Faculté des sciences économiques,
sociales, politiques et de communication
École des sciences politiques et sociales (PSAD)

Beyond Methodological Nationalism: Modelling Cross-National Health Spending through Graph-Theoretic and Relational Indicators of International Trade Networks

A quantitative analysis based on UN Comtrade and World Bank WDI data (2000–2019)

Auteur : Amandine Jacob
Promoteur : Mr. Philippe Bocquier
Lecteur : Mr. Gonzague Vannoorenberghe
Année académique : 2024 – 2025
Master de spécialisation en Méthodes Quantitatives en Sciences Sociales

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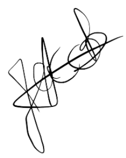

Acknowledgments

I present within these pages my second master's thesis, born of many hours of reflection, with the hope that it may, in some measure, shed light on the questions it seeks to explore.

At the outset, I wish to extend my deepest gratitude to my supervisor, Mr. Philippe Bocquier, whose generous time, steadfast support, and thoughtful guidance have been of great value throughout this work. Further thanks go to my family, my friends, and my aunt Sophie for proofreading, as well as to the many people with whom I shared these intense but memorable working days (and nights).

Finally, I would like to express my gratitude to UCLouvain for providing students with opportunities to thrive beyond academics, and particularly to the student association "La Fédération Wallonne des Régionales de l'UCLouvain", which allowed me to experience one more unforgettable and worthwhile year.

Amandine

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Table of Acronyms

WDI	World Development Indicators
FCT	Fundamental Cause Theory
DHS	Demographic and Health Survey
GDP	Gross Domestic Product
API	Application Programming Interface
NA	Missing Value
PCA	Principal Component Analysis
PLM	Panel Linear Model
FE	Fixed Effects
RE	Random Effects
HE	Health Expenditures
STD	Standardized
CI	Confidence Interval
SE	Standard Error
PPP	Purchasing Power Parity
WTW	World Trade Web
ITN	International Trade Network
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
LM	Linear Model

1. Introduction

1.1. Contextualization

"Society does not consist of individuals, but expresses the sum of interrelations in which these individuals stand" (Marx, 1993). In the same vein, international trade can be understood not as the sum of isolated national economies but as a web of relations. Far from being a simple marketplace of goods, international trade constitutes one of the main structuring forces of globalization, shaping unequal relations between states where some dominate global flows while others remain peripheral. These positions are not merely a reflection of economic size but also reveal deeper imbalances embedded in the global trade network, resulting from structural dependencies and long-standing hierarchies. Far from a flat arena of equal exchange, globalization therefore produces differentiated opportunities and vulnerabilities for countries integrated into the system in uneven ways.

Yet, much of the comparative research in the social sciences still approaches countries as if they were autonomous and homogeneous entities, defined exclusively by their internal characteristics. This methodological nationalism assumes that the nation-state is the natural and exclusive unit of analysis, thereby obscuring the systemic interdependencies and hierarchies that emerge when states are situated within wider relational structures. In the field of international trade, this bias is reinforced by the widespread use of gravity models, which focus on bilateral country pairs and largely ignore the networked nature of global exchanges. Such approaches tend to reduce the complexity of international relations to dyadic interactions and underestimate the ways in which countries' structural positions, whether central, peripheral or intermediary, condition their economic and social trajectories.

Against this backdrop, relational approaches have gained momentum, emphasizing that countries should not be seen as isolated units but as nodes embedded in systems of interdependence. Network analysis in particular offers powerful tools to map these relations, uncover asymmetries, and identify structural positions that shape access to resources and influence. This perspective resonates with broader sociological theories, such as the Fundamental Cause Theory (FCT), which stresses that inequalities persist because access to critical resources is unevenly distributed across social structures. By extension, at the global scale, the differentiated capacity of countries to leverage trade integration translates into broader inequalities in access to key resources. This raises the question of whether such structural asymmetries also affect the ability of states to invest in social sectors. In particular, several studies have begun to explore the link between international integration and health expenditures, investigating whether countries' positions in the global trade network may condition their capacity to allocate resources to healthcare.

Addressing such questions requires appropriate tools to capture the relational nature of flows in a way that goes beyond country-level aggregates. In the field of demography, and particularly in the study of migration, Courgeau (1988) developed statistical indicators to account for the relative scale of flows between populations. Their specificity lies in adjusting observed flows for the size of the populations at origin and destination, thereby uncovering structural patterns that raw flow data alone would obscure. However, despite their significance in migration research, Courgeau's indicators have not yet been systematically applied to international trade.

1.2. Objective and research question

Building on this conceptual gap, Bocquier (2024) has suggested that Courgeau's indicators, initially designed for the study of migration flows, could also be applied to international trade. Following this intuition, the objective of the present study is twofold. First, it aims to adapt and operationalize these demographic indicators to the context of global trade flows in order to capture structural features such as integration and trade asymmetry. Second, it seeks to assess whether the positions that countries occupy in the world trade network, as revealed by these indicators, help explain cross-national variation in health expenditures.

Accordingly, the central research question guiding this work is :

How do network-derived indicators, based on a weighted and directed representation of countries' positions in the global trade structure, contribute to explaining disparities in health expenditure?

To investigate this question, the analysis is guided by two hypotheses. The first builds on the idea that trade relations should be examined within the overall structure of the global network rather than as isolated dyads. Thus, it posits that *network-derived indicators, based on a weighted and directed representation of countries' positions in the global trade structure, significantly influence countries' aggregate health expenditure (H1).* The second follows from the observation that conventional centrality measures capture only limited aspects of structural position. In contrast, indicators derived from demographic research, such as those developed by Courgeau (1988), situate flows within the wider distribution of exchanges. Hence, the second hypothesis suggests that *these demographically derived indicators of trade relations provide a better explanation of disparities in health expenditure than conventional network centrality measures (H2).*

1.3. Empirical strategy

To address these hypotheses, the research adopts a quantitative approach based on international trade data from the UN Comtrade database, covering import flows between 103 countries from 2000 to 2019. These flows are aggregated into five-year intervals to smooth short-term fluctuations and combined with World Bank indicators on GDP and health expenditures. All data processing and statistical analyses are conducted in the statistical software *R*.

The empirical strategy is organized into three main stages. The first step consists of building weighted and directed trade matrices and computing indicators that reflect countries' structural positions in the global network. These include conventional network centrality measures, such as strength, betweenness, closeness, harmonic, and eigenvector centrality, together with indicators adapted from demographic research, namely intensity and dissymmetry. All indicators are first standardized to allow for comparability across countries and periods. However, the shape of their distributions made it necessary to restrict the analysis to four measures, namely strength, harmonic, intensity, and dissymmetry since the others proved unsuitable for meaningful cross-national comparison. The second part of the procedure applies multivariate methods, notably Principal Component Analysis (PCA) to capture the main axes of variation in countries' positions within the global trade structure, and hierarchical clustering (Ward's method) to derive typologies of countries with similar profiles. The third and final stage conducts explanatory testing through panel regressions, with health expenditure as the dependent variable. Hence, the analysis compares three alternative specifications, namely models using the standardized indicators directly, models based on PCA dimensions, and models relying on the cluster typology. Once these baseline models are estimated, an extended version is introduced by incorporating geopolitical controls such as political regime, landlocked status, and continent of location. The improvement in model fit is then assessed using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), alongside conventional significance tests, so as to determine the extent to which the geopolitical model enhances the explanation of cross-national disparities in health expenditure.

2. Theoretical Literature

2.1. Critique of Methodological Nationalism

In social science research, international comparisons are very often carried out between countries, as if these represented homogeneous, coherent, and comparable entities. This assumption is concretely reflected in surveys such as the DHS or national censuses, which aim to compare living standards, health conditions, or demographic dynamics from one country to another. This analytical reflex rests on the implicit assumption that society coincides with the nation-state, defined as a sovereign political unit whose legitimacy is derived from the idea of a unified national community (Gellner, 1983). This concept of the nation-state draws its roots from two founding ideologies. The first, of essentialist inspiration, conceives of the nation as a natural, given, and timeless entity. The second, of evolutionary orientation, regards nation-states as the universal outcome of the development of modern societies (Anderson, 1983). Indeed, this belief in the nation-state as a natural, homogeneous, and self-sufficient entity rests on a founding myth of modernity, namely the nation's power of integration and closure (Malet, 2005). Inherited from a European historical perspective, the nation is perceived as a solidaristic community, defined as much by what it includes as by what it excludes. In other words, as sociologist W. G. Sumner (1840–1910) argued, every society is structured around an in-group that distinguishes itself, protects itself, or asserts its value in relation to out-groups. This logic underlies what several authors refer to as *Methodological Nationalism*. This concept is defined as "the result of the historical formation of both modernity and the social sciences that cohered around processes of nation-state formation" (Beeghley, 1998; Calhoun, 1999). In other words, it is the tendency to regard the nation-state as the natural and exclusive unit of analysis for social phenomena. Chernilo, (2011) proposes an analytical distinction between two forms of methodological nationalism, theoretical and historical, which he develops into ten arguments aimed at questioning the explanatory centrality of the nation-state in the analysis of modernity. Table 1 below synthesizes five of these arguments.

Table 1. *Chernilo's typology of Methodological Nationalism.*

Form	N°	Argument	Definition
Theoretical	(4)	Internalist	*« The nation-state is an isolated, self-sufficient and endogenously developing unit. »*
	(5)	International system	*« The world is naturally divided into an indefinite number of formally analogous national units and the international system is composed now by nearly 200 of those units. »*
Historical	(8)	Reification	*« Any attempt at studying the nation-state with conventional social scientific tools is bound to naturalize its most important features. »*
	(9)	Eurocentrism	*« As the nation-state is mostly a European institution, methodological nationalism becomes another expression of the social sciences' inextricable Eurocentrism. »*
	(10)	Rise and fall	*« The co-evolution of the social sciences and the nation-state ties their destinies closely together; the social sciences' current crisis is explicated by the nation-state's own historical decline. »*

Source : Chernilo (2011)

In his discussion in *Developing Analytical Tools Against Methodological Nationalism: A Case Study on Mortality*, Bocquier (2024) builds on these five arguments to reinforce the critique of methodological nationalism as a unit of analysis in the demographic field. He seeks to promote methods that move away from the state or the nation as the basic unit of analysis (argument 4), and to encourage a more holistic approach in which societies at different geographical scales are connected through power relationships (argument 5). He also warns against the risk of naturalizing the characteristics of states (argument 8), reproducing a Eurocentric vision that disregards other historical trajectories (argument 9), and remaining attached to an analytical model based on the nation-state, even though this model is increasingly ill-suited to understanding contemporary social transformations (argument 10). Indeed, according to Malet (2005), most so-called "comparative" research therefore amounts to a mere juxtaposition of national studies. This bias has been widely criticized in contemporary literature, with several authors showing that methodological nationalism obscures transnational dynamics and underestimates the interconnections between societies in a world where globalization intensifies the flows of trade, people, and ideas (Chernilo, 2011; Wimmer & Glick Schiller, 2002). Indeed, even when international comparisons are accompanied by statistical adjustments, such as weighting results by demographic size or Gross Domestic Product (GDP) or subdividing large states into regional units, they remain grounded in a logic of juxtaposition in which each country continues to be analyzed separately as a self-contained entity. From this perspective, social phenomena cannot be fully understood by remaining confined within the boundaries of the nation-state, but must instead be apprehended through the relations that entities maintain with one another (Milioni, 2024). Given these limitations, a growing body of scholarship advocates moving beyond the logic of comparison between supposedly equivalent units and adopting a relational perspective. Rather than conceiving countries as independent entities, this perspective conceptualizes them as nodes embedded within systems of interdependence structured by exchanges, asymmetries, and power relations. In this view, what matters is not the entity itself but its position within the global system.

2.2. Towards a relational approach to inequalities

Rather than conceiving countries as self-contained entities defined exclusively by their internal characteristics, it is crucial to view them as units embedded within relational systems. A relational approach seeks not only to account for the position that a country occupies within international exchanges, but also to examine the extent to which this position is associated with structural inequalities across societies (Hafner-Burton et al., 2009).

2.2.1. The Fundamental Cause Theory

The *Fundamental Cause Theory* (FCT), formulated by Link & Phelan (1995), argues that social inequalities in health persist over time because they are rooted in unequal access to "flexible resources," namely knowledge, money, power, prestige, and beneficial social networks. In their retrospective, Clouston & Link (2021) specify that these resources enable more advantaged groups to appropriate new medical knowledge or preventive innovations more quickly and effectively, regardless of the disease in question or the prevailing health context. In other words, as effective strategies for prevention or treatment emerge, it is individuals with higher socioeconomic status who are the first to mobilize them for protection, thereby reproducing and even reinforcing existing inequalities. Several studies confirm that socioeconomic inequalities are systematically more pronounced for diseases that can be prevented or treated. For example, Mackenbach et al. (2015), using data from 16 European countries, show that the risk of mortality from preventable causes is systematically higher among less educated individuals, and that this gradient is much less pronounced for diseases with limited possibilities for action or prevention. Similarly, Rydland et al. (2020), in a study comparing 20 countries based on the

European Social Survey, find that educational disparities are significant only for conditions that are highly dependent on prevention or access to care, which reinforces the idea that access to resources plays a central role in the production of inequalities. Consequently, health protective resources such as knowledge, financial means or access to care prove effective only for those able to mobilize them. Put differently, health inequalities cannot be explained solely by the attributes of individuals or groups but must be understood as the outcome of differentiated positions within social structures in which certain actors are structurally advantaged (Clouston & Link, 2021).

2.2.2. Exchange relations as a structure of inequality

This relational approach, although applied to the field of health in the work of Clouston & Link (2021), rests on a general assumption that disparities in access to resources depend on the position an actor occupies within a hierarchical structure of interdependence. At the international level, global trade is organized as a structured network in which some countries concentrate a disproportionate share of import and export relations, while others remain weakly connected and more dependent on a few dominant partners (Fan et al., 2014). This raises the question of how the position a country occupies within the international trade network may influence its access to strategic resources and, consequently, contribute to the reproduction or even the intensification of structural inequalities between societies.

2.3. Capturing interdependence through network analysis

2.3.1. Network analysis

Understanding these interdependencies between states therefore requires methodological tools capable of capturing such structural interactions. From this perspective, network analysis emerges as a particularly relevant approach for mapping dependencies, identifying hierarchies, and revealing the relative positions occupied by different actors (Emirbayer, 1997). *Network analysis* consists in describing and modeling the relational structure among a set of actors, focusing on the relations themselves such as collaboration, dependence or exchange, rather than on individual attributes. In this respect, it contrasts with the categorical approach, which groups actors according to their characteristics in order to derive average effects without taking into account the interactions among them (Lazega, 1994).

2.3.2. The World Trade Web as a relational system

In this context, the analysis of international trade has recently been enriched by a theoretical and methodological approach derived from the study of complex networks. Referred to as the *International Trade Network* (ITN) or the *World Trade Web* (WTW), this network represents the set of import and export relations between countries at a given point in time. From this perspective, each trade relation between two countries is modeled as a weighted link in a graph, with its intensity determined by the monetary value of exchanged flows (Fan et al., 2014).

2.3.3. Bilateral trade flows

Bilateral trade exchanges involve two complementary flows, namely an exporting country delivering goods or services and an importing country receiving them. In theory, these flows should match since they describe the same transaction observed from two perspectives. In practice, however, notable discrepancies regularly emerge between export and import statistics, due to methodological differences, variations in coverage, or reporting practices. Several sources agree that import data are generally more comprehensive and reliable. This is explained by the fact that customs procedures are often stricter upon entry than upon exit, imports are recorded on a CIF (cost, insurance, and freight) basis, and these flows generate customs revenues, which provide a fiscal incentive for importing countries to report trade with greater accuracy. For all these reasons, research in international trade frequently relies on import flows to construct trade networks (Feenstra et al., 2005; Gaulier & Zignago, 2010).

3. Empirical literature

3.1. Historical approaches to modelling trade

3.1.1. Gravity Models

The empirical study of international trade has been dominated for decades by *Gravity Models*, which analogies trade flows to Newton's law of gravitation. In this framework, the volume of trade between two countries is proportional to the product of their economic "mass" and inversely proportional to the "distance" between them (Pöyhönen, 1963; Tinbergen, 1963). Formally, the basic gravity equation can be written as:

$$T_{ij} = G\frac{Y_i Y_j}{D_{ij}^{\gamma}} \tag{1}$$

where T_{ij} denotes trade from i to j, Y_i and Y_j are GDPs, D_{ij} represents distance, and G is a constant of proportionality.

3.1.2. Limitations of Gravity Models for structural analysis

While gravity models have proven remarkably successful in explaining bilateral trade patterns, their structure inherently treats each country-pair as an independent dyad. This dyadic focus overlooks the fact that countries are embedded in a global network of trade relationships, where indirect connections, intermediary partners, and broader structural patterns may strongly influence the intensity and direction of flows (De Benedictis & Tajoli, 2011; Fagiolo et al., 2009). As a result, several important aspects of the international trading system remain outside the scope of the gravity framework (Baldwin & Lopez-Gonzalez, 2015). Notably, trade between two countries can be significantly influenced by the network of their shared partners. Moreover, gravity models overlook system-wide topology, ignoring structural features such as highly connected "hub" countries, peripheral economies, or tightly knit regional clusters. Finally, by treating imports and exports symmetrically, these models obscure relational asymmetries, making it difficult to detect structural imbalances or dependencies (Chávez-Bustamante et al., 2023; Robinson et al., 2025). This has led to growing interest in network-based trade approaches, viewing countries as nodes in an interconnected system.

3.2. Network analysis in international trade

3.2.1. Graph Theory principles

Originally developed to address abstract problems in mathematics, *Graph Theory* has evolved into a versatile analytical framework used to model complex systems in fields as diverse as computer science, epidemiology, and international economics. The theory is based on the representation of systems as collections of *nodes* (or vertices) and *edges* (or links) that capture the relationships between them (Sadavare & Kulkarni, 2012). In the context of trade networks, nodes correspond to countries, while edges denote the existence of trade relationships between them, which can be directed or undirected, and weighted or unweighted, depending on whether the analysis considers the flow direction and the magnitude of exchanges (e.g., trade value) (De Benedictis & Tajoli, 2011). In their study of the WTW, Serrano & Boguñá (2003) were the first to apply graph theory to international trade. They show that graph theory enables the examination of the structural properties of the global trading system, moving beyond the isolated dyadic focus of gravity models. Indeed, it facilitates the analysis of both direct connections and indirect pathways through third-party partners, thereby revealing how a country's position in the network can influence its market access, vulnerability to shocks, or dependence on specific trade relationships (De Benedictis & Tajoli, 2011; Serrano, 2003).

Consequently, Graph Theory reveals the systemic organization of global trade, shedding light on structural patterns that influence economic opportunities, vulnerabilities, and the transmission of shocks across countries. As Fagiolo et al. (2009) emphasize, analyzing the topological properties of the WTW and their evolution over time is essential for addressing key questions in international trade.

3.2.2. Advantages over binary or unweighted models

Empirical analyses of the WTW show that binary representations, which record only the presence or absence of trade links, fail to reflect the heterogeneity and economic significance of these connections. Specifically, research has shown that link weights follow a stable log-normal distribution, with evidence of a shrinking "rich-club" of dominant countries controlling much of world trade (Bhattacharya et al., 2008). On the other hand, Fagiolo et al., (2008) quantify this heterogeneity by showing that most trade links are relatively weak while a small number of strong connections form cohesive clusters which a binary network view would overlook. Moreover, by filtering the network using residuals from a gravity model, research

{Citation}demonstrates that the resulting residual ITN exhibits a markedly different structure from the original which underscores how weighted analysis can uncover deeper and otherwise hidden interdependencies (Fagiolo et al., 2009).

