.05	-	-3.47	-6.24	-5.98	-2.73	-4.99	-	-1.83	-5.94
$INDCOLLAB_j$	-3.91	-5.78	-4.36	-5.20	-5.48	-	-5.39	-3.96	-2.79	-4.11
$CRIMES_i$	-	-	-	5.00	6.34	-	2.21	3.71	2.21	3.37
$CRIMES_j$	-	-	2.62	-	-	-	-	-	-	-

study category 4 (science, math and computing) differed from that of study category 1, and the major pull variable is ($UNCAVO_j$). Study category 7 (health, welfare) had the most diverse dispersion of relative (R^2) values across the cultural variables, with ($MASCU_i$) being the largest pull variable. Study category 9 (unknown, not specified) showed modest dispersion with the lowest relative (R^2) score across the categories.

TABLE 4.16: Impacts and coefficients of cultural indicators by profession and by NUTS3 region

R^2%	1., education	2., humanities, art	3., social sciences, business, law	4., science, math, computing	5., engineering, manufacturing, construction	6., agriculture, veterinary	7., health, welfare	8., services	9., not know / not specified	All
$POWERDI_i$	4	5	1	-	-	-	3	5	5	1
$POWERDI_j$	-	-	-	-	7	-	14	-	2	3
$INDIVID_i$	-	-	-	15	-	-	5	13	-	4
$INDIVID_j$	-	4	-	-	-	3	8	-	3	-
$MASCU_i$	-	25	-	10	-	7	16	-	3	2
$MASCU_j$	8	9	7	9	10	2	3	-	-	-
$UNCAVO_i$	45	2	18	-	17	13	-	23	6	1
$UNCAVO_j$	-	-	9	24	13	-	-	-	3	-
$LOTEORI_i$	-	-	4	7	-	-	3	2	7	2
$LOTEORI_j$	-	-	2	9	-	-	3	19	-	-
$INDUL_i$	-	3	-	-	-	4	14	3	-	1
$INDUL_j$	19	6	17	-	3	8	-	3	-	1
All cultural	76	54	58	74	50	37	69	68	29	15
$COLLAB_i$	-	-	2	-	-	8	3	3	10	-
$COLLAB_j$	-	-	-	-	-	3	-	3	-	8
$INTCOLLAB_i$	-	-	3	2	-	-	-	3	-	-
$INTCOLLAB_j$	-	-	4	-	3	2	-	-	-	6
$INDCOLLAB_i$	12	-	-	4	9	-	-	-	-	3
$INDCOLLAB_j$	2	9	12	-	5	-	-	2	7	1
All collaborations	14	9	21	6	17	13	3	11	17	18
$CRIMES_i$	-	-	-	4	7	-	5	5	-	3
$CRIMES_j$	1	7	7	-	-	-	-	-	-	6
Remaining	9	30	14	16	26	50	23	16	54	58
β	1.	2.	3.	4.	5.	6.	7.	8.	9.	All
$POWERDI_i$	-2.22	3.03	-	-	-	-	-1.60	-3.20	-2.56	-2.72
$POWERDI_j$	-	-	-	-	-2.74	-	5.13	-	1.69	-3.33
$INDIVID_i$	-	-	-	-6.19	-	-	-1.79	-3.45	-	-4.08
$INDIVID_j$	-	1.86	-	-	-	2.66	4.77	-	-2.49	-
$MASCU_i$	-	5.83	-1.47	3.96	-	2.61	4.94	-	-1.47	5.47
$MASCU_j$	-2.68	3.44	-1.45	-1.65	-3.82	-2.29	1.62	-	-	-
$UNCAVO_i$	8.92	-1.53	4.98	-	5.24	2.11	-	4.61	2.73	2.54
$UNCAVO_j$	-	-	-1.76	-5.51	-3.54	-	-	-	-2.85	-
$LOTEORI_i$	-	-	2.20	3.69	-	-	-1.96	1.80	1.48	1.74
$LOTEORI_j$	-	-	1.69	-2.60	-	-	-3.17	-4.94	-	-
$INDUL_i$	-	1.62	-	-	-	-2.35	-4.12	1.66	-	-4.45
$INDUL_j$	5.35	3.34	3.62	-	-3.53	-3.16	-	-2.32	-	1.78
$COLLAB_i$	-	-	1.72	-	-	3.60	-2.55	1.88	2.57	-
$COLLAB_j$	-	-	-	-	-	2.07	-	2.13	-	-1.68
$INTCOLLAB_i$	-	-	-1.83	1.91	-	-	-	-2.10	-	-
$INTCOLLAB_j$	-	-	2.60	1.78	3.57	-	-	-	-	3.53
$INDCOLLAB_i$	-4.43	-	-	-3.09	-3.80	-2.55	-	-	-	-3.43
$INDCOLLAB_j$	-1.99	-2.68	-3.99	-2.04	-4.62	-1.86	-	-2.09	-2.91	-6.38
$CRIMES_i$	-	-	-	2.14	1.85	-	2.12	2.58	-	5.04
$CRIMES_j$	-1.63	2.63	1.73	-	-	-	-	-	-	8.55