3.2.3. Centrality indicators

De Benedictis & Tajoli (2011) said that "the use of indices that capture a country's position relative to all others in the trade network makes it possible to account for the interdependence of bilateral trade flows and the influence of connections with all partners". Centrality measures, developed within graph theory, aim to quantify the relative importance of a node in relation to the entire network or to its immediate neighborhood. Thus, they enable researchers to describe how countries' structural positions shape integration, influence, and vulnerability, thereby complementing traditional bilateral approaches. Early applications in trade networks demonstrated that these metrics can reveal core-periphery patterns, dominant hubs, and brokerage roles that remain hidden in gravity-based or binary models (Fagiolo et al., 2009). The following points reviews the main centrality indicators explored in the literature.

- ***Strength centrality***, the weighted analogue of degree centrality, has been widely employed to capture a country's level of integration into the ITN by summing the total value of flows linked to a country. Barigozzi (2010) uses this measure to quantify trade intensity, showing that countries with high strength are often regional or global hubs with substantial influence over neighboring economies. Similarly, other authors demonstrate that incorporating link weights into centrality calculations significantly alters rankings, revealing that some countries with modest numbers of partners become highly central once trade volumes are considered (Opsahl et al., 2010).

- ***Closeness centrality*** is applied to investigate market accessibility and the efficiency of trade connections. In other words, this measure assesses centrality based on a node's proximity to all others, using the minimal sum of geodesic distances that connect it to the rest of the network (Freeman, 1978). Research shows that high closeness scores often correspond to geographically strategic economies or those with diversified partnerships, enabling rapid access to a large share of the global market (De Benedictis & Tajoli, 2011). In empirical trade networks, the presence of disconnected components limits the applicability of traditional closeness centrality, as infinite distances between nodes in different components result in undefined or null values (Opsahl et al., 2010).

To overcome this issue, Rochat (2009) introduced ***harmonic centrality*** as an alternative measure that replaces infinite distances with zero, allowing the computation of proximity scores even in disconnected graphs. This property makes harmonic centrality particularly relevant for the analysis of international trade networks, where incomplete or missing links are frequent.

- ***Betweenness centrality*** quantifies the proportion of shortest paths between other countries that pass through a given country, thereby reflecting its role as an intermediary or gatekeeper within the network. A country attains high betweenness when it lies on numerous shortest paths connecting other pairs of countries, positioning it as a strategic hub. Such a position carries significant strategic implications, as it can be leveraged to influence or control the circulation of goods, information, and resources across the network. Empirical studies have shown that high-betweenness countries often exercise strategic control over regional trade corridors and play a pivotal role in facilitating intercontinental flows (De Benedictis & Tajoli, 2011; Freeman, 1978).

- Finally, ***Eigenvector centrality*** is commonly used to capture influence derived from being connected to other central economies. Studies have shown that this indicator stresses the interconnectedness of advanced economies in dense clusters of influential partners, such as those forming the "core" of the WTW. original formulation supports its application to trade networks where not only the number of connections but also the prestige of partners matters (Bonacich, 2007).

3.3. Structural indices of trade flows

3.3.1. From raw weights to structural measures

In trade network analysis, link weights are typically expressed in monetary value, which makes them highly correlated with country size and GDP. This dependence can mask the underlying structural patterns of the network and bias centrality measures presented earlier, as large economies mechanically appear more central regardless of their relational position (Fagiolo et al., 2009). Existing approaches often address this bias by normalizing trade values with respect to economic size, for instance by dividing flows by one or both trading partners' GDPs (Almog et al., 2015). While such adjustments mitigate size-related biases, they remain confined to a bilateral perspective, whereby each trade flow is assessed solely in relation to the two countries it connects. This approach overlooks the position of the flow within the global distribution of exchanges and thus cannot determine whether it is disproportionately strong or weak when compared to the full set of relationships in the network.

3.3.2. Insights from Courgeau's (1988) study of migration flows

In a critical reassessment of traditional migration flows analyses focused solely on raw volumes, Courgeau, (1988) proposed moving beyond a purely descriptive accounting of flows to capture not only their structural but also their relative dimension. This means that, rather than limiting the analysis to the absolute number of migrants between two regions, the author introduced a framework that contextualizes flows in relation to the demographic size of the entities involved and to the overall dynamics of the network. The first step of the approach consists in computing the *Gross Intensity Index*, which expresses the observed flow between two regions i and j as a share of the potential demographic mass involved :

$$G_{ij} = \frac{M_{ij}}{P_i \cdot P_j} \tag{2}$$

where M_{ij} denotes the number of migrants from region i to region j , and P_i and P_j represent the populations of the origin and destination regions respectively. This indicator contextualizes the observed flow by relating it to the potential demographic mass of exchanges. The same volume of migrants may therefore carry different structural significance depending on whether it involves two large metropolitan areas or two small, sparsely populated regions.

Courgeau then complemented this index with the *Relative Intensity Index*, which positions each bilateral relationship within the overall system by comparing its gross intensity to the mean intensity observed across all pairs :

$$R_{ij} = \frac{G_{ij}}{\overline{G}} = \frac{\dfrac{M_{ij}}{P_i \cdot P_j}}{\dfrac{\sum_i \sum_j M_{ij}}{\sum_i \sum_j P_i \cdot P_j}} \tag{3}$$

where $\bar{G}$ is the average gross intensity over the entire set of flows. This second index positions each bilateral relationship in relation to an expected average norm, constructed from all flows within the system. A flow is thus assessed as more or less intense not only in light of the size of the populations involved, but also in relation to what is usual within the global system. It therefore introduces a genuinely relational and structural measure, paving the way for interpretations in terms of hierarchies, inequalities, and asymmetries between regions.

3.3.3. Measuring asymmetry in trade relations

Building on Courgeau's (1988) work on migration flows, Bocquier (2024) proposed adapting Eq. 2 and Eq. 3 to the study of international trade. In this adaptation, the population sizes used in Courgeau's original measures are replaced by the GDPs of trading partners, making it possible to account for differences in country size when comparing trade flows. The gross intensity, then, reflects the strength of a trade relationship relative to the economic size of the countries involved, while the relative intensity places this relationship in the context of all flows in the global network, showing whether it is stronger or weaker than the average. From the resulting matrix of relative intensities, an intensity index can be computed to summarize the overall strength of the relationship, and a dissymmetry index can be derived to capture trade imbalances between partners. As a reflection, Bocquier (2024) suggests that these originally demographic-based indicators could be applied to international trade networks, although their empirical relevance in this field remains to be demonstrated.

3.4. Trade network position and social outcomes

3.4.1. Economic and social implications

Some research has shown that a country's position within the global trade network is closely tied to its broader economic and social outcomes. Richmond (2019) demonstrates that centrality shapes financial dynamics, with trade-network centrality predicting differences in interest rates and currency risk premia. Therefore, more central countries tend to enjoy lower interest rates and reduced currency risk, reflecting their stronger integration into global markets. Beyond purely financial channels, Ferrier et al. (2016) highlight that the international trade network acts as a conduit for technology diffusion, whereby highly connected countries tend to exhibit greater technological intensity and absorptive capacity. This effect extends beyond direct bilateral exchanges, as indirect connections through shared partners significantly contribute to capacity building and development. Collectively, these findings suggest that a country's structural position in the network can influence its access to resources, innovations, and opportunities, thereby shaping long-term development trajectories.

3.4.2. Public health expenditure implications

The capacity to access goods, services, advancements, and prospects afforded by a favorable structural position in the global trade network is not confined to purely economic gains. It also extends to domains directly relevant to population well-being, such as the availability of pharmaceuticals, medical technologies, and health-related infrastructure. In this sense, a country's embeddedness in the trade network can shape both the diversity and reliability of health-related supplies, which in turn influences the scope for investment in healthcare systems. Within public health economics, health expenditure has thus been widely employed as a key indicator of this investment capacity, reflecting not only policy priorities but also the economic means to sustain them over time (Byaro et al., 2021; Frenk & Moon, 2013).

A substantial body of research finds that greater trade openness is associated with positive health outcomes. Herzer (2017) and Owen & Wu (2007) report that integration into global markets can enhance life expectancy and health investment through channels such as income growth, technology transfer, and improved nutritional standards. At the subnational level, authors have shown that openness in Chinese cities promotes population health via employment growth, wage increases, and greater public health spending, although these gains may be offset by environmental degradation (Ou et al., 2023). Similarly, Byaro et al. (2021) document reductions in under-five mortality and increases in life expectancy across developing countries linked to higher trade openness.

Conversely, other studies emphasize the potential for trade integration to produce uneven or even adverse health effects. Antonietti et al. (2022) find that during the COVID-19 pandemic, countries with higher network centrality faced greater infection and mortality rates, suggesting that central positions can also amplify vulnerability to transnational health shocks. On the other hand, some authors highlight that while increased trade can raise living standards and enable higher spending on health and education, it can also exacerbate intra-national inequalities that undermine health equity (Byaro et al., 2021). Indeed, Prell et al. (2015) further show that positions in trade hierarchies are associated with disparities in environmental burden and mortality, indicating that structural advantages do not uniformly translate into better health outcomes.

Overall, current research offers divergent conclusions as some studies link trade integration to better health outcomes, while others raise alarms about increased vulnerabilities or inequality.

These conflicting results often stem from differences in the measured outcomes, the explored contexts, and, more importantly, the methodological approaches used. In particular, studies in the health domain largely rely on aggregate indicators like trade-to-GDP ratios or bilateral volumes, typically omitting any consideration of countries' relational structure within the global trading system. As Labonté & Schrecker (2007) point out, empirical studies on trade and health often neglect the structural and relational dimensions of global markets, which limits the ability to assess how integration into international systems shapes health-related resources and expenditures.

3.5. Research question and Hypotheses

Studies have shown that methodological nationalism is often embedded in statistical analyses, whereby countries are treated as independent units defined solely by their internal characteristics. This perspective overlooks the fact that states are embedded in systems of structured interdependence, where relative position can shape access to resources, opportunities, and influence. In the context of international trade, most empirical studies address size effects by adjusting flows for GDP or for the sum of GDPs of trading partners. While this mitigates the influence of economic size, such adjustments remain confined to a bilateral perspective and rarely situate each trade flow within the overall distribution of global exchanges. As a result, they cannot determine whether a given link is disproportionately strong or weak compared to global patterns, nor can they capture directional asymmetries between partners. In migration research, Courgeau (1988) addressed this limitation by developing a relational approach that positions each flow in the context of the entire network, enabling genuinely comparative, system-wide analysis. Yet, no equivalent framework has been developed in trade research, where such a network-wide perspective remains absent. This methodological gap also characterizes research linking trade and health expenditure, where analyses often rely on aggregate openness measures or bilateral trade volumes, without assessing how structural position in the trade network may condition access to health-related goods and the capacity to invest in healthcare.

Therefore, and in line with the investigations of Bocquier (2024), this study aims to address the following research question:

How do network-derived indicators, based on a weighted and directed representation of countries' positions in the global trade structure, contribute to explaining disparities in health expenditure ?

In this regard, the present study addresses this question by introducing structural indicators adapted from demography, incorporating a measure of relative economic strength, and situating each trade flow within the overall distribution of the global network. This approach accounts for both the weight (GDP) and the direction of trade flows. The originality of this work lies in its combination of network analysis, international economics, and demographic methods to assess whether structural positions in the global trade network help explain inequalities in health expenditure.

Based on this approach and the literature explored, the following two hypotheses are formulated:

H1: *Network-derived indicators, based on a weighted and directed representation of countries' positions in the global trade structure, significantly influence countries' aggregate health expenditure.*

H2: *Demographically derived indicators of trade relations provide a better explanation of disparities in health expenditure than conventional network centrality measures.*

4. Methodology

This section presents the quantitative data and methodological approach adopted to address the research question. It introduces the sources of trade and health statistics, the treatment of imported data, the construction of indicators, and the analytical procedures mobilized to examine the relationship between structural positions in the global trade network and cross-national disparities in health expenditure. All subsequent analyses are carried out using the statistical software *R*.

4.1. Data collection

4.1.1. International trade flows

The analysis begins with the collection of international trade statistics, focusing on annual import flows of goods. Given their greater reliability compared to export records, as discussed in Section 2.3.3, imports are preferred. The data are sourced from the United Nations Comtrade database, one of the most widely used repositories of official international trade statistics. UN Comtrade provides both monthly and annual trade data for many countries, allowing cross-country comparisons. Each trade flow is recorded as a transaction between a *Reporter* country, which reports and receives the import, and a *Partner* country, the origin of the goods. The traded volume is expressed in monetary terms (U.S. dollars), under the variable named *Primary Value*. Specifically, the data were downloaded year by year from the official UN Comtrade website in CSV format. These files were then converted into data frames in the statistical software *R* and aggregated into five-year periods to identify medium-term structural dynamics. This dataset constitutes the empirical foundation for all analyses conducted in this study.

4.1.2. Health expenditure

The central aim of this study is to assess whether a country's structural position within global trade networks is correlated with its long-term investment in health. To explore this potential relationship, current health expenditure per capita in purchasing power parity terms (PPP), an indicator variable taken from the World Bank's World Development Indicators (WDI) database (*SH.XPD.CHEX.PP.CD*), is used as the dependent variable in the panel regression analysis. Absolute per capita values are preferred to ratios relative to GDP in order to avoid scale effects that can obscure interpretation. For example, richer countries may spend proportionally less of their income on certain basic needs compared to poorer countries, even if their absolute spending levels are much higher. This measure therefore better captures what countries are actually willing to spend on health in real dollar terms.

For each country and for each of the four five-year periods 2000–2004, 2005–2009, 2010–2014 and 2015–2019, the mean of the natural logarithm of this indicator is calculated. Log-transforming the data reduces skewness, facilitates cross-country comparisons and allows coefficients to be interpreted in percentage terms. Due to widespread missing values prior to 2000, the analysis is limited to the 2000–2019 period.

4.1.3. Gross Domestic Product (GDP)

As discussed in our critique of methodological nationalism (Section 2.1.), the Gross Domestic Product (GDP) is included as a normalization factor in order to account for the relative economic size of each country in the analysis of trade flows. In this context, the nominal GDP represents the total value of goods and services produced within a country during a given year. The data are retrieved using the WDI package, which provides access to the World Bank's database API, and the specific indicator employed is *NY.GDP.MKTP.CD*, corresponding to GDP in current US dollars. For each country included in the analysis, we then compute the average GDP over the period 2000–2019 using the following formula,

$$\text{mean\_gdp}_i = \frac{1}{n_i} \sum_{t=2000}^{2019} GDP_{i,t} \tag{4}$$

where n_i represents the number of years with available data for country i.

To enhance the visualization of the substantial dispersion in average GDP values across countries, a base-10 logarithmic transformation ($\log_{10}$) is applied as illustrated in Figure 1. This approach compresses extreme variations while preserving proportional relationships, thereby facilitating interpretation of each country's relative economic weight. The resulting distribution is characterized by a pronounced rightward tail, corresponding to a few major economies, whereas the left side is concentrated with countries exhibiting particularly low average GDP levels.

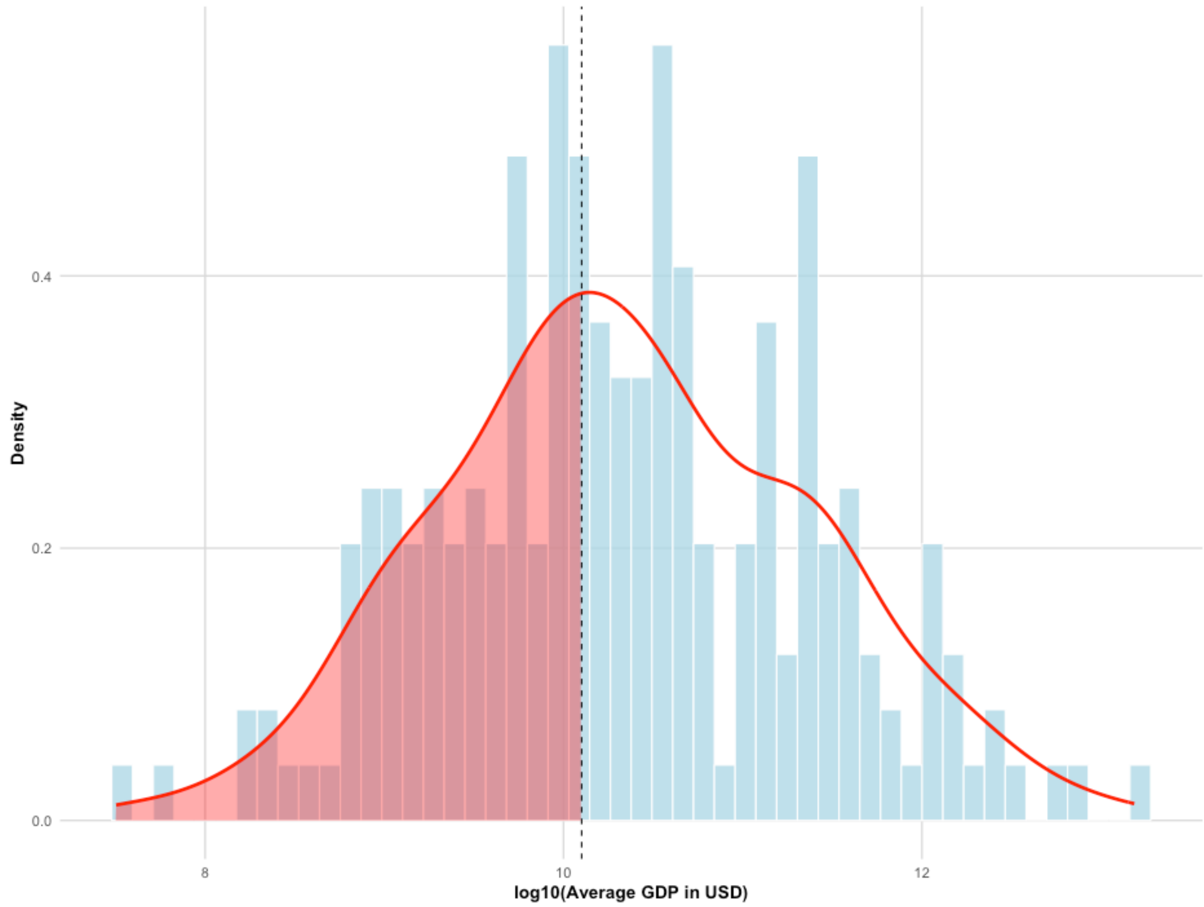

Figure 1. *Distribution of countries' average GDP (2000-2019)*

To enhance comparability across countries, we retained only the 120 countries with the highest average GDPs over the 2000–2019 period. This threshold was established on the basis of the distribution's shape, and, as shown by the red zone in the chart, the excluded countries are concentrated in its lower segment. The selection cutoff, marked by a vertical dashed line, therefore ensures that the analysis focuses on countries most actively engaged in international economic relations. In addition, this procedure avoids the inclusion of countries with marginal economic weight or incomplete trade data, which could otherwise introduce statistical noise and distort the interpretation of network structures.