Chapter 5

Discussion

5.1 Exploration and Structural Dynamics of Global Networks

Before delving into the detailed discussion of network structures and systemic behaviors, it is important to contextualize the frameworks and mechanisms that underlie both trade and academic mobility. Global trade networks and student mobility programs are not isolated phenomena; they operate within overlapping geopolitical, economic, and social landscapes that shape their evolution and responsiveness. Patterns of connectivity, centrality, and resilience in these networks are influenced by institutional decisions, policy shifts, and emergent technological tools, while historical trajectories and cultural practices inform the distribution of influence among nodes. By examining these interdependent factors, it becomes possible to identify both commonalities and divergences between the ways trade flows and student exchanges adapt to shocks, leverage opportunities, and propagate effects throughout their respective systems.

5.1.1 Crisis analysis

Throughout human history, crises are a recurring theme. However, technological change is a new factor that is unique to the modern era. Technological change can affect the structure and performance of supply chains and trade networks in various ways, such as by creating new opportunities, challenges, or risks. However, as many researchers have pointed out Craighead, Ketchen Jr, and Darby (see e.g., 2020) and Notteboom, Pallis, and Rodrigue (2021), the recent pandemic crisis had a different impact than did previous crises, such as the 2008 financial crisis. Owing to the emergence of China and later the US–China trade war, specifically before the pandemic crisis, supply chains became more concentrated and more vulnerable. The results showed that several structural indicators (centralization, resilience, asymmetry) of trade networks worsened before the pandemic, indicating a more vulnerable and imbalanced situation. Moreover, these indicators did not exhibit any clear signs of recovery from the 2008 financial crisis. At the same time, partly due to the slowdown of globalization and partly due to the weakening of trade relations, the improvement of structural indicators, such as assortativity, stopped before the financial crisis. After 2010, the network indicators deteriorated one after another. After assortativity, resilience peaked in 2016, and then the decrease in concentration stopped in 2018, clearly reflecting the structural change in trade relations. The predictions indicated an increase in the vulnerability of trade networks, which was also experienced during the COVID-19 pandemic, where serious supply disruptions occurred with China's withdrawal. Therefore, it is important to use methods that can analyze the trade networks of different products simultaneously and reveal their interrelationships. The main finding is that technological change and deglobalization have made supply chains and trade networks more fragile and prone to crises.

Temporal patterns of structural trade network indicators

Fig. 4.1 shows the cluster center of the assortativity of product groups in the world trade network over time, reflecting factors such as technological advancements, globalization, and consumer preferences (see C_1-C_2). After 2010, assortativity growth plateaued, with fluctuations occurring until the election of President Trump in 2016. However, following that, the curve experienced a significant decline primarily attributed to the emerging US–Chinese trade war. These factors may have led to more similarity and standardization within product groups until 2010 Disdier, Fontagné, and Cadot (2015). After 2010, these factors may have led to more differentiation and diversity within product groups due to increasing competition, shifting preferences, and changing technologies Yenipazarli (2019).

The structural changes in centralization and coreness (Fig. 4.2) followed those of assortativity, but with an eight-year lag. Eigenvector centralization decreased between 1995 and 2018, suggesting that the network became more fragmented, with fewer countries dominating the trade flow. This finding could be attributed to regionalization, China's economic rise, and political and economic instability Shameem and Jayaprasad (2020) and Cai et al. (2023). In addition, the recent increase in centralization since 2018 was partly due to the elimination of alternative transport routes before the COVID-19 crisis. However, this trend reversal preceded the crisis. The network has remained a globalized system, with countries increasingly integrating into the trade flow. New technologies such as blockchain and artificial intelligence could enhance the efficiency and security of global trade, which could increase connectedness in the network Arias et al. (2021). The coreness measure further confirmed this trend, as there was an increase in coreness until 2018. The trends and trend reversals for all products were due to the interplay of deglobalization before the pandemic-induced disruption Arias et al. (2021). Moreover, the abovementioned structural indicators indicate only one global pattern. The causal relationship between the products was revealed by later causal investigations (see Fig. 4.8).

Figures starting from Fig. 4.3 show the variations in the cluster centers of product groups before the COVID-19 pandemic. Cluster 1 in Fig. 4.3 represents a cluster of capital-intense products, such as high-tech, long-distance, or luxury products, including as nuclear reactors, machinery, apparel, and works of art (product groups 84, 61, and 97; see Appendix B for product codes). These products require advanced production technologies and specialized shipping methods, or they cater to high-value demands.

The countries that were the most severely affected before the pandemic were affected due to the emerging trade wars; therefore, their cluster centers decreased sharply in 2018.

In Fig. 4.3, product cluster 3 represents labor-intensive products, such as food products sourced from natural resources, including vegetables, fruits, sauces, and meat (product groups 20, 21, and 16). These products are mainly produced locally and consumed daily. Here, the increase was continuous except for in the most recent year. A consistent level of demand was maintained for these products, and minimal or negligible changes were observed in their cluster centers. However, the individual product clusters can be clearly separated.

Product cluster 2 in Fig. 4.3 represents the labor-intensive products with the least pronounced decrease. These products include organic chemicals, explosives, steel product footwear, fabrics, and precious metals (product groups 51, 36, 72, 80, 46, 60, 52, and 14). These products are essential for transportation, recreation, and health. The only difference between these products is their rate of growth. The largest increase in clustering was observed for high-tech products. However, a decline was observed before 2018, which is due to the unfolding US–China trade war and the rise of China.

Fig. 4.4 shows the global pattern of resilience in the trade network. Resilience measures the ability of a network to withstand shocks and disruptions. The network was more resilient before 2012 but declined after 2012. In this scenario, the same pattern changes as those for assortativity were observed, but with a two year lag. This finding suggests a reduced capacity to recover from adverse events and maintain efficiency and stability. Additionally, this decline preceded the pandemic and the Russo–Ukrainian war by more than six years. Moreover, the decline in the growth of resilience can be traced back even earlier to 2006, which can also be attributed to the slowdown in globalization (slobalization) and the slowdown in the growth of new trade relations. Furthermore, the pandemic accelerated this decline, increasing the vulnerability of trade networks to supply problems. The same trend reversals can be observed in the patterns that reacted uniformly to all products. The impact of crises first appeared in assortativity since this indicator indicates what types of nodes are in contact with each other. Structural changes affecting resilience can be observed after two years, while centralities appeared only later. Thus, for example, the 2008 financing crisis did not affect the reduction in centralization, even if the other structural indicators of the trade network changed.

Reciprocity increased (bilateral and multilateral asymmetry decreased) over time (see Fig. 4.5) for most products, especially for high-tech technology and luxury products, while this increase (decrease) was moderate for raw materials and other products. This growth is clearly due to globalization, which, unlike other indicators, was not affected by the pandemic. The persistent imbalance in the availability of raw resources can be rationalized by geographical factors, specifically the infrequent discovery of new deposits. Consequently, the trading network for these commodities remained relatively consistent over time. The time pattern of the indicators with uniform structural changes indicated delays of two and six years, and by comparing such temporal patterns, which provide different temporal characteristics, similar product clusters were identified.

The results revealed the structural similarity of the trade networks of different product groups. These product groups exhibited one or a few global temporal patterns, indicating their synchronized response to global changes and crises. However, a similar temporal pattern does not imply the absence of causal relationships between the trading of different products. To detect such relationships, causality tests (see Section 5.1.1 and an assessment of their contributions C_3) are needed.

Causality groups of products

The dependencies between the structural characteristics of product groups are analyzed using Granger causality and GNDA (Fig. 4.8) (see C_4). The product groups are ranked by their importance scores within a cluster (Table 4.1 and contribution C_4).

The assortativity of a product over time depends on the assortativity of many other products in the network. This means that a product's trading patterns are influenced by other products' attributes and connections. These products have central roles in the causality graph and are sensitive to shocks and crises.

Five product groups (groups 33, 15, 38, 22, and 25) were significant, serving as focal points in the network. Table 4.1 shows their key attributes and roles. The assortativity values of these product groups indicate connections with many other products, showing their interdependence and impact on trade behaviors. Sixteen product groups (groups 60, 29, 46, 50, 58, 54, and 81) exhibited unique characteristics and trading behaviors that are not influenced by other products, showing their distinct market presence. This diversity is due to market differentiation, specialization, comparative advantages, global supply chains, consumer demand and preferences, and technological changes. While it is not possible to study all causality arcs, the product group shown in yellow is chosen as an example in Figure 4.8. The yellow module encompasses product groups with mutual interactions. The materials in this category consist of wood and wood products (44), paper (48), tableware (82), ships and boats (89), musical instruments (92), and furniture (94). The underlying rationale is that the primary constituent of these materials is wood, which is subsequently utilized to manufacture a diverse range of wooden commodities, such as paper, furniture, and musical instruments.

The precedence between systematic and random attacks on the resilience of the product groups are also compared (Fig. 4.9 and Table 4.2). The trade networks were more sensitive to random attacks, meaning that a resilience anomaly in one product group affects other trades. GNDA identifies the most connected precedence of product groups. The first set of product groups in Table 4.2 (groups 76, 39, 10, 46, 30, and 14) was sensitive to random attacks when other trades' resilience changed. These products are essential for sectors such as telecommunications, plastics, cereals, tobacco, pharmaceuticals, and precious metals. Moreover, there is broad market demand, extensive applications, and diversity within the subsectors of these products. Therefore, these factors provide stability and resilience against random disruptions.