For each of the 120 selected countries, a second average GDP is then computed for each five-year period, as shown in Eq. 5. Hence, this value is used to normalize bilateral trade flows in the construction of the subsequent intensity matrices.

$$\overline{GDP}_{i,p} = \frac{1}{n_{i,p}} \sum_{t \in p} GDP_{i,t} \tag{5}$$

In this formula, $\overline{GDP_{i,p}}$ denotes the average GDP of country i during period p, $n_{i,p}$ is the number of available annual observations, and $GDP_{i,t}$ is the nominal GDP in year t.

4.1.4. Sample definition

Based on the imported and cleaned up data[1], the final sample is restricted to countries for which complete information is available throughout the 2000–2019 period. Specifically, it includes only those countries that appear in the bilateral trade flow datasets for each of the four five-year intervals, for which GDP and total health expenditure data are available, and that are ranked among the 120 countries with the highest average GDP over the study period. This selection yields a final sample of 103 countries, as listed in Appendix 1.

4.1.5. Unit of analysis

The analysis involves two successive units of observation. First, at the relational level, the unit of analysis is the bilateral trade flow from country i to country j during a five-year period. Second, for the network-based analysis and subsequent panel regressions, the unit of analysis becomes the country-period pair. Therefore, each observation corresponds to a country's position in the international trade network over one of four period intervals (2000–2004, 2005–2009, 2010–2014, 2015–2019), as captured through structural indicators.

4.2. Structuring trade data

4.2.1. Normalization of bilateral trade flows

As discussed in Section 3.3.2, the indices developed by Courgeau (1988) introduced a structural interpretation of migratory flows by adjusting them to the size of the entities involved, through the concepts of *Gross Intensity* and *Relative Intensity* (Eq. 2 and 3, respectively). In this work, the same normalization logic is applied to the study of bilateral trade flows between countries.

[1] The dataset is cleaned to retain only valid bilateral flows between recognized sovereign countries. This included the removal of aggregate regions, non-sovereign entities, unmatched ISO codes, and observations with missing or zero Primary Value.

However, the volume of trade between country i and country j is normalized not by population, as in the original migration framework, but by their respective GDPs.

4.2.2. Extending the Gross Intensity Index to trade flows

Building on this normalization, we develop a *Relative Trade Index,* presented in Eq. 6, directly derived from the Gross Intensity Index (Eq. 2), which further adjusts bilateral trade volumes to reflect the structural weight of each country's economy in the global system. By incorporating GDP into the baseline, this new index captures whether a trade relationship is stronger or weaker than expected given the countries' economic sizes,

$$G_{ij}^{*} = \frac{M_{ij}}{GDP_i \cdot GDP_j} \tag{6}$$

where M_{ij} is the average value of imports from country j to country i over the period. This standardization aims to adjust for the mechanical effect of economic size on trade volumes, thereby enabling a structural interpretation of the trade network. However, several empirical limitations have emerged in practice. One issue is that the formulation creates significant numerical instability when one of the two countries has a very low GDP, which mechanically causes the index value to spike. Another problem is that it tends to overrepresent economically marginal countries. Indeed, relatively modest trade flows may appear disproportionately intense simply because they involve a small economy. This can later distort the interpretation of network indicators by assigning exaggerated structural importance to peripheral countries.

Beyond these empirical issues, it is also important to stress that the original G_{ij} index was not conceived for network analysis but for the study of bilateral flows in migration research. Its direct transposition to trade networks is therefore problematic, as the multiplicative denominator exaggerates asymmetries in a way that is ill-suited to relational structures. To overcome these shortcomings, we adopt an additive variant in which the denominator is no longer the product of the two countries' GDPs, but their sum. This adjustment ensures that bilateral trade flows are evaluated relative to the combined economic weight of both partner and reporter, while remaining consistent with the comparative logic of normalization. The modified relative intensity is therefore computed according to Eq. 7 below.

$$G_{ij}^{*} = \frac{M_{ij}}{GDP_i + GDP_j} \tag{7}$$

This alternative weighting preserves the adjustment for countries' economic size while improving the numerical stability of the indicator. By avoiding the distortions generated when multiplying highly unequal values, it produces a more coherent and interpretable weighted trade network.

4.2.3. Standardized Relative Trade Intensity Index

Following the construction of the modified Relative Trade Index described above, a second indicator is introduced to evaluate the strength of each bilateral trade flow relative to the global average. This *Relative Trade Intensity Index*, defined in Eq. 8, builds directly on Courgeau's (1988) Eq. 3 by comparing each normalized trade flow to a systemic benchmark. It thus allows the identification of trade ties that are exceptionally intense or weak within the global trade network. In practice, the relative trade intensity index R_{ij}^{*} is computed as the ratio between the normalized bilateral trade intensity G_{ij}^{*} and the average of all such intensities observed during the same period[2].

$$R_{ij}^{*} = \frac{G_{ij}^{*}}{\overline{G^{*}}^{(t)}} \tag{8}$$

Computing this indicator for each period independently is essential, as it ensures that trade flows are evaluated relative to contemporaneous GDP levels. Since countries' economic sizes fluctuate, using GDP data from a different period would distort results by artificially inflating or deflating trade intensity. Period-specific normalization avoids these biases and ensures consistency with the actual economic context.

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[2] The average $\overline{G^{*}}^{(t)}$ is computed as the arithmetic mean of all normalized bilateral trade intensities observed during period t, i.e.,

$$\mathrm{G}^{*(t)} = \frac{1}{N_t} \sum_i \sum_{j \neq i} \frac{M_{ij}^{(t)}}{GDP_i^{(t)} + GDP_j^{(t)}}$$

where N_t denotes the number of observed country pairs (i, j) in the system during that period.

4.2.4. Construction of Relative Trade Intensity Matrices

To analyze the structure of trade flows from a network perspective, a square matrix is constructed for each five-year period, representing all bilateral exchanges among the selected countries. In each matrix, rows correspond to importing countries (reporters), columns to exporting countries (partners), and each cell records the value of the Relative Trade Intensity Index between the two, as computed in Eq. 8. This format provides the foundation for applying graph-theoretic tools, which require complete and comparable dyadic relationships across periods.

The available empirical data do not cover all bilateral flows, as some exchanges are missing from the Comtrade database, either because they were not reported or because they did not occur. To maintain structural comparability of the matrices across periods, it is therefore essential to rely on a consistent set of countries. Accordingly, each country must appear as both an importer (row) and an exporter (column) in every matrix, even when certain flows are absent or unreported. To meet this requirement, the full set of all possible country pairs is generated manually, ensuring the construction of square matrices for each period. When a given bilateral flow is not recorded in the source data, the corresponding cell is left blank, and the relative trade intensity is recorded as a missing value (NA). Unlike earlier exploratory versions of the code, no arbitrary floor value is imputed for these absences in the final version. Indeed, an initial option was to replace missing flows with a small non-zero constant to prevent technical errors in later indicator computation steps, such as division by zero or logarithmic transformations. However, this method proved unsatisfactory, as it introduced an excessively high number of fictitious trade flows, entries that did not correspond to any real exchange. This problem was particularly acute in earlier periods, where over 60% of potential flows were missing. Thus, imputing all of them would have artificially inflated network indicators and obscured the true structure of trade relations.

Given that many missing flows concern countries with low GDP or limited participation in world trade, the adopted strategy involved reducing the sample to the 120 countries with the highest average GDP, as shown in Section 4.1.3. This filtering greatly reduces the occurrence of missing flows and results in a denser, more analytically coherent dataset. The choice therefore reflects a trade-off between country coverage and data quality, favoring a smaller but cleaner and more interpretable sample. Hence, each matrix retains a consistent structure with the same set of countries in rows and columns (120 × 120)[3]. When converted into graphs, all countries are systematically included as nodes, even when they have no active trade relationships during a given period. Moreover, the functions provided by the *igraph* package for computing centrality measures ignore missing links but retain all network nodes. NA values are therefore excluded from calculations without altering the network structure or causing computational errors. These matrices ultimately provide the foundation for the network analysis that follows.

4.3. Constructing the trade network

4.3.1. Representing trade as a directed and weighted graph

As discussed in Section 3.2, the application of graph theory is particularly well suited to the objectives of this research, as it allows for the analysis of the international trade system not as a collection of isolated entities, but as a relational network, in which the structural position of each node (i.e., country) is as relevant as its individual trade performance. The matrices constructed in Section 4.2.4 are transformed into graph objects using the *igraph* package in R, yielding directed and weighted graphs. Edges are oriented from the reporting country *i* to the partner country *j*, and their weights reflect the relative trade intensity between the two, as defined in Eq. 8. These directed graphs account for the fact that trade flows from country i to country j may differ in magnitude from those in the opposite direction ($i \rightarrow j \neq j \rightarrow i$), and the associated edge weights reflect the monetary value of bilateral exchanges (Ou et al., 2023).

As previously discussed, this type of representation allows for a more nuanced understanding of international trade networks by capturing not only the connectivity between countries, but also the scale and direction of their trade. These dimensions are essential for analyzing power dynamics and patterns of economic interdependence. For example, it allows us to distinguish between a marginal country engaged in a few highly concentrated trade relations and another that maintains numerous trade relations, but with low volume.

4.3.2. Computing Centrality indicators

[3] At this stage of the analysis, matrices include the full set of 120 countries. The reduction to 103 (see Section 4.1.4) occurs later, when the health expenditure variable is introduced into the dataset, leading to the exclusion of countries with missing values.

To explore the hierarchical structure of global trade, various measures of centrality can be calculated from directed and weighted trade networks. Each indicator reflects the specific dimension of a country's position in the network, such as influence, dependence, or connectivity, and contributes to a multidimensional understanding of economic centrality. Regarding Section 3.2.3, the following measures are tested in this study.

Strength Centrality

The strength centrality is the weighted equivalent of degree centrality. It measures the total weight of outgoing links from a node, reflecting the intensity of its reported import flows (i.e., flows from the country i to its partners). In other words, it measures a country's level of economic integration into the global trade network, based on the cumulative intensity of its trade relations rather than the mere count of its trading partners,

$$\mathrm{Strength}(i) = \sum_{j \neq i} w_{ij} \tag{9}$$

where w_{ij} denotes the weight of the edge from country i to country j, corresponding to the relative intensity of trade as defined in Eq. 8. A higher value indicates a stronger involvement in trade, regardless of the number of partners.

Betweenness centrality

Betweenness centrality quantifies the extent to which a country acts as an intermediary in trade flows between other countries. It is defined as the number of shortest paths connecting all pairs of countries that pass through a given country i :

$$\mathrm{Betweenness}(i) = \sum_{s \neq i \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}} \tag{10}$$

where σ_{st} is the total number of shortest paths from country s to country t, and $\sigma_{st}(i)$ is the number of those paths that pass through country i.

As an example, consider a simplified trade network involving five countries labelled A, B, C, D, and E. If the most efficient route from country A to country E consistently passes through country C, and this pattern is repeated across several other pairs of countries, then country C will appear frequently on the shortest paths between them. As a result, country C will exhibit a high betweenness centrality score.

Closeness Centrality

Closeness centrality captures how close a country is, on average, to all other countries in the trade network. It is computed as the inverse of the sum of the shortest path lengths from a given country i to every other country j in the network :

$$\text{Closeness}(i) = \frac{n-1}{\sum_{j \neq i} d(i,j)} \tag{11}$$

where n is the total number of countries, and $d(i,j)$ denotes the length of the shortest path from country i to country j. In weighted graphs, this distance is computed using the inverse of edge weights (i.e., $1/w_{ij}$) to reflect the cost or rarity of the connection. In other words, closeness centrality measures how efficiently a country can reach all others in the network. A high closeness score suggests that a country is structurally well-positioned to access the rest of the system.

Harmonic centrality

Harmonic centrality is better suited to networks where not all nodes are reachable from every other node, a situation that occurs in empirical trade networks due to missing bilateral flows. Instead of summing distances, it sums the reciprocals of the distances to all other nodes. It is thus defined as the "sum of the inverted distances instead of the inverted sum of the distances, which avoids cases where an infinite distance dominates the others" (Rochat, 2009). By convention, an isolated node has a harmonic centrality of 0,

$$\text{Harmonic}(i) = \sum_{j \neq i} \frac{1}{d(i,j)} \tag{12}$$

where $d(i,j)$ is the length of the shortest path from country i to country j, computed as the inverse of trade intensity (i.e., $d(i,j) = 1/w_{ij}$) in weighted networks. Unlike standard closeness centrality, harmonic centrality remains defined even when some nodes are unreachable, since unreachable nodes simply contribute zero to the sum (as $1/\infty = 0$).

In other words, harmonic centrality evaluates how easily a country can reach others, while tolerating the existence of disconnected pairs. A country with high harmonic centrality can be interpreted as having relatively short trade paths to many others, even if not to all.

Eigenvector centrality

Eigenvector centrality measures a country's importance within the network not only based on the number or intensity of its connections, but also on the centrality of the countries it is connected to. Technically, this indicator corresponds to the principal eigenvector of the weighted adjacency matrix, meaning that each country's score is determined in proportion to the scores of its trading partners, weighted by the strength of the connections.

$$x_i = \frac{1}{\lambda} \sum_j w_{ij} x_j \tag{13}$$

Where x_i is the eigenvector centrality score of country i, w_{ij} is the weight of the directed edge from country i to country j, and λ is the largest eigenvalue of the matrix W. In this formulation, a country will score highly if it is connected to others that are themselves well-connected, creating a recursive measure of structural influence. In other words, eigenvector centrality captures not just the direct reach of a country, but also the prestige or influence of its trading partners.

4.4. Measuring bilateral trade interaction

While the previous section examined the structural hierarchy of countries based on their position within the global trade network, the present section shifts the analysis toward the bilateral properties of trade relations. Building on the relational approach developed by Courgeau (1988) and extended to economic flows by Bocquier (2024), two complementary indicators are constructed. The first is the *Dyssimmetry* index and the second is the *Intensity index*, both designed to capture not the quantity of connections but the directionality and relative strength of links between country pairs.

4.4.1. The Dissymmetry Index

The dissymmetry indicator quantifies the directional imbalance in normalized trade flows between two countries. Inspired by Courgeau's (1988) work on migration and adapted to economic flows, this measure has been reinterpreted in the context of bilateral import dependencies. Hence, for any dyad (i, j), the *Dissymmetry Index* is computed,

$$D_{ij} = \log(R^*_{ij}) - \log(R^*_{ji}) = \log\left(\frac{R^*_{ij}}{R^*_{ji}}\right) \quad (14)$$

where R^*_{ij} represents the relative trade intensity of imports by country i from j, normalized by their combined GDP and R^*_{ji} represents the reverse import flow by j from i. A positive value of D_{ij} indicates that country i imports more intensively from j than vice versa, suggesting a greater reliance on that bilateral relationship. A negative value indicates the opposite, while values near zero reflect balanced reciprocal import relations.

The dissymmetry indicator is anti-symmetric ($D_{ij} = -D_{ji}$) and summarizes a country's overall position in the network by averaging its dissymmetry scores across all trading partners:

$$\bar{D}_i = \frac{1}{N-1} \sum_{\substack{j=1 \\ j \neq i}}^{N} D_{ij} \quad (15)$$

This average indicates whether a country tends to be more dependent on imports from other countries (positive dissymmetry) or whether other countries are more dependent on it (negative dissymmetry), in the context of bilateral trade relations. In practical terms, a *positive dissymmetry value* signals an *unfavourable dependence* on external suppliers, while a *negative value* indicates a *favourable structural position*, as other countries rely more heavily on its exports

4.4.2. The Bilateral Intensity Index

The strength centrality indicator measures the aggregated intensity of a country's outgoing trade flows with all its partners, thereby reflecting its overall level of integration within the global trade network. While this measure is valuable for assessing a country's general trade prominence, it tends to emphasize relationships with the largest partners. To complement this perspective, the present study introduces a second indicator based on bilateral intensity, which captures the typical level of economic integration with partners by assigning equal weight to each trade relationship. Specifically, for each country, the median[4] of the symmetrical trade intensity indices with all partners is computed, as defined by the *Intensity Index* in Eq. 16 above.

$$I_{ij} = \log\left(R^*_{ij} + R^*_{ji}\right) \tag{16}$$

Thus, while strength reflects extensive integration, the median bilateral intensity captures intensive integration by highlighting the typical trade density of a country's bilateral relationships. In other words, strength measures "how much" a country trades in total, whereas median bilateral intensity measures "how strongly" it trades with each partner on average. These two indicators are therefore complementary, as a country may hold a central position in the global network while maintaining generally weak bilateral ties, or vice versa.

Together with the dissymmetry indicator and the centrality measures, they offer a fuller picture of how power and integration are distributed in bilateral trade relations, going beyond what simple centrality metrics can show.

4.5. Ensuring cross-indicator comparability

4.5.1. Z-score standardization

In this study, the centrality, dissymmetry, and bilateral intensity indicators exhibit widely varying scales and units, complicating direct comparisons. To make these indicators comparable and suitable for subsequent multivariate analyses, a Z-score standardization is applied for each five-year period. This transformation consists of placing all indicators on a common scale following a standard normal distribution $N(0,1)$, as detailed in Eq. 17 below,

$$z_i = \frac{x_i - \bar{x}}{s(x)} \tag{17}$$

where $\bar{x}$ and $s(x)$ represent, respectively, the mean and standard deviation of the indicator calculated per period.

[4] The median is chosen because the distribution of bilateral intensities is highly skewed and influenced by extreme values, unlike the mean, which is used for more symmetrically distributed indicators such as dissymmetry.

Z-score standardization is particularly appropriate here because it preserves the relative differences between values even when data dispersion is low. Unlike min-max normalization, which rescales all values to the interval [0,1] and can artificially exaggerate small differences when variance is low, the Z-score maintains proportional distances and avoids excessive compression effects.

4.5.2. Descriptive statistics of standardized indicators

Following the Z-score standardization, a series of descriptive analyses were conducted to explore the statistical properties of the standardized indicators across the four five-year periods. These diagnostics provide insight into the distributional shapes, asymmetries, and temporal evolution of the standardized scores.

Distributional properties of indicators

Table 2 summarizes the distribution of each standardized indicator across all observations, pooling the four periods. In addition to the mean, the median and quartile values (Q1, Q3) provide information on the central tendency and spread of the scores, while the minimum and maximum reflect the overall range of variability observed for each indicator.

Table 2. *Descriptive statistics of standardized network indicators (Z-scores)*

Indicator	Min.	Q1	Median	Mean	Q3	Max.
Strength	-0.997	-0.617	-0.210	0.078	0.445	5.074
Betweenness	-0.539	-0.479	-0.310	0.048	0.060	6.894
Harmonic	-1.535	-0.593	0.007	0.117	0.714	3.196
Closeness	-3.452	-0.627	0.218	0.049	0.858	1.800
Eigenvector	-0.134	-0.116	-0.092	-0.038	-0.092	10.771
Dissymmetry [mean]	-2.568	-0.744	-0.110	-0.021	0.581	3.050
Intensity [median]	-2.712	-0.473	0.117	0.103	0.832	1.846

Note : All reported statistics are rounded to 3 d.p.

As expected, following Z-score standardization, the means of all indicators are close to zero, confirming the proper application of the transformation. However, the range of values varies substantially across indicators. For instance, eigenvector centrality reaches a maximum of 10.771, while betweenness and strength also exhibit relatively high maxima (6.894 and 5.074, respectively), indicating greater dispersion and the presence of outlying values. By contrast, the indicators for dissymmetry (median = −0.110) and intensity (median = 0.117) display a more compact distribution, with quartile values contained between approximately −0.75 and 0.83, suggesting greater cross-country homogeneity.