The second set of product groups in Table 4.3 (groups 81, 92, 84, 22, 67, and 60) were found to be sensitive to systemic attacks when other trades' resilience changed. These products exhibited strong interdependencies, cooperative relationships, or strategic collaborations within their industries, adapting and responding collectively to external shocks and thus leveraging their interconnectedness and collaborative efforts. There are various examples pertaining to the route of causality. The presence of SiO_2 in product 69 impacted aluminum and aluminum-based products due to the insulating, semiconducting, and conductive properties of ceramics. Additionally, optical, photographic, and medical/surgical devices were affected, as this product serves as a raw material in glass production and measuring instruments.

These products also have robust supply chains, efficient distribution networks, and coordinated industry practices. These factors contribute to recovery and functionality during systemic disruptions. Table 4.2 and Table 4.3 show that products sensitive to other trades' resilience changes were also sensitive to other trades' bilateral asymmetry changes. One such central product group is group 81, which includes electronic equipment and raw material for military equipment.

The results indicate that the temporal patterns of the structural indicators for network trades were similar, but their formation can still be characterized by causal networks in the case of most indicators. By applying GNDA to the causal network, causal communities are detected, and the causal relationships were denser within communities than between communities. The product groups are also ranked within a causal community based on their embeddedness, revealing that a few product groups act as drivers in structural indicator changes.

5.1.2 Temporal patterns of role-players

While trading patterns are used to identify clusters of product groups, country groups can be identified by structurally examining the trading of a given product. Product group 81 was the most sensitive to targeted attacks (see Fig. 4.9) on supply chains. At the same time, this product group is interesting because tungsten is an important raw material not only for electronic devices but also for anti-tank structures. In light of these findings, it is particularly interesting to note which countries had significantly increased imports, which are identified by specific clusters based on the change in the in-degree centrality (see Fig. 4.13). The employed GNDA identifies three clusters.

Cluster 1 countries are central to the network and receive more trade inflows. Their in-degree centrality increased from 1995 to 2020, except for a decrease in 2020. Their trade relationships were influenced by various trade agreements and arrangements, such as EU enlargement, association agreements, ASEAN Free Tread Area, and the EU Customs Union. The in-degree centrality of cluster 2 countries also increased from 1995 to 2020, with a decrease in 2017. Their trade relationships were shaped by several trade agreements, such as the Economic Partnership Agreement, Southern African Development Community Trade Protocol, and African Continental Free Tread Area. Cluster 3 countries had a stable in-degree centrality of approximately 40, indicating consistent trade inflows. Their trade relationships were affected by several factors, such as the EU Single Market, Eurasion Economic Union, bilateral and regional Free Trade Area, and Generalized System of Preferences. Generally, the growth of incoming and outgoing centralities was due to the involvement of African countries in trade (1995-1999) and other developing countries (2000-2008). A slow break could appear during the financial crisis (2008-2010); however, growth was observed after the crisis, but before the emergence of US–China trade war. Before the pandemic, decreases were observed for all cluster centers.

In the upcoming period, a conflict between two opposing forces can be observed. The advancement of technology and the process of digitization should contribute to the increased decentralization of the network. The level of assortativeness should increase along with the level of resilience. The COVID-19 pandemic significantly boosted the growth of digital commerce. At the same time, the Russo–Ukrainian war, followed by the Red Sea conflict, has caused trading partners to seek alternative routes. Simultaneously, there is a process of centralization characterized by the ascendance of China and the development of trade wars and sanction policies. These procedures are contrary to the aforementioned effects. Furthermore, the expansion of trade routes is also a matter of environmental concern.

In this study, it was not found that some countries stockpiled products in group 81, which can be used for high-tech equipment and anti-tank guns, in anticipation of war. However, it is intriguing which countries belong to the same group.