Additionally, harmonic, betweenness, and strength have negative median values, indicating that most countries score below the standardized mean. Conversely, closeness shows a positive median (0.218), suggesting that a majority of countries are positioned in the upper part of the standardized distribution.

To complement these statistics, Figure 2 presents histograms and estimated density curves for each indicator, pooled across all periods. These visualizations facilitate the detection of asymmetries, extreme values, and distributional patterns that may not be fully captured by summary statistics alone.

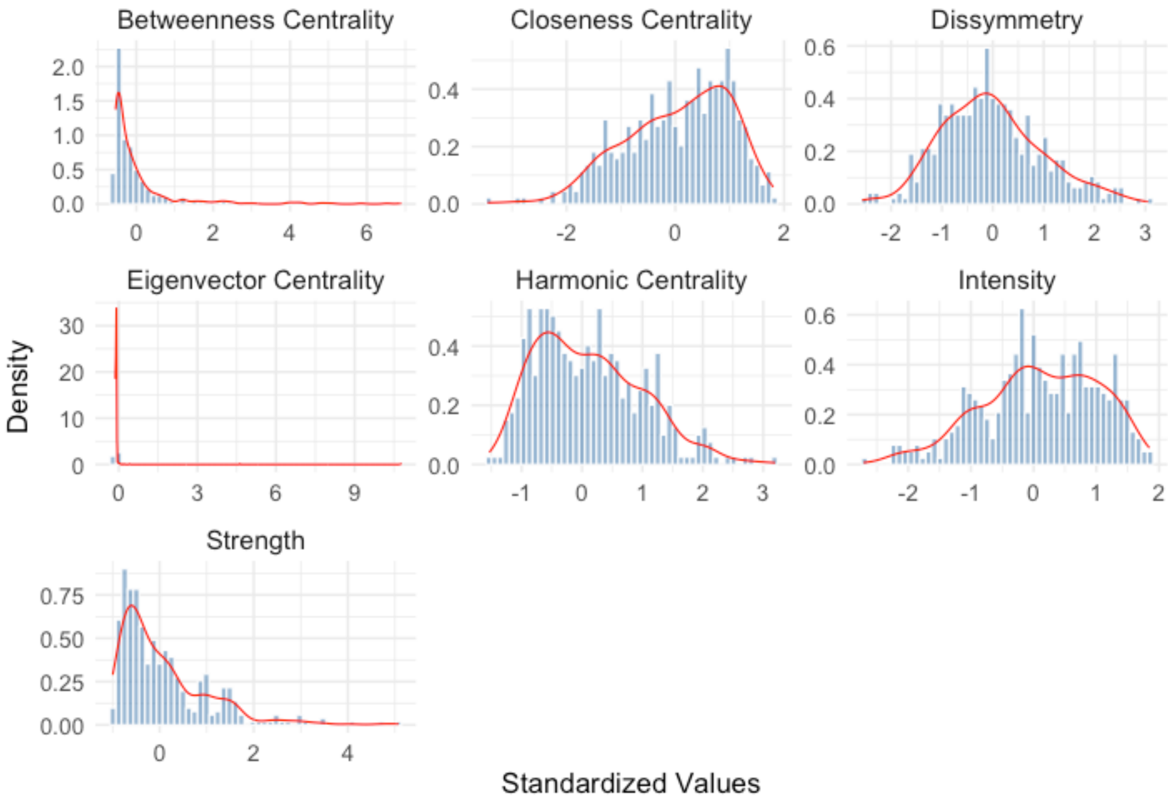

Figure 2. *Histograms with density curves of standardized network indicators*

The histograms show that *betweenness* and *eigenvector* exhibit highly unbalanced distributions. In both cases, most values are concentrated at very low levels, while a small number of substantially higher observations appear visually isolated in the right tail. This extreme contrast suggests that these indicators fail to differentiate effectively across most cases and are instead dominated by a few atypical values, which may ultimately distort the analysis.

By contrast, the remaining indicators exhibit more regular and interpretable distributions. *Strength*, although skewed, displays a continuous shape without abrupt breaks or isolated outliers. *Closeness* also appears stable, with moderate density and balanced tails. *Dissymmetry* stands out for its nearly symmetric and well-spread distribution, suggesting that the indicator is statistically robust. *Harmonic* and *intensity* show slightly more irregular density patterns, with minor bumps or dips, but no visually identifiable extreme values.

Evolution and dispersion of indicators over time

To build on the distributional analysis, Figure 3 displays boxplots of each standardized indicator across the four time periods. These visualizations enable a clearer assessment of temporal stability and highlight whether dispersion patterns remain consistent over time.

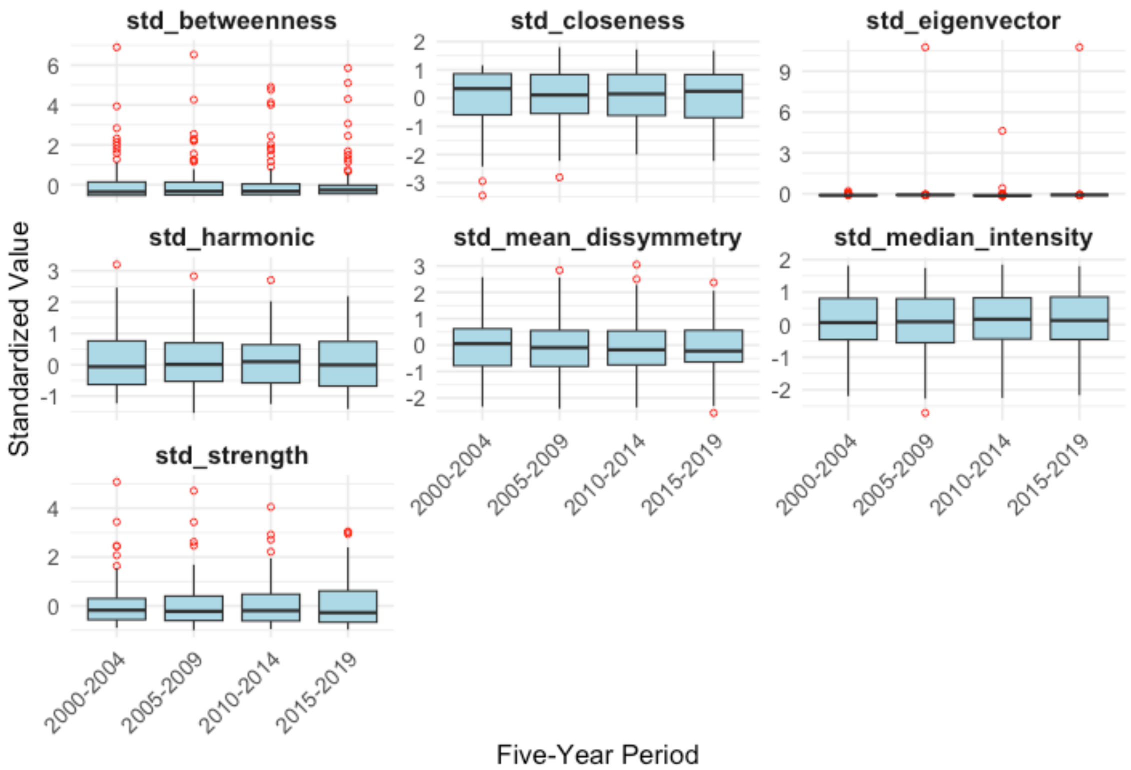

Figure 3. *Boxplots of standardized network indicators by period*

A general temporal stability is observed across most indicators, both in terms of medians and interquartile ranges. While several measures display occasional extreme values, *eigenvector* and *betweenness* centralities are particularly notable for their highly compressed distributions. Indeed, most countries exhibit values close to zero, while a small number of cases stand out with disproportionately high scores. These outliers likely correspond to countries occupying structurally dominant positions in the trade network, either as global hubs (*eigenvector*) or as critical intermediaries linking different parts of the network (*betweenness*). This pronounced concentration may hinder their ability to capture more nuanced or intermediate positions within the global structure.

In summary, the statistical and graphical analysis reveals marked contrasts between the indicators. While all are centered on zero by construction, some exhibit well-spread distributions, whereas others show excessive compression around the mean. This is particularly true for centrality measures such as *eigenvector* and *betweenness*, where most of the countries display values very close to zero, with only a few isolated cases standing out with extreme scores. This configuration limits their ability to capture gradual differences between countries. The analysis will therefore focus on a subset of indicators whose statistical properties are deemed more appropriate for comparative purposes.

4.5.3. Final set of indicators included for modelling

Based on the preceding descriptive analysis, three indicators were excluded from further modelling: *betweenness*, *eigenvector*, and *closeness*. Betweenness and eigenvector centralities exhibited highly compressed distributions, with most countries clustered around zero and a small number of disproportionately high outliers. This pattern suggests that these measures primarily capture extreme structural positions in the network, limiting their ability to reflect more gradual or intermediate differences across countries.

Although the distributions of closeness and harmonic appeared broadly similar in terms of interquartile range and overall spread, the choice to retain harmonic centrality over closeness is based in theoretical considerations. In directed and potentially sparse networks such as international trade, many country pairs do not maintain direct bilateral flows, as previously discussed in Section 4.2.4. This results in disconnected nodes and infinite path lengths, making closeness centrality unstable or undefined. Harmonic centrality, by summing the inverse of reachable distances only, remains consistently defined. It therefore provides a more reliable measure of geodesic accessibility, particularly in trade networks characterized by asymmetry and structural gaps.

In conclusion, the final set of indicators selected for modelling includes *strength, harmonic, bilateral intensity, and dissymmetry.* Since all four variables were standardized as Z-scores (mean = 0, standard deviation = 1), Table 3 below serves as an interpretive guide by providing a qualitative assessment of each indicator based on the Z-score's deviation from the mean.

Table 3. *Interpretive grid for the four retained indicators (Z-scores)*

Z-score range	Strength	Harmonic	Dissymmetry	Intensity
> +1.0	*Very intense trade*	*Strong central connectivity*	*Strong import dependence*	*Very high bilateral integration*
+0.5 to +1.0	*Sustained trade*	*Well connected*	*Moderate import dependence*	*High bilateral integration*
0 to +0.5	*Moderately integrated*	*Slightly central*	*Mild import dependence*	*Moderate bilateral integration*
0 to –0.5	*Moderately marginalised*	*Slightly peripheral*	*Mild trade advantage*	*Low bilateral integration*
–0.5 to –1.0	*Weak trade*	*Weak connectivity*	*Moderate trade advantage*	*Weak bilateral integration*
< –1.0	*Very limited trade*	*Highly peripheral*	*Strong trade advantage*	*Very weak bilateral integration*

4.5.4. Correlation matrix of the indicators

Before conducting any regression analysis, it is essential to assess the potential interdependence between explanatory variables. The classical linear model assumes that predictors are not strongly correlated, as multicollinearity may bias coefficient estimates and reduce the interpretability of the results. To verify this assumption, we compute the pairwise *Pearson correlations* between the four standardized network indicators retained.

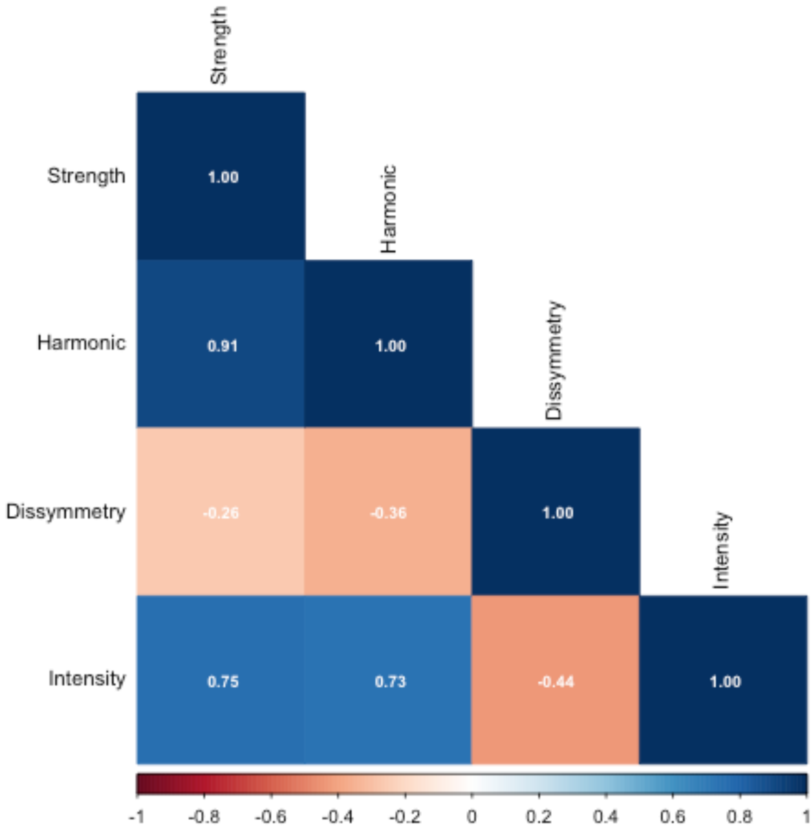

Figure 4. *Correlation matrix of standardized network indicators*

The matrix in Figure 4 shows a very strong positive correlation between Strength and Harmonic Centrality (r = 0.91), suggesting that these two measures largely capture the same structural dimension of the network, namely global connectivity and integration. Similarly, Intensity is positively correlated with both Strength (r = 0.75) and Harmonic (r = 0.73), indicating that countries which are highly connected also tend to engage in denser bilateral trade flows. In contrast, Dissymmetry is weakly or negatively correlated with the other indicators, especially with Harmonic (r = –0.36) and Intensity (r = –0.44). This suggests that the dissymmetry index captures a distinct dimension of trade relationships and thus provides complementary information. Building on these descriptive insights, the next section introduces the modelling strategy used to assess how countries' positions in the global trade network relate to health spending outcomes.

4.6. Modelling

4.6.1. Construction of explanatory variables

The final methodological step aims to test the central hypothesis of this study, which assumes that the structural positions of countries within the global trade network may influence their aggregate health expenditures.

To this end, three sets of explanatory variables are successively mobilized, each representing a different way of measuring the structural position of a country:

1) an approach based on *standardized raw indicators*,
2) a typology derived from *hierarchical clustering*,
3) a *Principal Component Analysis* (PCA).

These sets are integrated into a linear panel regression model to compare their explanatory power. The objective is to determine which representation of the global trade structure best accounts for the inequalities observed in health expenditures.

Standardized raw indicators (X_raw)

This first explanatory dataset is based on the standardized values (Z-scores) of the four selected indicators, calculated for each country and period. These variables provide a direct and independent representation of the structural dimensions characterizing a country's position within the network. By isolating each indicator, this approach enables a separate assessment of their individual influence on health expenditures. It serves as a baseline model, capturing the potential linear effects of specific centrality or asymmetry measures on aggregate health spending, without assuming any underlying structure or interdependence among the indicators.

Hierarchical clustering (X_cluster)

In the second approach, the standardized indicators are aggregated into structural profiles using hierarchical clustering based on Ward's method. The clustering is constructed independently of the period, ensuring that cluster profiles remain comparable over time.

The optimal number of clusters is determined using a dual strategy that combines visual inspection of dendrograms to identify natural segmentation thresholds, followed by statistical validation using the *NbClust* function, which applies multiple evaluation criteria to identify the best number of clusters (e.g., Calinski-Harabasz, Silhouette index). In order to provide a clearer representation of the different cluster profiles, a synthetic score is computed for each cluster,

$$\text{Score}_{\text{cluster}} = \bar{Z}_{\text{strength}} + \bar{Z}_{\text{harmonic}} + \bar{Z}_{\text{dissymmetry}} + \bar{Z}_{\text{intensity}} \tag{18}$$

where each $\bar{Z}$ denotes the mean standardized value of a given indicator within the cluster. Clusters are then re-ranked according to this score, from the highest to the lowest. The resulting ordinal variable, *cluster_ranked*, is then used in the explanatory models and plot visualizations.

Principal Component Analysis (X_pca)

Lastly, the set of indicators is combined using PCA. This method reduces the dimensionality of the dataset by transforming the original potentially correlated indicators into orthogonal components that maximize the variance explained. Each country is thus projected into a two-dimensional factor space that captures the main structural patterns underlying its position in the network. This transformation serves to condense the information contained in the original variables while retaining most of the variation, to enable cross-country comparisons, and, to evaluate whether a country's structural position can be meaningfully represented through one or two continuous latent dimensions, rather than through a raw combination of correlated measures.

4.6.2. Panel Regression Model

To analyze how the structural position of countries in the trade network evolves over time and affects health expenditures, the study relies on a panel data approach using *Panel Linear Models* (PLM) where the dependent variable is modelled as a function of trade indicators indexed by country and time. This framework captures both temporal changes within countries and structural differences across them.

Random Effects

Let us recall that the analysis is based on a dataset in which each country is observed four times, corresponding to consecutive five-year periods (2000–2004 to 2015–2019). This structure involves repeated observations for the same units over time, which violates the independence assumption of standard OLS regression. To account for this longitudinal nature, panel regression models are used.

Two main specifications are generally considered in panel data analysis :

- The *fixed effects* (FE) model, which controls unobserved country-specific characteristics that remain constant over time.
- The *random effects* (RE) model, which assumes that these unobserved effects are not correlated with the explanatory variables.

Given that the analysis aims to compare the effects of both time-invariant characteristics and time-varying factors, such as changes in a country's cluster membership over time, the random effects approach is preferred. In a fixed effects model, variables constant over time for a given country are absorbed by the country-specific intercepts and excluded from estimation. This would be limiting here, as PCA dimensions and cluster profiles retain the same structural meaning across periods, even if countries shift between groups. Random effects preserve both within-country changes and between-country differences, allowing these time-invariant characteristics to be included in explaining health expenditures.

Accordingly, three random effects panel regressions are estimated, each based on one of the three sets of explanatory variables constructed in the analysis.

4.6.3. Inclusion of Geopolitical Control Variables

To isolate and assess the independent effect of countries' positions within the trade network, a second model is estimated that incorporates a set of geopolitical control variables, both time-invariant and time-varying. The inclusion of these variables accounts for structural heterogeneity among countries that is not directly related to their network position. By capturing salient contextual factors, the model mitigates the risk of confounding, thereby reducing the likelihood of omitted variable bias and enhancing the robustness and validity of the estimates.

First, a *landlocked status* indicator distinguishes between coastal and landlocked states. The idea is that landlocked countries face structural disadvantages in accessing global markets, due to higher transportation costs and logistical constraints (Faye et al., 2004). Therefore, we can imagine that this variable may influence their capacity to engage in international trade and, indirectly, their economic development and investment in public goods such as healthcare. This binary variable was manually constructed by identifying the 44 landlocked countries worldwide.

Then, the *locations' continent* is included as a categorical control variable to examine whether countries sharing broad geographical proximity also share structural characteristics that may influence both their integration into the global trade network and their health expenditure patterns. Countries sharing the same continent frequently benefit from shared infrastructure systems (e.g., roads, ports, ICT networks), institutional frameworks, or regional cooperation agreements, all factors that can systematically shape trade connectivity and socio-economic development (Vidya & Taghizadeh-Hesary, 2021). Therefore, including this variable helps to account for such macro-regional effects and ensures that the estimated impact of network-related indicators is not confounded by these shared geographical and institutional contexts.