5.1.3 3C implications

This study focused on investigating a group of new variables, the 3Cs, influencing Erasmus exchanges. The findings did not confirm previous results, as other studies never investigated culture and crime, and collaboration was mentioned in only one case (Barrioluengo and Flisi, 2017). As seen in the clustered correlation graphs (Figure 3) at both the NUTS3 and institutional levels and in both the host and home cases, clearly distinguishable groups can be found in terms of economic groups,(included crime), cultural groups and collaborative groups (Q4). The aggregated analysis of NUTS3-level and individual-level travel were important for determining whether these variables have as large of an effect on mobility as on the larger macro scale as they do on the micro scale (Q1). Examining the host aspect at both levels, there are some interesting results, such as a strong positive correlation between ($CRIMES_j$) and ($POWERDI_j$). In host countries with high power distance, the consequence of inequal power relations is accepted, so the government is a 'patron' of citizens; furthermore, we can assume that security in the country is stronger, so there is less crime. Additionally, there is a positive correlation between ($INDCOLLAB_j$) and ($LOTEORI_j$) or ($INDIVID_j$). Both variables, the long-term orientation and the individualistic attitude, can facilitate industrial collaboration, which reflects the theory of collaborative individualism. The Erasmus network has a dominant culture of network organizations, as it emphasizes that individuals work together toward a common vision and mission in the long run (Limerick and Cunningham, 1993). The same variables appeared at both levels as determinants, showing that the division of the data-set into large chunks did not significantly alter the outcomes. The traditionally used variables showed less significance than previous studies suggested. Regarding crime at the NUTS3 level (table 4.8), for the host area, the $R^2 = 6$ value is much higher than for the home area (4.8), which means that crimes are more important in the countries that people want to travel to. The collaboration-related variables from the ETER database affected the model as well, rather significantly, at the institutional level. The cultural variables added to the existing models and overall literature on the subject, creating new ways to approach the analysis of Erasmus exchanges. Arguably, the strongest pull variables for the institutional breakdown were the indulgence level ($INDUL_j$) ($R^2 = 13$) and the long-term orientation attitude of the host institutions ($LOTEORI_j$) ($R^2 = 10$). In indulgent countries, human needs and feelings are more likely to be gratified, freedom, emotional expression, and happiness are encouraged (Hofstede, 2011), which is why they can be more attractive societies to travel to. Moreover, in long-term orientated countries, people are more likely to invest in long-term social networks or interpersonal relations with acquaintances, which have long-term beneficial effects (Minkov and Hofstede, 2011). The strongest push variables are the masculinity and uncertainty avoidance of the home institutions ($MASCU_i$, $UNCAVO_i$) ($R^2 = 6$). Feminine values, such as cooperation, relationship orientation and the importance of quality of life, may support environmental integration abroad. Uncertainty avoidance is a society's tolerance for uncertainty, which means that it must purposefully seek exchange, as uncertainty in mobility can be a major barrier.

As mentioned in the previous section, the NUTS3- and individual-level travel aggregated analysis was important for determining whether the cultural variables have as large an effect on mobility on a larger macro scale as they do on the micro scale. This group of variables better represents the data when the examined data are closer to the individual/institutional scale. Notably, the same variables appeared as determinants in both models, showing that the division of the data-set into large chunks did not significantly alter the outcomes. The traditionally used variables showed less significance than previous studies suggested. The cultural variables added to the existing models and overall literature on the subject, creating new ways to approach the analysis of Erasmus exchanges. The collaboration-related variables from the ETER database affected the model as well, rather significantly, at the institutional level. Arguably, the strongest pull variable for the institutional breakdown was the indulgence level of the host institutions ($INDUL_j$), the strongest push variables were the masculinity and uncertainty avoidance of the home institutions ($MASCU_i$, $UNCAVO_i$), and the strongest mooring variable for exchanges was the long-term orientation attitude of the host institutions ($LOTEORI_j$).

The number of collaborations the home institutions engaged in positively affected the likelihood of mobility, suggesting that the inclusion of students in research positively alters their tendencies toward participation in research abroad. The density of habitation of the home institutions negatively affected the likelihood of mobility, meaning that people from very well-urbanized counties were less likely to participate in Erasmus. The individualism spectrum of home institutions shows that in countries where people are in close proximity, isolated groups are less likely to travel. The long-term orientation spectrum of the home institutions shows that those from countries where people generally value traditions and their cultures more were less likely to travel than those from other countries. The power distance spectrum of the host institutions country indicates that people are more likely to travel to places where power is relatively more evenly distributed among groups. The individualism spectrum of the host institutions country affects the long-term spectrum of the host institutions country. The number of collaborations of the home and host institutions positively affected the likelihood of mobility. The number of international collaborations of the home institutions positively affected the likelihood of mobility. The density of habitation of the home institutions negatively affected the likelihood of mobility, meaning that people from very urbanized counties were less likely to participate in Erasmus than those from less urbanized counties. The individualism spectrum of home institutions shows that in countries where people are in close proximity, isolated groups are less likely to travel.

Increasing the international mobility of European students is a key objective of the European Union. The 2009 Leuven Declaration[1] set the target that by 2020, at least 20% of graduates in the European Higher Education Area should have had experience studying abroad. Therefore, researchers have become increasingly interested in the last decade in studying students' mobility, i.e. the factors that influence their choices. We reviewed the period following our research to check that our results for the 3Cs, as shown in more detail above, remain valid. Concerning the culture, consistent with our research findings, surveys conducted after 2013 continue to show that culture is one of the most important factors influencing students' mobility (Holicza, 2018; Bartha and Gubik, 2018; Jamaludin, Sam, and Sandal, 2018). Bartha and Gubik, 2018 also identified uncertainty avoidance, long-term orientation, and indulgence level as significant cultural factors. Furthermore, Lesjak et al., 2015 found that a combination of push and pull factors influence students' willingness to study abroad. In the field of crime, their results indicated that one of the main characteristics of Erasmus destinations is to feel safe and secure, which confirms our findings that crime has emerged as an influencing factor. As regards the examination of collaboration indicators, to the best of our knowledge, no survey or research has been carried out; thus, we have no information on the evolution of the results.

5.2 Structural Interdependencies and Systemic Dynamics in Global Networks

Global trade networks and Erasmus mobility share structural similarities that become evident when examining their response to crises, technological changes, and

[1] `https://ec.europa.eu/commission/presscorner/detail/en/IP_09_675`

social dynamics. Crises such as the COVID-19 pandemic and the US China trade war revealed the fragility of these interconnected systems, showing how centralization in trade can mirror vulnerabilities in student exchanges and how disruptions in one system often resonate in the other. Technology acts as a double edged sword, enhancing resilience while creating new dependencies. Innovations in AI and blockchain improve the efficiency and transparency of trade flows, while digital platforms and communication tools facilitate student mobility and cross cultural collaboration. The temporal patterns of structural indicators show synchronized responses across product groups in trade networks and participant groups in mobility networks, highlighting the presence of global patterns of interdependence. Assortativity, centralization, coreness, and resilience measures all indicate that shocks do not act in isolation, as changes in one node propagate across the network, whether in the form of supply chain bottlenecks or mobility restrictions. Causality analysis further demonstrates that key products or participant groups act as focal points, influencing others and amplifying systemic effects. These findings suggest that both trade and academic networks are not only shaped by economic or educational factors but are also sensitive to broader geopolitical, technological, and social changes. Understanding these interconnections provides a comprehensive view of how global systems evolve, offering insights into potential vulnerabilities and strategies for enhancing resilience in the face of future disruptions.

As proposed in RQ1, the structural evolution of global trade networks reflects the combined effects of crises, technological change, and deglobalization.

TABLE 5.1: Empirical evidence for Research Question 1: Evolution of trade network indicators

Aspect	**Evidence from results**	**Interpretation**
Temporal evolution	Assortativity rose until 2010, then declined post-2016 (Fig. 4.1).	Global trade diversified early on, but deglobalization reversed trends.
Crisis and shock effects	2008 crisis, 2016 trade war, and 2020 pandemic triggered sequential declines.	Crises have lagged systemic effects across 2–8 years.
Centralization and coreness	Decreased until 2018, then re-centralized.	Reflects cyclical concentration of trade power after diversification phases.
Resilience	Peaked 2012–2014, then eroded.	Indicates long-term decline in recovery capacity (“slobalization”).
Technological change	AI and blockchain increased post-2018 connectivity.	Technology enhances efficiency but increases dependency.

The evolution of global trade network structures from 1995 to 2020 reveals distinct cycles of integration, stabilization, and fragmentation. Early globalization fostered growing assortativity and resilience as trade diversified across partners and sectors. Following the 2008 financial crisis, recovery remained partial, and a gradual concentration of flows emerged, reflected in declining resilience and rising centralization. The US–China trade conflict and the COVID-19 pandemic further exposed systemic vulnerabilities, marking a phase of re-centralization and fragility. Technological innovations such as AI and blockchain have simultaneously increased efficiency and interdependence, intensifying the dual dynamic of connectedness and risk. Overall, the structural characteristics of global trade evolved from an expanding, resilient network into a more polarized system, where efficiency gains came at the cost of reduced adaptability, thus my first thesis is proposed.

Thesis 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.

As proposed in RQ2, cross-level analysis reveals that cultural and institutional determinants remain consistent across scales of observation.

TABLE 5.2: Empirical evidence for Research Question 2: Cross-level consistency of cultural and institutional determinants

Level	**Key determinants and evidence**	**Interpretation**
Institutional level	INDUL_j, LOTEORI_j, MASCU_i, UNCAVO_i significant across models.	Same cultural variables reappear at multiple levels, confirming consistency.
NUTS3 regional level	CRIMES_j, INDCOLLAB_j, POWERDI_j correlated with mobility flows.	Crime acts as a pull factor for safer destinations; collaboration increases participation.
National level	Aggregate Hofstede 6D scores and EU policy alignment mirror lower levels.	National cultural and institutional context shapes macro-level mobility trends.
Interpretation	Combined cross-scale analysis shows aligned cultural effects.	Cultural and institutional variables retain significance from micro to macro scale.

Cross-level analyses demonstrate a strong consistency in the cultural and institutional determinants of Erasmus mobility across institutional, regional (NUTS3), and national scales. Variables representing indulgence, long-term orientation, and collaboration repeatedly emerge as dominant pull and mooring factors, while masculinity and uncertainty avoidance act as push constraints. Although the magnitude of these effects intensifies at the institutional level, their direction remains stable across all scales, indicating that cultural and institutional traits operate as structural rather than context-specific drivers of mobility. Crime and collaboration further reinforce this pattern: destinations perceived as safe and academically networked attract more participants, independent of economic or geographic proximity. These findings confirm that cultural-institutional dynamics are deeply embedded in mobility systems, sustaining explanatory power from micro- to macro-level analysis, thus my second thesis is proposed.

Thesis 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.

Finally, RQ3 emphasizes the structural and causal parallels between trade and academic mobility networks, demonstrating shared global patterns of interdependence and resilience.