Finally, the *political regime type* is incorporated, based on the *Polity2* score from the Center for Systemic Peace's Polity5 dataset, averaged over each quinquennial period. The Polity2 index ranges from −10 (fully autocratic) to +10 (fully democratic). Following established thresholds in comparative politics (Marshall et al., 2019), regimes are classified into three categories: *Democracy* (≥ 6), *Autocracy* (≤ −6), and *Anocracy* (intermediate values). This classification accounts for institutional differences that may shape both external economic relations and domestic policy priorities, including public spending on health.

The geopolitical control variables incorporated into the second model, together with their type and coding, are summarized in Table 4.

Table 4. *Geopolitical control variables summary*

Control variable	Type	Coding
Landlocked status	Binary	1 = landlocked, 0 = coastal
Continent	Categorical	Africa, America, Asia, Europe, Oceania
Political regime type	Categorical	Democracy (≥6), Autocracy (≤−6), Anocracy (-5 to 5)

4.6.4. Evaluating Model Fit Improvement with AIC and BIC

The next step after estimating the control model is to compare its performance with that of the baseline without-control model using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). These two criteria are widely used in model selection because they assess not only the quality of the model's fit to the observed data but also its parsimony, by introducing a penalty that increases with the number of estimated parameters. The idea is to avoid overfitting, where a model fits the sample data extremely well but loses predictive accuracy when applied to new data. AIC applies a relatively lighter penalty for complexity, which means it tends to favor models that achieve a better fit even if they are slightly more complex. BIC, in contrast, applies a stronger penalty, particularly in large samples, which leads it to prefer simpler and more parsimonious specifications when the improvement in fit is not substantial. In both cases, lower values indicate a better balance between explanatory power and simplicity. Comparing AIC and BIC for the two models therefore allows us to determine whether the inclusion of control variables improves model performance sufficiently to justify the additional complexity they introduce.

Methodologically, because the *plm* package in *R* does not provide a *LogLik* method for panel models, it is not possible to directly compute AIC and BIC statistics on plm objects. To address this, we implemented a custom *logLik.plm* function that re-fits an equivalent *lm* model using the same formula and data as the plm object. While this approach technically approximates the panel estimation, it yields the same AIC and BIC values that would be obtained if *logLik* were directly available for plm models, ensuring valid model comparisons.

5. Results

5.1. Country clustering and typology profiles

5.1.1. Optimal number of clusters

The results of the hierarchical clustering using Ward's method, as outlined in Section 4.6.1 consistently supports the choice of five clusters. This number is determined through both visual inspection of the dendrograms and statistical validation using the functions provided by the *NBClust* package[5]. Figure 5 illustrates the structure of the dendrogram in which five distinct groups emerge clearly at an intermediate height threshold.

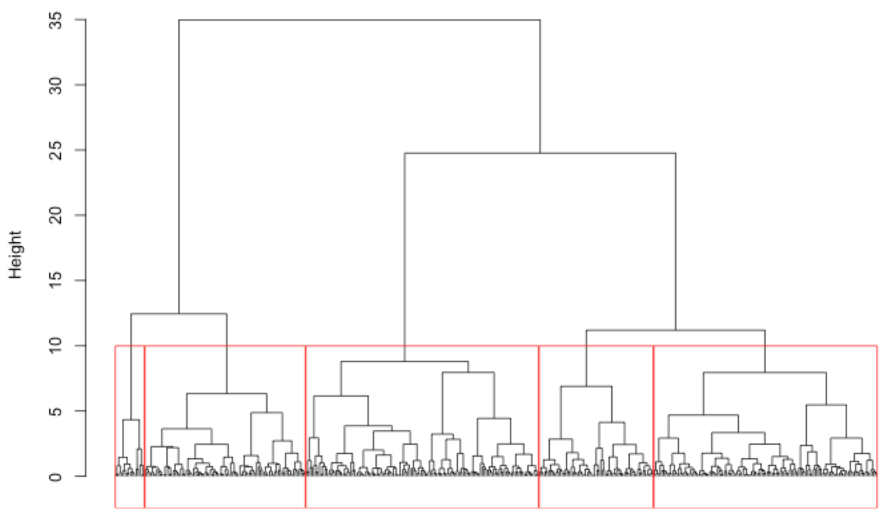

Figure 5. *Hierarchical clustering dendrogram*

The subsequent cluster analysis is therefore based on the assignment of each country to one of these five clusters for each period.

5.1.2. Cluster profiling

To characterize the structural positions associated with each cluster, we compute a single, time-invariant profile by taking the simple average of the four standardized network indicators across all country–period observations assigned to that cluster. Table 5 displays these averaged values, alongside a composite score, as computed in Eq. 18, which is used to rank the clusters from the

[5] Appendix 2 presents the output of the NbClust analysis, including the values of the D index and Hubert's statistic, as well as the second derivative.

most central and economically integrated to the least, taking into account both the intensity and the balance of their trade relations, as well as the number of countries assigned to each cluster.

Table 5. *Average values of standardized network indicators by cluster*

Cluster	Strength	Harmonic	Dissymmetry	Intensity	Score	Cluster ranked
1	1.103	1.120	-0.516	1.068	2.776	**2**
2	0.004	0.240	-0.419	0.386	0.211	**3**
3	3.121	2.239	-0.111	1.567	6.815	**1**
4	-0.623	-0.626	-0.709	-0.161	-2.120	**5**
5	-0.600	-0.599	1.052	-0.892	-1.040	**4**

Looking at the composite scores, we can clearly distinguish a hierarchy among the clusters, with Cluster ranked 1 standing out as the most central and economically integrated group, combining very high values of Strength, Harmonic, and Intensity with a balanced dissymmetry. At the opposite end, Cluster ranked 5 appears as the most marginalized, characterized by low connectivity, weak trade intensity, and only a moderate trade advantage, as indicated by its negative dissymmetry value (–0.709), which means that, on average, these countries export relatively more to their partners than they import from them**.** Between these two extremes, the remaining clusters display varying degrees of network integration and trade balance. Cluster ranked 2 remains strongly integrated and central but with a moderate trade advantage, while Cluster ranked 3 holds a more intermediate role with moderate and relatively balanced exchanges. Finally, Cluster ranked 4, although slightly more connected than the most marginal group, shows low trade intensity and a strong dependence on imports. In order to facilitate interpretation, Table 6 provides a qualitative profile for each cluster ranked, based on the averaged indicator values shown in Table 5. These profile definitions summarize the typical structural position of countries in each group.

Table 6. *Qualitative profile definitions of each cluster ranked*

Cluster ranked	Profile definition
1	*Highly integrated and central, with intense and balanced bilateral trade.*
2	*Strongly integrated and central, with dense trade and moderate trade advantage.*
3	*Intermediate position, with moderate and relatively balanced trade.*
4	*Low connectivity, limited trade, and strong import dependence.*
5	*Marginalized in the network, with weak trade and low bilateral integration.*

The subsequent cluster-based analyses will therefore rely on the classification provided by cluster ranked.

5.1.3. Country distribution and dynamics

While clusters were deliberately constructed to ensure consistent structural profiles across periods, individual countries are allowed to change cluster membership over time. This dynamic aspect is illustrated in Appendix 3, which displays each country's cluster assignment by period, sorted according to the volatility of cluster switches, and in the summary table below, which shows the number of countries per cluster in each period.

Table 7. *Number of countries per cluster by period*

Period	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
2000-2004	4	21	27	36	15
2005-2009	4	22	30	32	15
2010-2014	4	23	33	27	16
2015-2019	4	21	31	31	16

Note : Cluster = Cluster ranked

Table 7 shows that the number of countries in each cluster remains relatively stable between 2000 and 2019. On the other hand, Appendix 3 reveals that some countries change clusters frequently, with up to three shifts over the four periods. This indicates that, although the overall profiles remain stable, certain countries experience notable structural repositioning within the trade network (e.g. Guatemala, Kenya, Ecuador, Iran). Such movements may reflect rapid changes in their connectivity, trade intensity, or trade balance, possibly linked to major economic or political events. Conversely, many countries maintain the same profile throughout the entire period, reflecting a strong structural inertia in these economies. In parallel, the world map below provides a visual representation of cluster membership by country for the 2015 to 2019 period. Moreover, the interactive dashboard link in Appendix 4 offers a detailed visualization of country-level cluster membership across all four periods.

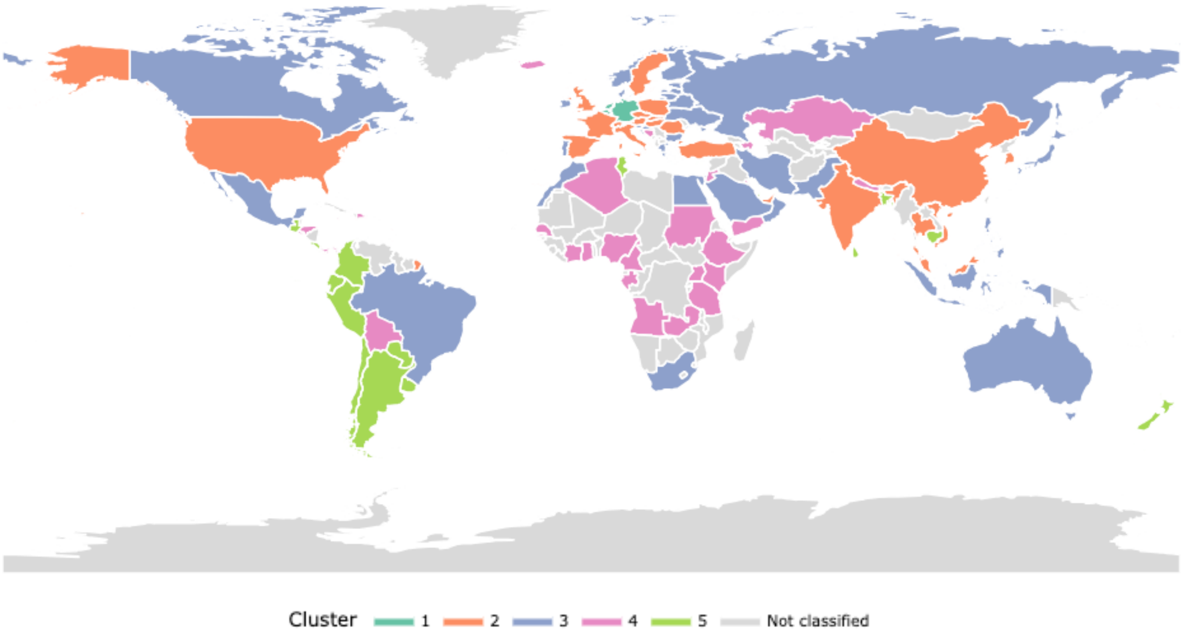

Figure 6. *Geographical distribution of clusters (2015 - 2019)*

A glance at the maps from 2000 to 2019 shows that, over time, Sub-Saharan Africa tends to concentrate mainly in Cluster 4, whereas in the early 2000s a few countries still belonged to cluster 1. In contrast, in the Andean region, several countries gradually shift towards Cluster 5, characterized by low centrality, low intensity, and strong dependence on their partners, who regard these countries as key players in trade. Furthermore, Cluster 1 remains visually concentrated in Central Europe and is composed of countries that do not represent large geographical areas. More generally, the mapping also confirms that countries tend to remain relatively stable within their assigned cluster over time.

5.2. Two-dimensional PCA analysis and country positioning

5.2.1. Variance explained and structural contribution of indicators

PCA reduces the dimensionality of the dataset by projecting the four standardized network indicators onto a two-dimensional space, while preserving most of the original variance. Hence,

Table 8 reports the percentage of variance explained by the first and second principal components as well as their cumulative contribution.

Table 8. *Proportion of variance explained by the first two components*

	Explained variance [%]	Cumul [%]
Component 1	70.09	
Component 2	20.68	90.77

Together, the first two principal components account for just over 90% of the total variance observed across the four indicators. This high proportion suggests that the main information from the original dataset can be effectively summarized within a two-dimensional space. Specifically, the first component alone explains approximately 70% of the variance and thus represents the primary axis of differentiation between countries based on their structural trade positions. The second component, while less dominant (20.68%), captures an additional and independent source of variation. Therefore, it is essential to assess the contribution of each indicator to these two components.

Table 9. *Contributions of each indicator to the first two components*

	PCA dimensions	
	Component 1	Component 2
Strength	0.92	0.30
Harmonic	0.93	0.19
Dissymmetry	-0.54	0.84
Intensity	0.89	-0.01

Note: Contributions are expressed as proportions (0–1)

The contribution scores displayed in Table 9 help clarify the structural meaning of the two principal components. As we may have expected from the correlation matrix in Figure 4, Component 1 is consistently defined by high positive contributions from Strength, Harmonic, and Intensity, all of which exceed 0.89. This suggests that the first component captures a connectivity and integration axis, summarizing how strongly and centrally countries are embedded within the international network. In particular, the role of Intensity indicates that countries scoring high on this dimension are not only well connected, but also engage in dense, frequent trade exchanges. In contrast, Component 2 is overwhelmingly shaped by Dissymmetry, which shows very strong positive contributions (0.84), while the influence of other indicators is marginal or even negative. This means that a high score on Component 2 indicates that a country maintains unbalanced trade relations, often characterized by dependence on a few dominant partners, as opposed to more reciprocal or diversified exchanges. Together, these two dimensions allow us to position countries in a simplified space reflecting both their level of integration in the network and the balance of their trade flows.

5.2.2. Cluster projection onto principal components

The scatter plot in Figure 7 displays the projection of all 103 countries onto the first two principal components for the 2015-2019 period, with each point colored and shaped according to its cluster assignment, as defined in Section 5.1. The horizontal axis (Dim1) reflects the degree of integration and centrality within the trade network, while the vertical axis (Dim2) captures trade asymmetry, as previously discussed. Moreover, the ellipse centered at the origin, with a radius of one standard deviation, encompasses countries whose network characteristics lie closest to the overall mean on both dimensions.

Figure 7. *Country cluster positions in the PCA Space (2015 – 2019)*[6]

[6] Scatter plots for other periods are provided in Appendix X or can be viewed interactively with country coordinates at : https://amandine-jacob.shinyapps.io/trade_network_dashboard

Examining Figure 7 and comparing the scatter plots over time (see Appendix 5) shows that the five clusters consistently occupy distinct and stable regions in the space defined by the first two principal components. Cluster 1 is consistently located at the far right of the integration axis, a position that reflects a very high level of centrality in the global import network. These countries also show quite unfavorable trade asymmetry indicating for instance that Belgium, despite its strong integration and pivotal role as a trade hub in Europe, relies heavily on imports from key partners which structurally places it in a position of dependency. Cluster 2, slightly lower and to the left of Cluster 1, combines high integration with moderate asymmetry; its position suggests strong participation in global trade while maintaining a certain balance in trade relations. Cluster 3 lies near the center of the graph and represents the most neutral profile, with average levels of both integration and asymmetry, reflecting an intermediary role in the network. Cluster 4 is found in the upper-left quadrant, marked by low centrality and high positive asymmetry, which points to a dependence on imports, a situation particularly common among Sub-Saharan African countries. Finally, Cluster 5 is in the bottom-left corner, bringing together peripheral countries with low integration and negative asymmetry, reflecting a trade position that is less dependent and sometimes more advantageous than their partners.

5.2.3. Structural trajectories of emblematic countries over time

To look at how the positions of emblematic countries have evolved over the entire analysis period, Figure 8 provides a visual overview of the paths taken by emblematic countries within the two-dimensional PCA space, showing their position within each cluster profile across time.

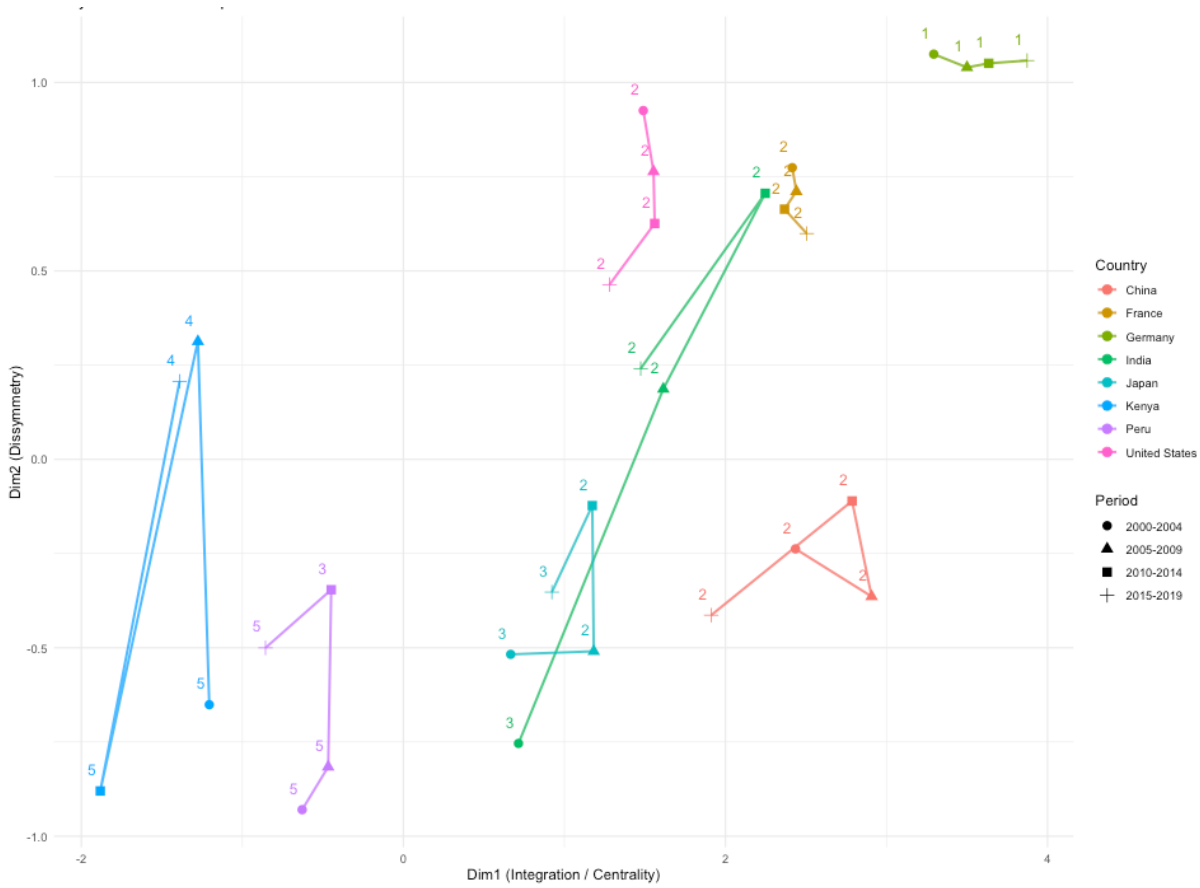

Figure 8. *PCA trajectories of emblematic countries*

Figure 8 above depicts the trajectories of eight emblematic countries in the two-dimensional PCA space, where Dimension 1 reflects integration and centrality, while Dimension 2 captures dissymmetry. We note that the numbers indicate the cluster membership for each period, and the lines trace the evolution of each country's relative position within the trade network. Overall, we find that over time most countries tend to shift primarily along Dimension 2 rather than along Dimension 1, which suggests that changes in their structural position are more frequently driven by variations in trade asymmetries than by changes in overall connectivity or centrality. For instance, the United States and France gradually move toward more negative values on the dissymmetry axis (Dim 2), which indicates a reduced dependence on imports from their trading partners and thus a stronger position as suppliers. In contrast, countries such as Peru and India follow the opposite trend, as their upward trajectories reflect increasing dissymmetry and therefore a growing dependence on external suppliers compared to the beginning of the period. Therefore, although shifts along Dimension 2 are widespread, their direction and meaning may differ significantly across countries. Furthermore, France and Germany stand out for their remarkable stability, maintaining their position in Clusters 2 and 1, respectively, throughout the twenty-year period. This suggests that their central and integrated role remains firmly established over time. While China also remains in Cluster 2 across all four periods, some countries exhibit noticeable transitions from one cluster to another. For instance, India moves from Cluster 3 to Cluster 2, and Kenya from Cluster 5 to 4, shedding light on the fact that positions are not fixed but subject to structural reconfigurations over time.