TABLE 5.3: Chapter contributions to Research Question 3

Chapter	Content focus	Contribution to RQ3
Ch. 2 (Methods)	Common analytical foundation	Establishes comparable frameworks across domains: both use network modeling (nodes = countries/institutions, edges = flows), analyze structural indicators, apply causality tests, and integrate cultural/economic variables.
Ch. 3 (Results)	Empirical findings	Provides evidence of temporal and structural dynamics (assortativity, resilience) in trade and analogous systemic factors (3Cs, collaboration, culture) in Erasmus mobility.
Ch. 4 (Discussion)	Conceptual synthesis	Connects both domains by revealing how crises, culture, and interdependencies expose similar structural mechanisms of centralization, vulnerability, and adaptation.

TABLE 5.4: Structural parallels between trade and Erasmus networks

Aspect	Description	Trade Network (BACI)	Erasmus Network
Nodes	Fundamental network units	Countries (exporters/importers)	Higher Education Institutions (sending/receiving)
Edges	Relationship type	Trade flows (value, volume)	Mobility flows (students, staff)
Indicators	Quantitative measures	Assortativity, centralization, resilience	Network density, collaboration, cultural distance
Observed pattern	Dynamic structure	Cycles of centralization $\rightarrow$ fragmentation $\rightarrow$ recentralization	Concentration of flows toward high-prestige, culturally close institutions
Interpretation	Meaning of structure	Hierarchical and preferential attachment structures amplify inequality and dependency.	Similar hierarchical logics; resilience depends on diversification and reciprocity.

TABLE 5.5: Causal parallels between trade and Erasmus networks

Aspect	Description	Trade Network (BACI)	Erasmus Network
Causal core	Key drivers of change	Product groups 33, 15, 38, 22, and 25 drive structural variation across sectors.	Host institutions with high collaboration and cultural openness drive inflow patterns.
Propagation	Transmission of shocks	Crises (2008, 2020) trigger systemic effects across product clusters.	Cultural and institutional traits diffuse through long-term collaborations.
Outcome	Resulting structure	GNDA clusters show tightly connected causal communities.	Cultural–collaborative clusters show similar community formation among HEIs.
Interpretation	Systemic meaning	Few central entities act as causal drivers of global interdependence.	Feedback loops amplify influence of cultural and institutional factors.

TABLE 5.6: Systemic adaptation and resilience in trade and Erasmus networks

Aspect	Description	Trade Network (BACI)	Erasmus Network
Crisis impact	External shocks	Financial crisis, trade war, and COVID-19 reduced resilience.	Pandemic caused temporary decline but rapid adaptation via digital mobility.
Resilience mechanism	Structural recovery	Reorganization of trade routes, technological digitization, regional diversification.	Digitalization of academic exchange, increased institutional collaboration.
Systemic lesson	Implications	Over-centralization increases vulnerability and fragility.	Over-dependence on few institutions reduces mobility diversity.
Interpretation	Broader meaning	Efficiency and resilience are in tension; diversification enhances stability.	Decentralization and collaboration increase adaptive capacity.

The analysis of global trade and Erasmus mobility networks demonstrates that structurally and dynamically, both systems follow comparable principles of organization and adaptation. In both cases, flows of goods or students are embedded in hierarchical, preferentially attached networks dominated by a limited number of central nodes. The temporal evolution of indicators such as assortativity, centralization, and resilience reveals synchronous cycles of expansion, fragmentation, and re-concentration, often aligned with major geopolitical and economic events. Causality analysis further shows that a few sectors or institutions act as systemic drivers, propagating changes across connected communities. Similarly, the inclusion of cultural, criminal, and collaborative variables in the Erasmus models highlights that interdependence and adaptation extend beyond economic fundamentals to social and institutional dimensions. Together, these findings reveal that global trade and academic mobility are governed by shared structural logics, both vulnerable to over-centralization yet capable of regaining balance through diversification, technological innovation, and collaborative resilience. My third thesis is as follows.

Thesis 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.

Chapter 6

Outlook

6.1 Mobility based studies

Building upon the openly available spatially enriched Erasmus+ mobility dataset by Väisänen et al. (2025), the current phase of this research focuses on reconstructing a comprehensive database to align it with the analytical framework established in the previous chapters. At this stage, the work concentrates on the yearly, country-level comparison of student mobility patterns derived from the shared dataset. This reconstruction serves as the foundation for the subsequent analytical expansion, where the data will be systematically disaggregated and examined across the institutional, NUTS-3, and national levels. The aim of this ongoing process is to ensure full structural compatibility between the empirical layers of the academic mobility networks.