5.3. Results of Panel Linear Models

5.3.1. Panel regression results

We estimate three panel linear models with random effects, as discussed in Section 4.6.2, in order to explain cross-national variation in health expenditures based on different representations of countries' structural position in the trade network. Table 10 below presents the results of these regressions, each using a distinct set of explanatory variables: raw network indicators (*X_raw*), principal component scores (*X_pca*), and cluster-based typologies (*X_cluster*).

Note that, since the dependent variable is log-transformed (see Section 4.1.2), all reported estimates, including coefficients, standard errors, and confidence intervals are exponentiated (e^{β}) to allow interpretation on the original scale of health expenditures. Thus, the values are interpreted as multiplicative ratios, with $e^{\beta} > 1$ indicating a positive association with health expenditures and $0 < e^{\beta} < 1$ indicating a negative association[7].

[7] When coefficients are exponentiated e^{β}, the 95% confidence interval is interpreted relative to 1. Interval values entirely above 1 indicate a significant positive association, interval values entirely below 1 indicate a significant negative association, and intervals including 1 indicate no statistical significance.

Table 10. *Panel regression results of trade network position on health expenditures*

	Dependant variable – Health Expenditures (log)		
	Coef.		**SE**
X_Raw			
HE*Network Indicators			
Strength	0.972 [0.770 / 1.227]		1.126
Harmonic	1.061 [0.868 / 1.296]		1.108
Dissymmetry	**0.911*** [0.837 / 0.992]		1.044
Intensity	**1.654***** [1.392 / 1.964]		1.092
Model Statistics	**N**	**R^2**	**Adj. R^2**
	412	0.125	0.117
X_Cluster			
HE*Cluster (*Ref. = 1*)			
Cluster 2	**0.276*** [0.095 / 0.804]		1.725
Cluster 3	**0.246**** [0.086 / 0.708]		1.713
Cluster 4	**0.156***** [0.054 / 0.450]		1.716
Cluster 5	**0.196**** [0.068 / 0.566]		1.719
Model Statistics	**N**	**R^2**	**Adj. R^2**
	412	0.067	0.058
X_PCA			
HE*Principal Components			
Dimension 1	**1.310***** [1.202 / 1.427]		1.045
Dimension 2	0.955 [0.874 / 1.043]		1.046
Model Statistics	**N**	**R^2**	**Adj. R^2**
	412	0.089	0.084

Note : 95% confidence intervals in brackets; CI, SE and β are exponentiated values; + = $p < 0.1$, * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$.

*X_Raw * Health Expenditures*

For the first set of explanatory variables, consisting of standardized raw indicators of network position, *Intensity* emerges as the most influential factor. Among the four indicators, it shows the strongest and most statistically significant association with health expenditures (coef. = 1.654, CI: [1.392; 1.964], $p < 0.001$). This implies that, holding other factors constant, a one-standard-deviation increase in trade intensity is associated with an estimated 65% higher level of health expenditures. The narrow confidence interval, well above 1, indicates both the robustness and the precision of this effect, suggesting that countries more intensively engaged in trade relationships tend to allocate substantially greater resources to health. In contrast, *Dissymmetry* displays a negative and statistically significant association with health expenditures (coef. = 0.911, CI: [0.837; 0.992], $p < 0.05$). This implies that, all else being equal, a one-standard-deviation increase in the asymmetry of trade relationships is associated with an estimated 9%[8] decrease in health expenditures. The confidence interval lies just below 1, indicating that although the relationship reaches statistical significance, the effect size is moderate, and its magnitude is less robust than that of *Intensity*. This suggests that countries exhibiting a higher dependence on import in their trade relations tend to allocate slightly fewer resources to health, although this pattern is less pronounced and potentially more sensitive to sample variation. Notably, *Strength* and *Harmonic* centrality are not statistically significant in this model, suggesting that the indicators derived from migration theory (*Intensity* and *Dissymmetry*) are the ones most strongly associated with health expenditure levels. We also notice that the model explains approximately 11.7% of the variation in health expenditures across countries after adjusting for the number of predictors (Adj. $R^2 = 0.117$). In other words, we can say that differences in standardized raw network indicators account for just over one-tenth of the cross-national disparities in health spending.

*X_Cluster * Health Expenditures*

For the second model, based on the cluster typology, we see that all coefficients are below 1 and statistically significant, indicating systematically lower health expenditures for countries in Clusters 2 to 5 compared with those in cluster 1 (reference). The differences are substantial, ranging from approximately 72% lower expenditures in cluster 2 (coef. = 0.276, CI: [0.095;

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[8] When coefficients are exponentiated (e^{β}), the percentage change relative to the reference is obtained by calculating $(e^{\beta} - 1) \times 100\%$.

0.804], $p < 0.05$) to about 84% lower in cluster 4 (coef. = 0.156, CI: [0.054; 0.450], $p < 0.001$). Clusters 3 and 5 also display pronounced gaps, with roughly 75% and 80% lower expenditures, respectively. None of the associated confidence intervals include 1, underscoring the robustness of these negative correlations. This pattern confirms a clear hierarchy in health expenditure levels across structural profiles in the trade network, with cluster 1, characterized in Section 5.1.2 by high centrality, strong trade intensity, and low dissymmetry, exhibiting the highest average level of health expenditures across all structural profiles. We see that the cluster typology explains 5.8% of the variation in health expenditures across countries (Adj. R^2 = 0.058).

X_PCA * Health Expenditures

Finally, for the third model, based on principal component scores, only the first dimension is statistically significant. Dimension 1, interpreted as an axis of integration and centrality, shows a strong positive association with health expenditures (coef. = 1.310, CI: [1.202; 1.427], $p < 0.001$). This indicates that, holding other factors constant, a one-standard-deviation increase along this axis is associated with an estimated 31% higher level of health expenditures. The narrow confidence interval, entirely above 1, highlights both the consistency and the precision of this effect, suggesting that countries with greater centrality and integration in the trade network tend to allocate more resources to health. In contrast, Dimension 2, linked to the dissymmetry of trade relations, is not statistically significant (coef. = 0.955, CI: [0.874; 1.043]), with its confidence interval including 1, meaning that no association can be established between this dimension and health expenditures in the present model. The model explains 8.4% of the variation in health expenditures across countries (Adj. R^2 = 0.084). This suggests that the two principal components explain less than one-tenth of the observed differences in health spending between countries.

We see by the adjusted R^2 values that a large share of the variation in health expenditures remains unexplained, suggesting that other determinants may also exert a significant influence on cross-national differences in health spending. Therefore, it may be interesting to investigate whether a model including additional factors can account for part of this unexplained variation. We decided to focus the further analysis on the cluster-based model, as all cluster coefficients are statistically significant and point in the same direction, indicating a consistent relationship between structural profiles and health expenditures despite its lower adjusted R^2 compared to the other specifications. This makes it a relevant framework for examining whether the inclusion of additional factors can enhance the model's explanatory power.

5.3.2. Joint Significance Test of Cluster-based Model

Before extending the specification with control variables, it is important to assess whether the cluster-based typology, on its own, significantly contributes to explaining cross-country variation in health expenditures. To this end, a Wald test is conducted under the following null hypothesis:

$$H_0 : \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$$

That is, cluster membership has no explanatory power for health expenditures when compared to the reference group (Cluster 1).

$$\chi^2(4) = 29.14, \quad p < 0.001$$

The test strongly rejects the null hypothesis, indicating that the cluster-based typology as a whole significantly contributes to explaining cross-country variation in health expenditures. In other words, differences in cluster membership are systematically associated with differences in health spending levels. This joint significance reinforces the value of the cluster-based model and motivates further research to determine whether its explanatory power persists when additional control variables are incorporated into the model.

5.3.3. Model Extension with geopolitical control variables

As outlined in Section 4.6.3. and discussed after our first PLM results, we introduce a second regression with geopolitical control variables, such as a country's *landlocked* status (*landlocked*), its continental affiliation (*continent*), and its political regime (*regime*). This extension aims to assess whether the relationship between a country's position in the global trade network, captured through the cluster-based typology, and health expenditures remains robust once these contextual characteristics are taken into account. Table 11 below presents the results of this control regression.

Table 11. *Regression results of extended cluster-based model with geopolitical controls*

	Dependant variable – Health Expenditures (log)		
	Coef.		**SE**
HE*Cluster *(Ref. = Cluster 1)*			
Cluster 2 (vs. 1)	0.470+ [0.198 / 1.114]		1.554
Cluster 3 (vs. 1)	0.447+ [0.190 / 1.051]		1.548
Cluster 4 (vs. 1)	**0.323*** [0.135 / 0.772]		1.560
Cluster 5 (vs. 1)	**0.387*** [0.162 / 0.929]		1.562
Control variables			
HE*Regime (*Ref. = Anocracy)*			
Regime = Autocracy	1.084 [0.772 / 1.522]		1.189
Regime = Democracy	1.022 [0.832 / 1.254]		1.110
HE*Landlocked *(Ref. = False)*			
Landlocked = True	0.679 [0.426 / 1.082]		1.268
HE*Continent *(Ref. = Africa)*			
Continent = Americas	**4.018***** [2.316 / 6.971]		1.325
Continent = Asia	**2.535***** [1.521 / 4.223]		1.297
Continent = Europe	**8.530***** [5.066 / 14.361]		1.304
Continent = Oceania	**12.807***** [3.749 / 43.750]		1.872
Model statistics	**N**	**R^2**	**Adj. R^2**
	412	0.246	0.225

Note : 95% confidence intervals in brackets; CI, SE and β are exponentiated values; + = $p < 0.1$, * = $p < 0.05$, ** = $p < 0.01$,*** = $p < 0.001$.

The results of the control model presented in Table 11 reveal several noteworthy patterns. The inclusion of continent as a control variable was motivated by the idea that macro-regional location could capture shared characteristics not directly related to trade network position but potentially influencing both trade integration and health spending. This control aimed to reduce the risk of omitted variable bias by accounting for factors such as geographical proximity, regional infrastructure, institutional frameworks, and common policy environments. The results confirm that continent exerts a notably strong effect. Compared to Africa, all other regions display significantly higher expenditure levels, with especially large effects for Europe and

Oceania. This suggests that the effect of continent may reflect the fact that countries within the same region often share structural characteristics, such as similar levels of economic development, infrastructure, or patterns of regional cooperation, that can shape both their integration into the trade network and their allocation of resources to health.

Regarding the trade network clusters, all coefficients remain below 1, indicating lower health expenditure levels relative to cluster 1. However, compared to the uncontrolled model, the magnitude of these differences is somewhat reduced, and the significance levels for clusters 2 and 3 fall to the 0.1 threshold. This pattern suggests that part of the gap initially observed between these clusters and cluster 1 may be explained by these added geopolitical factors. Nevertheless, the persistent significance of clusters 4 and 5 indicates that structural position in the trade network continues to exert an independent influence on health spending even after accounting for these controls, implying that countries belonging to these two profiles tend to spend significantly less on health than those in more central and better-connected clusters, regardless of whether they are landlocked, located on a particular continent, or governed under a specific political regime. In other words, their relatively peripheral position in global trade appears to limit their health expenditure capacity in ways that cannot be fully explained by geography or politics alone. At the same time, the model achieves an adjusted R^2 of 0.225, representing an improvement over the uncontrolled model and suggesting that these variables capture a non-negligible share of the variance that was initially unexplained.

5.3.4. Model comparison using AIC and BIC

As discussed in Section 4.6.4, comparing the baseline cluster-only model with the extended model including geopolitical controls provides an additional assessment of whether the inclusion of these variables meaningfully improves model performance. Table 12 presents the results of this comparison using the AIC and the BIC. Both criteria evaluate model fit while penalizing unnecessary complexity, with lower values indicating a preferable balance between explanatory power and parsimony.

Table 12. *AIC vs BIC model comparison results*

Model	df	AIC	BIC
Cluster	6	1235.828	1259.954
Cluster + Controls	13	1055.422	1107.695

The output Table 12 shows that both AIC and BIC are considerably lower for the control model compared to the cluster-only specification which indicates that the added geopolitical variables meaningfully improve the model's explanatory power, even after accounting for the penalty associated with the increase in parameters. In other words, the control variables capture variance in health expenditures that the cluster-based typology alone could not account for, leading to a better-fitting model.

5.4. Discussion

The overall examination of the results reveals a clear structuring of the international trade network, in which the positions occupied by countries remain remarkably stable over time, while still allowing for specific dynamics among certain actors. Successive cluster maps show that some regional configurations persist throughout the entire period, as illustrated by the concentration of Sub-Saharan African countries in profiles characterized by low centrality, limited trade intensity, and strong import dependence (Cluster 4). In contrast, the most central and integrated countries are predominantly located in Europe, often in relatively small territories that nonetheless occupy strategic nodal positions (Cluster 1), thereby assuming a hub role in international trade. This geographical distribution thus reflects the weight of enduring structural factors, although it does not preclude more occasional reconfigurations.

Some regions, such as the Andean Americas, exemplify trajectories that shift towards more peripheral profiles, reflecting both a relative decline in integration and a deepening of trade imbalances. Furthermore, the analysis of trajectories in the principal component space reveals that these changes occur more prominently along the axis associated with trade dissymmetry than along that of overall integration. In other words, it is often variations in the balance of trade, rather than changes in the degree of connectivity, that reshape the structural position of certain countries within the network. This suggests that adjustments in trade dependence may weigh more heavily than gains or losses of partners in driving the reconfiguration of profiles.

From this perspective, the cluster typologies, derived from standardized indicators, confirm the existence of distinct and hierarchically ordered profiles according to their centrality, trade intensity, and balance of exchanges. The most integrated profiles, represented by Cluster 1, display high values in strength, accessibility, and intensity, whereas the most peripheral profiles, corresponding to Cluster 5, are characterized by lower connectivity and pronounced trade imbalances. This internal structuring of the network, clearly observed in the descriptive analyses, also finds an extension in the econometric results obtained from the different regressions. In the model based on raw indicators (X_raw), trade intensity emerges as the factor most strongly associated with health expenditures, suggesting that denser trade flows are linked to greater capacity for investment in health systems. Conversely, higher trade dissymmetry, reflecting greater dependence on imports, is correlated with lower health expenditures, which may indicate structural constraints on the fiscal space available for health. However, other centrality measures, such as strength and harmonic centrality, show no significant association, implying that the mere extent of connections is insufficient to explain health expenditure disparities, and that more structural or directional indicators better capture the relationship under study.

The principal component model (X_pca) highlights the central role of the integration and centrality axis (Dimension 1), which exhibits a positive and statistically significant association with health expenditures. In other words, countries occupying a central and highly integrated position within the trade network tend to allocate greater resources to their health systems. By contrast, the dimension associated with trade dissymmetry (Dimension 2) does not emerge as significant. This finding contrasts with the X_raw model, in which dissymmetry displayed a negative relationship with health expenditures. The difference suggests that the initially observed negative effect is not entirely autonomous, rather, it partly reflects the fact that countries heavily dependent on imports are also often less integrated and less central in the network. Once this interdependence is accounted for in the PCA, the degree of integration and centrality remains the primary determinant.

Finally, the results based on the cluster typology indicate that, all else being equal, countries belonging to Clusters 2 through 5 spend significantly less than those in Cluster 1, with particularly pronounced gaps for Clusters 4 and 5. For instance, countries such as Kenya and Peru, which oscillate between Clusters 4 and 5 over the study period, consistently display markedly lower health expenditure levels compared to highly central and integrated economies like Belgium, Germany, or Singapore, which remain firmly in Cluster 1 throughout. The introduction of geopolitical control variables, such as continental location, landlocked status, or political regime, substantially improves the model's explanatory capacity. However, this extension leads to a weakening of significance for Clusters 2 and 3, suggesting that part of the differences initially observed can be explained by these contextual characteristics. Nevertheless, the marked differences for Clusters 4 and 5 persist, indicating that structural position within the global trade network exerts an independent effect on health expenditure levels, beyond the sole geographical or institutional characteristics of countries.

Taken together, these results indicate that a country's structural position in the global trade network, as measured by Strength, Harmonic centrality, trade Intensity, and Dissymmetry, accounts for part of the observed disparities in health expenditure. The inclusion of geopolitical control variables tempers some of the observed relationships but does not alter the substantial gaps between extreme structural profiles, thereby confirming Hypothesis H1 that *a weighted and directed representation of countries' positions in the global trade structure significantly influences aggregate health expenditure levels.*

The analyses also show that relational indicators derived from the matrices proposed by Courgeau (1988) and adapted to international trade by Bocquier (2024), such as trade intensity (Intensity) and trade dissymmetry (Dissymmetry), capture structural dimensions of the global trade network that are not reflected by conventional centrality measures such as strength or harmonic centrality. In the X_Raw model, only intensity, which is positively associated with expenditure, and dissymmetry, which is negatively associated, emerge as significant, suggesting that they capture explanatory dimensions not conveyed by purely topological indicators. This pattern is echoed in the cluster structure, where the most pronounced expenditure gaps separate the most integrated and balanced profile, represented by Cluster 1 and characterized by high intensity and low dissymmetry, from the most peripheral and unbalanced profiles, corresponding to Clusters 4 and 5. The inclusion of geopolitical variables confirms this interpretation, as the marked difference between extreme profiles remains significant despite the attenuation of some gaps, indicating that these two dimensions retain independent explanatory power. Taken together, these results provide clear empirical support for Hypothesis H2, which states that *relational indicators offer a better explanation of expenditure disparities than conventional centrality measures.*

These results resonate with critiques in the literature of gravity models, which fail to capture the systemic interdependencies and hierarchical structures of the global trade network (De Benedictis & Tajoli, 2011; Fagiolo et al., 2009). By mobilising structural indicators adapted from the framework proposed by Courgeau (1988) and transposed to international trade by Bocquier (2024), the analysis incorporates relational dimensions such as trade intensity and dissymmetry, which are not reflected by classical centrality measures. The positive association between trade intensity and health expenditure is consistent with the findings of Herzer (2017) and Byaro et al. (2021), who show that greater integration into international trade can broaden the economic base and foster public investment in health, notably through income growth, technology diffusion, and improved access to medical goods. Conversely, the negative association between dissymmetry and health expenditure, which persists in the extended models, provides concrete evidence of the role of structural imbalances where high dependence on imports can constrain available fiscal space, reduce economic resilience, and ultimately limit the capacity for sustained investment in the health sector (Prell et al., 2015; Antonietti et al., 2022). These findings also echo the logic of the Fundamental Cause Theory (Link & Phelan, 1995; Clouston & Link, 2021), which posits that health inequalities persist because they are rooted in unequal access to flexible resources such as knowledge, money, power, or networks. In our results, central and highly integrated countries benefit from dense and balanced trade relations, which expand their economic and technological resources and translate into higher health expenditures. Conversely, peripheral and dependent countries face structural trade imbalances that restrict their fiscal capacity and resilience, thereby reproducing unequal health outcomes across the global system. In this sense, structural positions in the trade network may operate as a fundamental cause of health inequalities at the international level.

6. Conclusion

This study set out to examine whether a country's structural position within the global trade network helps explain cross-national disparities in health expenditure. The starting point was the recognition that most empirical work on trade and health relies on a methodological nationalism that treats countries as isolated units, adjusting for size effects through GDP but rarely considering the broader structure of interdependence in which they operate. By neglecting this systemic dimension, such approaches overlook the possibility that integration, peripheralization, and imbalances in trade relations may condition the economic means available for health investment. To address this gap, the study adopted a network-based framework that situates each bilateral trade flow within the entire distribution of exchanges. Structural indicators, originally developed for migration flows by Courgeau (1988) and adapted to trade by Bocquier (2024), were used alongside classical measures of network centrality. This allowed the analysis to capture not only the scale and accessibility of a country's trade connections but also their balance and relative weight in the global system. The methodology combined trade import data from the UN Comtrade database and macroeconomic indicators from the World Bank's WDI. It involved descriptive network analysis, dimensionality reduction, and typological profiling, followed by the modelling of health expenditure levels with the progressive incorporation of geopolitical control variables.

The findings point to a clear and persistent link between network position and health spending capacity. Countries that are both highly integrated into the trade network and maintain balanced trade relationships tend to exhibit higher levels of public investment in healthcare. Conversely, peripheral positions combined with strong trade imbalances are consistently associated with lower expenditure levels, a pattern that holds even when accounting for factors such as geography and political regime. These results support the idea that access to resources, technologies, and markets is not solely a function of national economic size but also of a country's embeddedness in the global trading system and the nature of its trade dependencies. In this sense, the findings bridge trade policy and public health planning, suggesting that strategies to improve health outcomes should not be isolated from the broader patterns of global economic interdependence. They also invite policymakers to reflect on how structural positions in trade networks can be actively shaped to strengthen health investment capacity. This may involve not only fostering greater integration through diversified and resilient trade partnerships but also mitigating vulnerabilities linked to excessive dependence on a narrow set of partners.

Ultimately, this work extends the understanding of the trade–health nexus by demonstrating that the relational and directional configuration of trade flows offers explanatory value beyond conventional centrality indicators or bilateral trade measures. The persistence of expenditure disparities across distinct structural profiles suggests that such inequalities are, to some extent, embedded within the architecture of the global trading system itself.

6.1. Limitations

As with any empirical study, the present analysis is subject to several limitations. A first concern relates to the coverage and quality of the data. Although the Comtrade database is the most comprehensive source for international trade statistics, it may suffer from reporting inconsistencies, particularly for developing countries. To mitigate this issue, import declarations were used instead of export reports, but discrepancies and missing values may still affect the accuracy of bilateral flows and derived network indicators. The study was also restricted to the period from 2000 onwards, since reliable data on health expenditures are unavailable for earlier years, which prevents capturing longer historical dynamics. Aggregating the data into five-year periods further improves comparability across time but may smooth short-term fluctuations and bias the measurement of structural change. In terms of scope, the analysis ultimately focused on 103 countries with consistent data, which ensures comparability but narrows geographical and economic diversity. In particular, several smaller or less economically dominant countries, which might present distinctive trade or health dynamics, are excluded from the analysis. As a result, the findings primarily reflect patterns among middle- and high-income economies, and their generalization to the global system should therefore be made with caution. Regarding indicators, the study retained a limited set, mainly Intensity, Dissymmetry, Strength, and Harmonic centrality. Eigenvector, Closeness, and Betweenness centrality were removed after distribution checks, a choice that improves stability but restricts scope. The use of principal component analysis to address correlations among indicators entails some loss of information, and the clustering procedure depends on the chosen number of groups, which may smooth internal heterogeneity. Finally, while the inclusion of geopolitical control variables enriches the interpretation, a considerable share of unexplained variance remains, suggesting that additional factors beyond trade structure and basic geopolitical attributes also shape health expenditure patterns.

6.2. Prospects for future research

The scope of this research is not intended to be exhaustive, and several avenues remain open for further investigation. One of the initial objectives was to compare the structure of trade in goods with that of services. However, the attempt to extract service flows from UN Comtrade quickly revealed a much lower number of observations and a very limited country coverage over the period 2000–2019. This prevented the construction of complete intensity and dissymmetry matrices, as well as related centrality measures, making a systematic comparison impossible. Future research could address this limitation by investigating alternative databases specifically devoted to international trade in services. While their temporal and geographical coverage is likely to be more limited, they could nevertheless provide a basis for testing whether the hierarchies identified in the trade of goods using the same set of network indicators also emerge in the global trade of services.

Beyond this, other extensions could enrich the analysis. Incorporating additional macroeconomic or health-related variables, or accounting for external shocks, would help to contextualize the network effects identified here. Methodological refinements such as using dynamic network models to better trace changes over time or building alternative network structures (e.g. multilayer or sector-specific instead of a single aggregated one), also represent promising directions. Finally, disaggregated analyses at the regional or sectoral level could shed light on whether the global hierarchies observed in this study mask differentiated trajectories across specific areas of the world economy.

7. References

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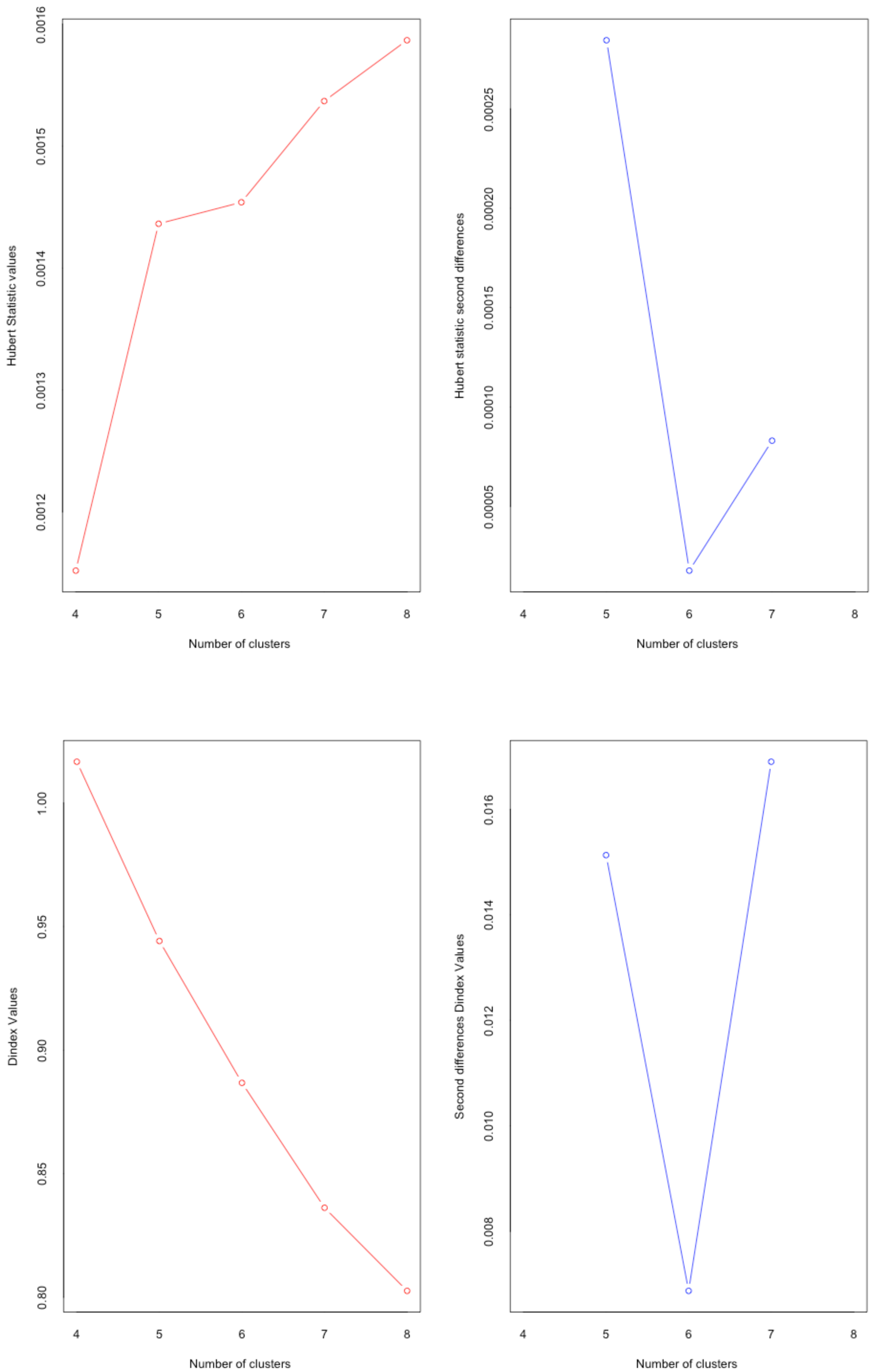
8. Appendices

Appendix 1 : List of countries included in the study (103)

ISO3	Country	ISO3	Country	ISO3	Country
DZA	Algeria	GHA	Ghana	PHL	Philippines
AGO	Angola	GRC	Greece	POL	Poland
ARG	Argentina	GTM	Guatemala	PRT	Portugal
AUS	Australia	HND	Honduras	QAT	Qatar
AUT	Austria	HUN	Hungary	ROU	Romania
AZE	Azerbaijan	ISL	Iceland	RUS	Russian Federation
BHR	Bahrain	IND	India	SAU	Saudi Arabia
BGD	Bangladesh	IDN	Indonesia	SEN	Senegal
BLR	Belarus	IRN	Iran, Islamic Rep.	SGP	Singapore
BEL	Belgium	IRL	Ireland	SVK	Slovak Republic
BOL	Bolivia	ISR	Israel	SVN	Slovenia
BIH	Bosnia & Herzegovina	ITA	Italy	ZAF	South Africa
BRA	Brazil	JAM	Jamaica	ESP	Spain
BGR	Bulgaria	JPN	Japan	LKA	Sri Lanka
KHM	Cambodia	JOR	Jordan	SDN	Sudan
CMR	Cameroon	KAZ	Kazakhstan	SWE	Sweden
CAN	Canada	KEN	Kenya	CHE	Switzerland
CHL	Chile	KOR	Korea, Rep.	TZA	Tanzania
CHN	China	KWT	Kuwait	THA	Thailand
COL	Colombia	LVA	Latvia	TTO	Trinidad & Tobago
CRI	Costa Rica	LBN	Lebanon	TUN	Tunisia
CIV	Cote d'Ivoire	LTU	Lithuania	TUR	Turkiye
HRV	Croatia	LUX	Luxembourg	UGA	Uganda
CYP	Cyprus	MYS	Malaysia	UKR	Ukraine
CZE	Czechia	MEX	Mexico	ARE	United Arab Emirates
DNK	Denmark	MAR	Morocco	GBR	United Kingdom
DOM	Dominican Republic	NPL	Nepal	USA	United States
ECU	Ecuador	NLD	Netherlands	URY	Uruguay
EGY	Egypt, Arab Rep.	NZL	New Zealand	VNM	Viet Nam
SLV	El Salvador	NGA	Nigeria	YEM	Yemen, Rep.
EST	Estonia	NOR	Norway	ZMB	Zambia
ETH	Ethiopia	OMN	Oman		
FIN	Finland	PAK	Pakistan		
FRA	France	PAN	Panama		
GAB	Gabon	PRY	Paraguay		
DEU	Germany	PER	Peru		

Appendix 2 : NbClust results for determining the optimal number of clusters



Appendix 3 : Countries ranked by frequency of cluster changes across periods[9]

ISO3	Country	2000-2004	2005-2009	2010-2014	2015-2019	N	Total	N Distinct
GTM	Guatemala	5	4	3	5	3	4	3
KEN	Kenya	5	4	5	4	3	3	2
ECU	Ecuador	5	5	3	5	2	4	2
IRN	Iran, Islamic Rep.	3	5	5	3	2	4	2
PER	Peru	5	5	3	5	2	4	2
BGD	Bangladesh	4	3	3	5	2	3	3
PAN	Panama	5	3	3	4	2	3	3
ISL	Iceland	4	4	5	4	2	2	2
JPN	Japan	3	2	2	3	2	2	2
KWT	Kuwait	4	5	5	4	2	2	2
CHL	Chile	3	3	3	5	1	2	2
EGY	Egypt, Arab Rep.	5	3	3	3	1	2	2
NZL	New Zealand	3	5	5	5	1	2	2
PAK	Pakistan	5	3	3	3	1	2	2
BHR	Bahrain	5	5	5	4	1	1	2
BLR	Belarus	4	3	3	3	1	1	2
KHM	Cambodia	4	4	5	5	1	1	2
CIV	Cote d'Ivoire	5	5	4	4	1	1	2
HRV	Croatia	4	4	4	3	1	1	2
CYP	Cyprus	4	5	5	5	1	1	2
EST	Estonia	4	4	3	3	1	1	2
GHA	Ghana	5	4	4	4	1	1	2
IND	India	3	2	2	2	1	1	2

[9] Note : *N* denotes the number of cluster changes across successive periods; *Total* indicates the total number of distinct clusters a country has occupied over the whole period; *N Distinct* represents the maximum amplitude of change, i.e. the largest gap between two clusters successively occupied.

ISO3	Country	2000-2004	2005-2009	2010-2014	2015-2019	N	Total	N Distinct
IDN	Indonesia	2	2	2	3	1	1	2
IRL	Ireland	2	3	3	3	1	1	2
KAZ	Kazakhstan	3	3	4	4	1	1	2
LTU	Lithuania	4	3	3	3	1	1	2
OMN	Oman	4	4	3	3	1	1	2
PRY	Paraguay	4	4	5	5	1	1	2
PHL	Philippines	2	3	3	3	1	1	2
QAT	Qatar	4	5	5	5	1	1	2
ROU	Romania	3	3	2	2	1	1	2
SVK	Slovak Republic	3	3	2	2	1	1	2
TUN	Tunisia	4	5	5	5	1	1	2
UKR	Ukraine	2	2	3	3	1	1	2
ARE	United Arab Emirates	3	2	2	2	1	1	2
DZA	Algeria	4	4	4	4	0	0	1
AGO	Angola	4	4	4	4	0	0	1
ARG	Argentina	5	5	5	5	0	0	1
AUS	Australia	3	3	3	3	0	0	1
AUT	Austria	2	2	2	2	0	0	1
AZE	Azerbaijan	4	4	4	4	0	0	1
BEL	Belgium	1	1	1	1	0	0	1
BOL	Bolivia	4	4	4	4	0	0	1
BIH	Bosnia and Herzegovina	4	4	4	4	0	0	1
BRA	Brazil	3	3	3	3	0	0	1
BGR	Bulgaria	3	3	3	3	0	0	1
CMR	Cameroon	4	4	4	4	0	0	1
CAN	Canada	3	3	3	3	0	0	1
CHN	China	2	2	2	2	0	0	1

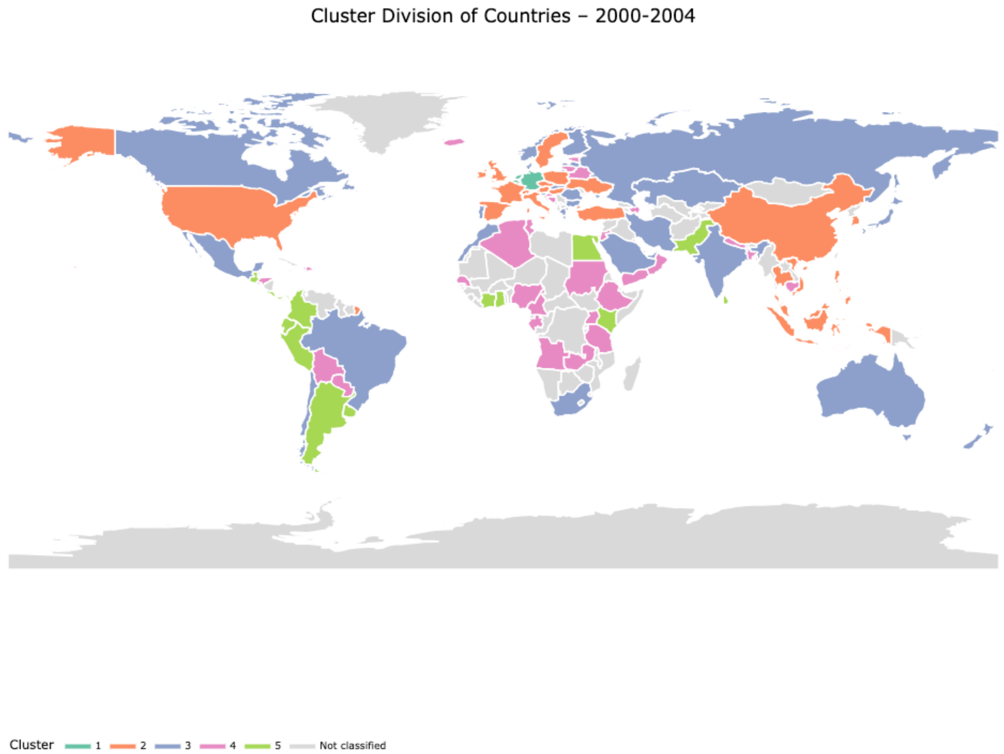
ISO3	Country	2000-2004	2005-2009	2010-2014	2015-2019	N	Total	N Distinct
COL	Colombia	5	5	5	5	0	0	1
CRI	Costa Rica	5	5	5	5	0	0	1
CZE	Czechia	2	2	2	2	0	0	1
DNK	Denmark	3	3	3	3	0	0	1
DOM	Dominican Republic	4	4	4	4	0	0	1
SLV	El Salvador	4	4	4	4	0	0	1
ETH	Ethiopia	4	4	4	4	0	0	1
FIN	Finland	3	3	3	3	0	0	1
FRA	France	2	2	2	2	0	0	1
GAB	Gabon	4	4	4	4	0	0	1
DEU	Germany	1	1	1	1	0	0	1
GRC	Greece	3	3	3	3	0	0	1
HND	Honduras	4	4	4	4	0	0	1
HUN	Hungary	2	2	2	2	0	0	1
ISR	Israel	3	3	3	3	0	0	1
ITA	Italy	2	2	2	2	0	0	1
JAM	Jamaica	4	4	4	4	0	0	1
JOR	Jordan	4	4	4	4	0	0	1
KOR	Korea, Rep.	2	2	2	2	0	0	1
LVA	Latvia	3	3	3	3	0	0	1
LBN	Lebanon	4	4	4	4	0	0	1
LUX	Luxembourg	3	3	3	3	0	0	1
MYS	Malaysia	2	2	2	2	0	0	1
MEX	Mexico	3	3	3	3	0	0	1
MAR	Morocco	3	3	3	3	0	0	1
NPL	Nepal	4	4	4	4	0	0	1
NLD	Netherlands	1	1	1	1	0	0	1
NGA	Nigeria	4	4	4	4	0	0	1