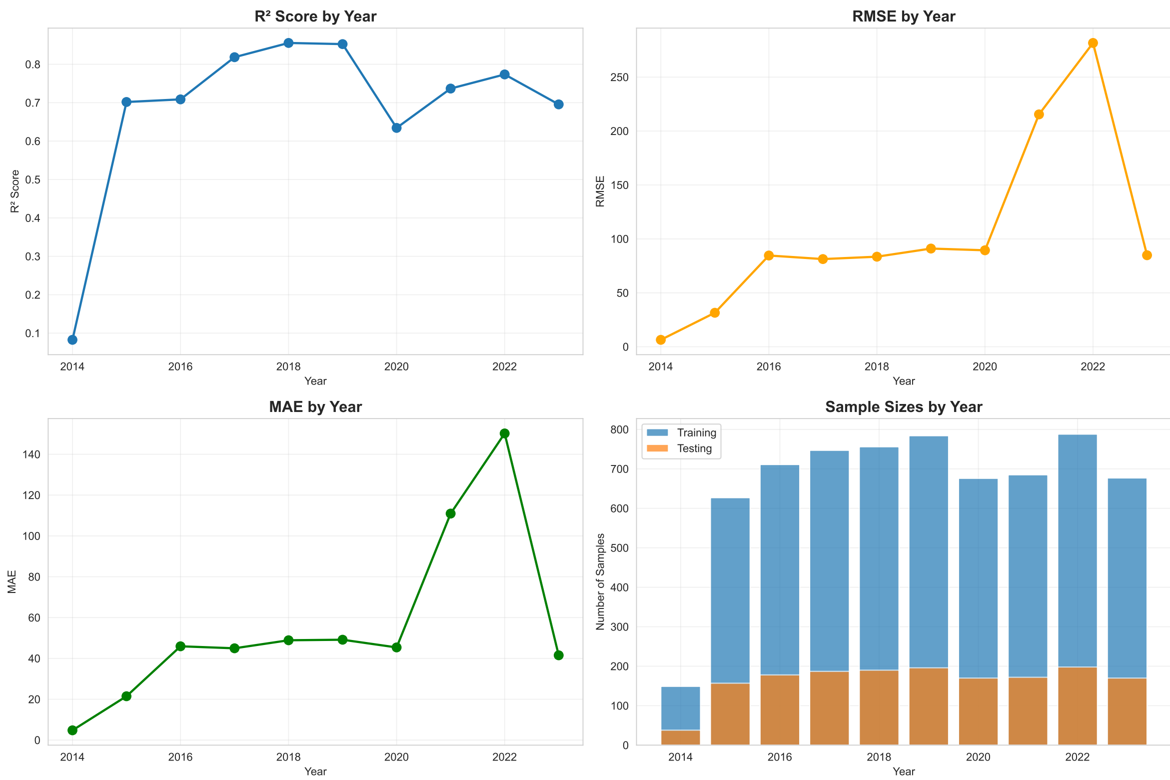

FIGURE 6.1: KPI's of model performance

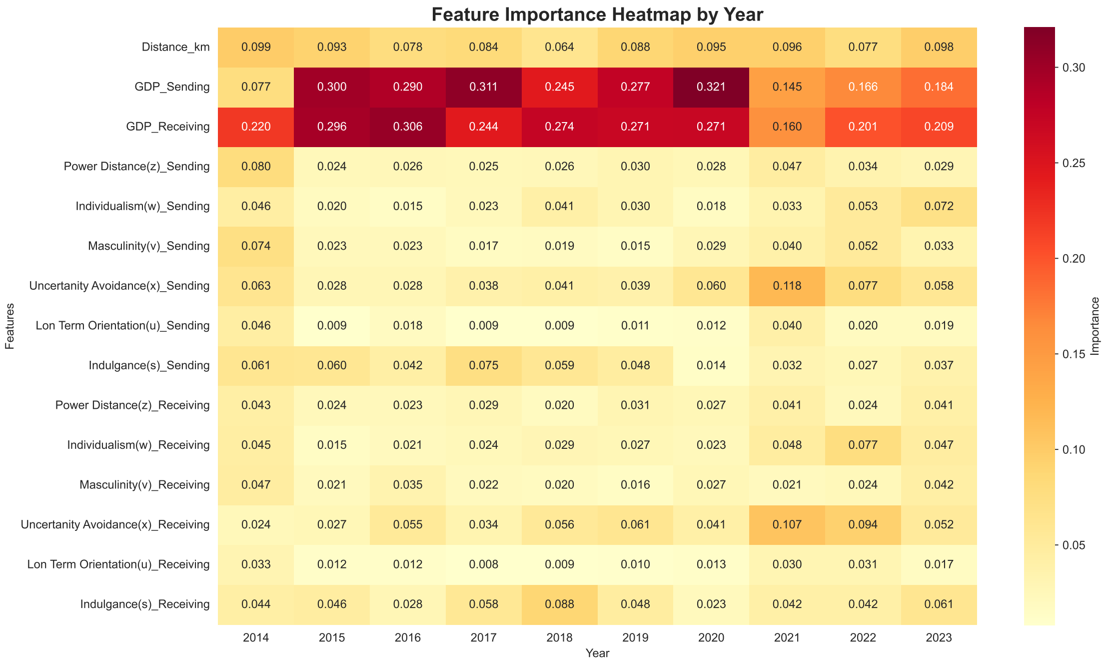

FIGURE 6.2: Feature importance of variables

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