ISO3	Country	2000-2004	2005-2009	2010-2014	2015-2019	N	Total	N Distinct
NOR	Norway	3	3	3	3	0	0	1
POL	Poland	2	2	2	2	0	0	1
PRT	Portugal	3	3	3	3	0	0	1
RUS	Russian Federation	3	3	3	3	0	0	1
SAU	Saudi Arabia	3	3	3	3	0	0	1
SEN	Senegal	4	4	4	4	0	0	1
SGP	Singapore	1	1	1	1	0	0	1
SVN	Slovenia	3	3	3	3	0	0	1
ZAF	South Africa	3	3	3	3	0	0	1
ESP	Spain	2	2	2	2	0	0	1
LKA	Sri Lanka	5	5	5	5	0	0	1
SDN	Sudan	4	4	4	4	0	0	1
SWE	Sweden	2	2	2	2	0	0	1
CHE	Switzerland	2	2	2	2	0	0	1
TZA	Tanzania	4	4	4	4	0	0	1
THA	Thailand	2	2	2	2	0	0	1
TTO	Trinidad and Tobago	4	4	4	4	0	0	1
TUR	Turkiye	2	2	2	2	0	0	1
UGA	Uganda	4	4	4	4	0	0	1
GBR	United Kingdom	2	2	2	2	0	0	1
USA	United States	2	2	2	2	0	0	1
URY	Uruguay	5	5	5	5	0	0	1
VNM	Viet Nam	2	2	2	2	0	0	1
YEM	Yemen, Rep.	4	4	4	4	0	0	1
ZMB	Zambia	4	4	4	4	0	0	1

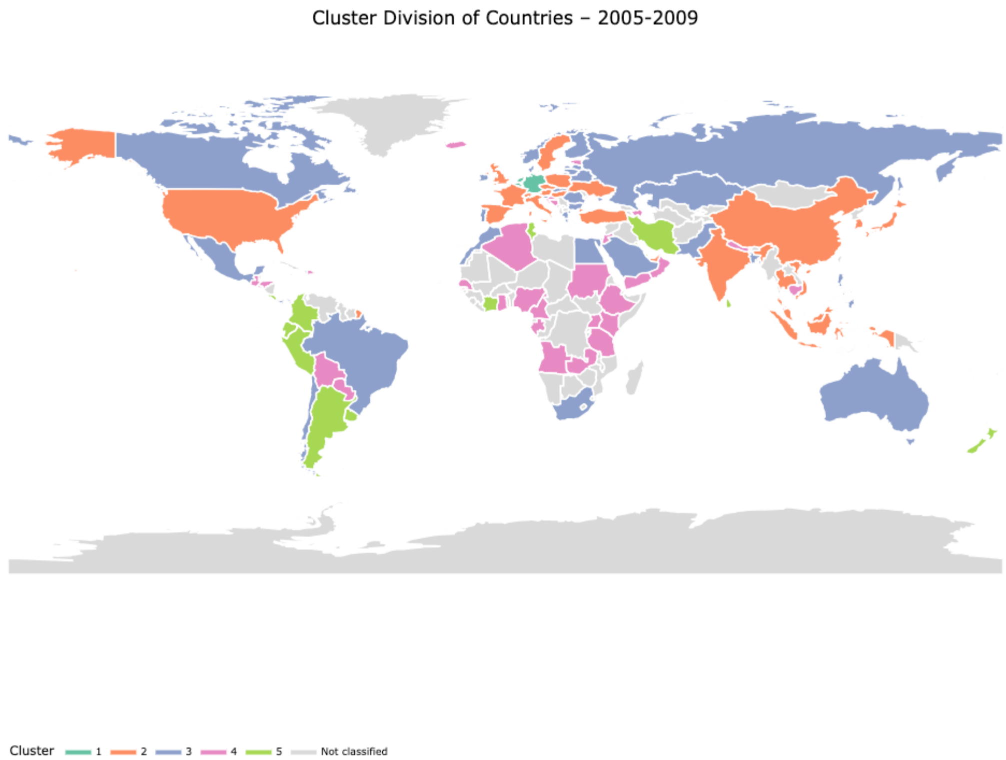
Appendix 4 : Global maps of country clusters by period, 2000–2019

The interactive dashboard, including the various scatter plots and interactive maps, can be accessed via the following link : https://amandine-jacob.shinyapps.io/trade_network_dashboard/

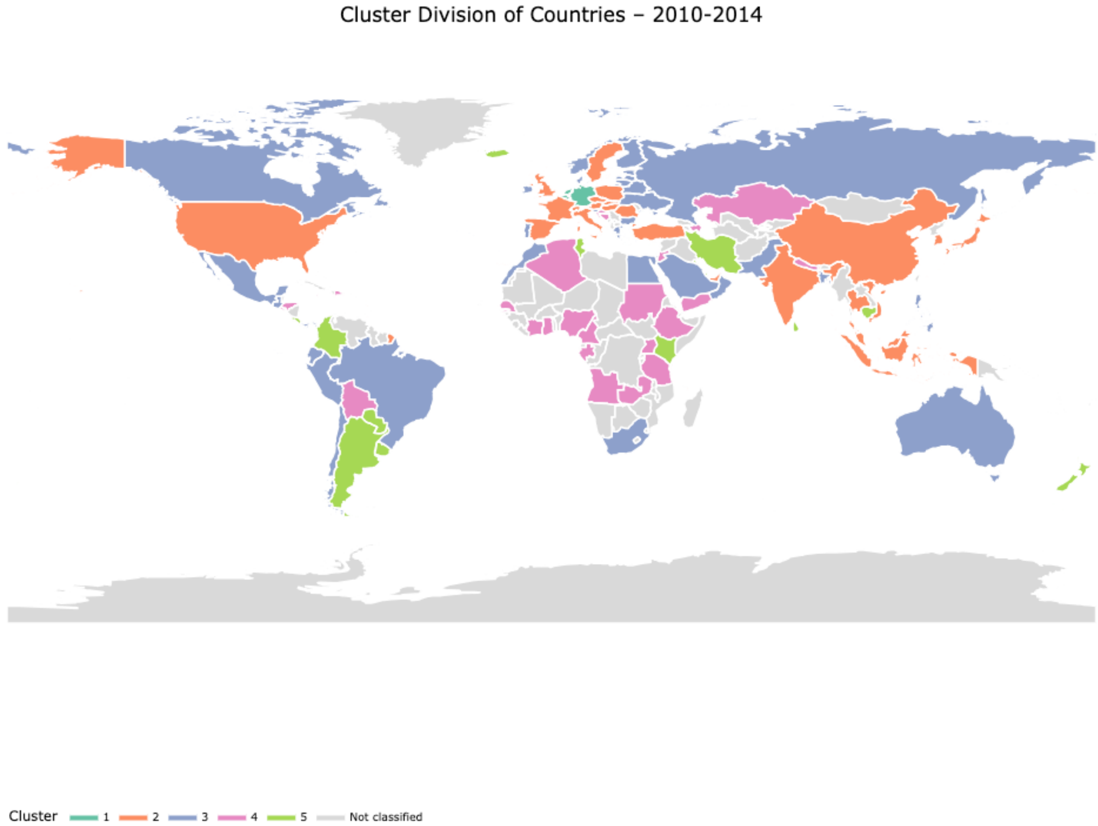
2000-2004



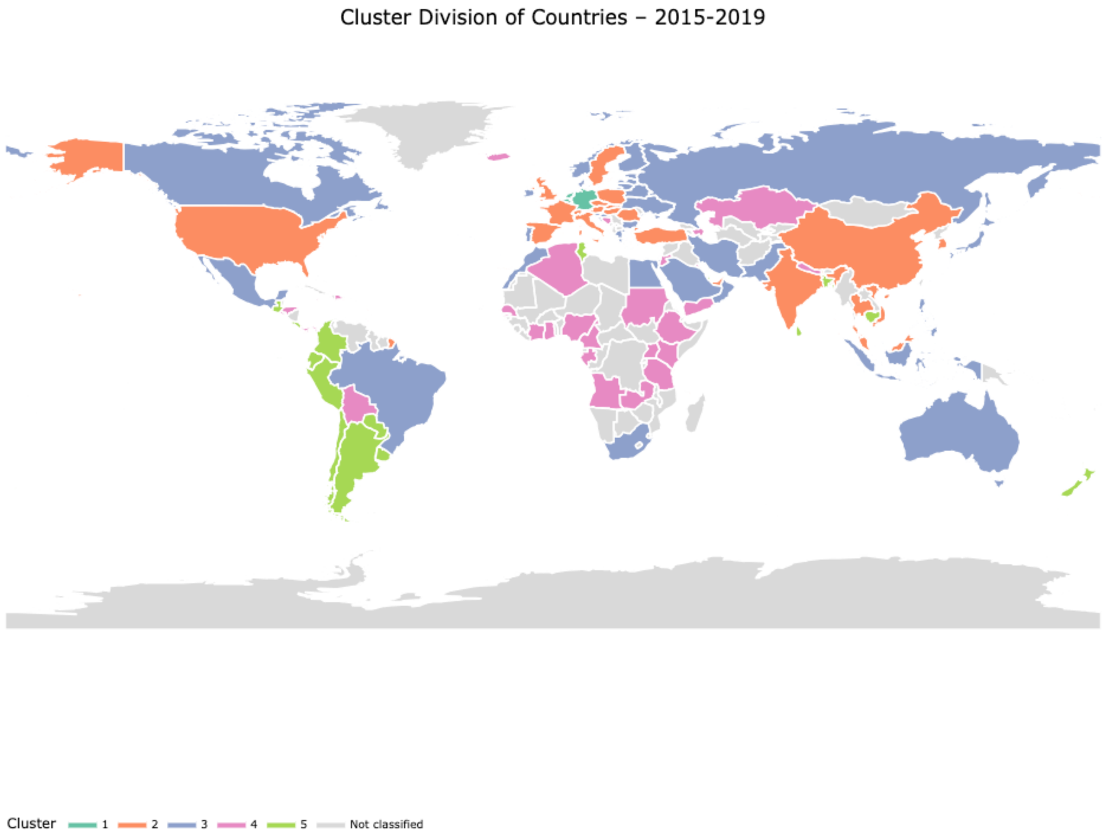
2005-2009



2010-2014

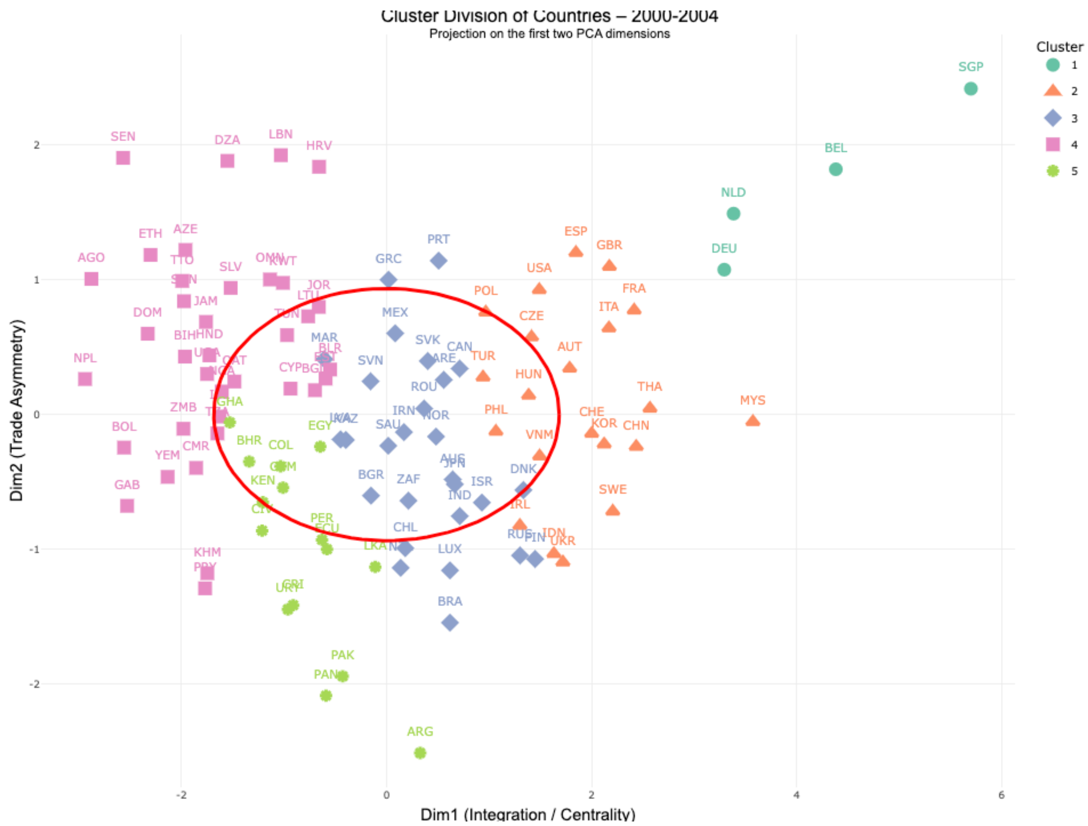


2015-2019

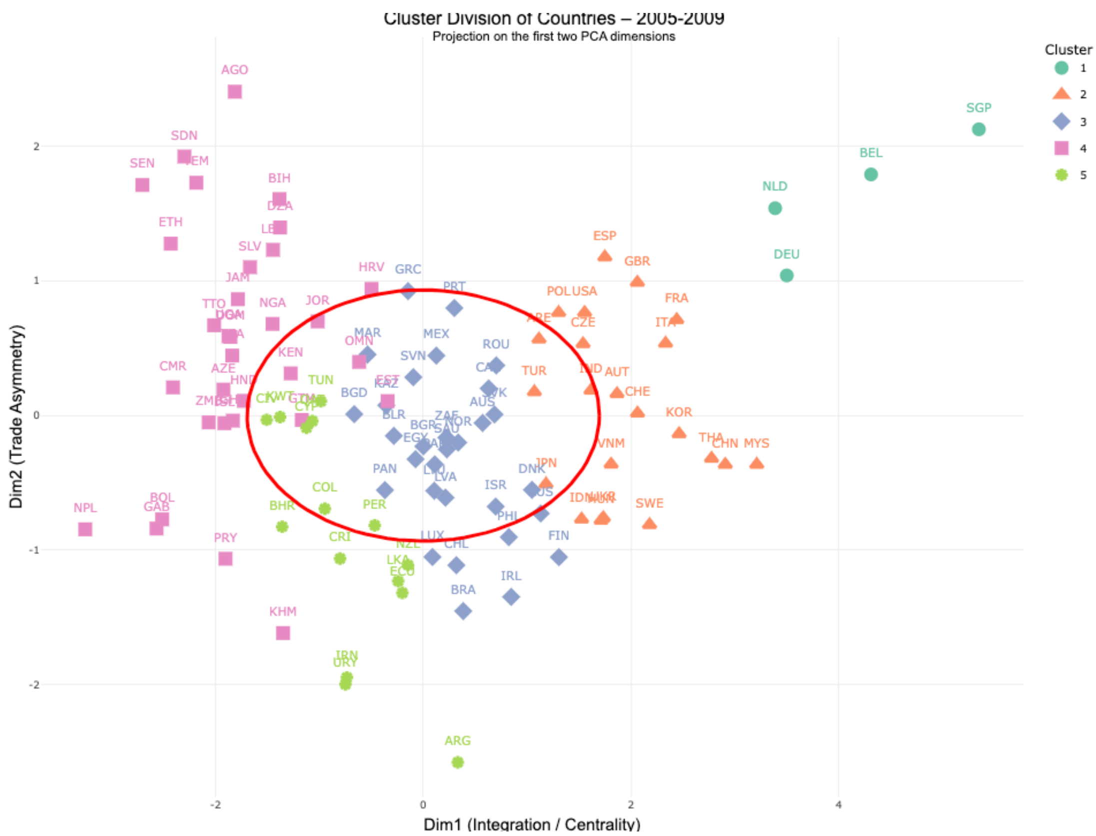


Appendix 5 : Cluster division of countries projected onto PCA dimensions, 2000–2019

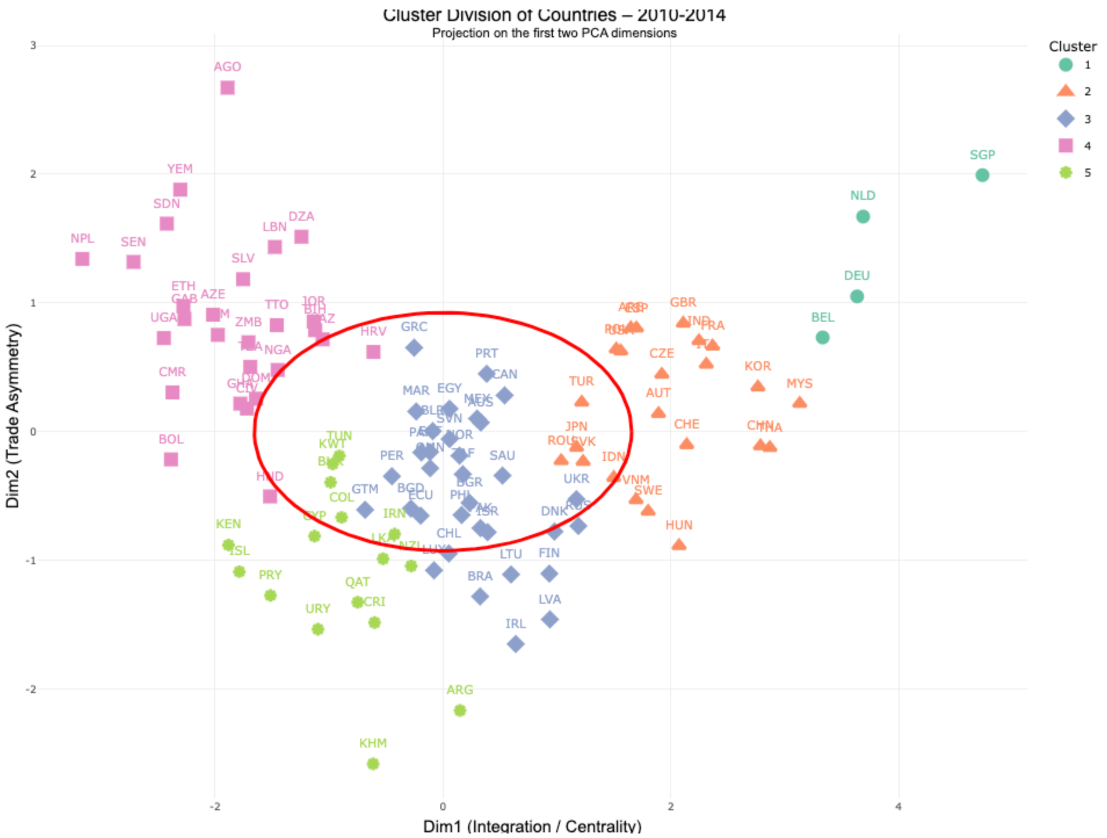
2000-2004



2005-2009



2010-2014



2014-2019

Abstract :

Much of the comparative research in the social sciences has been shaped by methodological nationalism, treating countries as self-contained units defined solely by their internal characteristics. In the field of international trade, this perspective is reinforced by the widespread use of gravity models, which reduce global exchanges to dyadic interactions and neglect the structural interdependencies between states. Building on recent critiques, this thesis adopts a relational approach to examine whether countries' positions in the world trade network help explain cross-national disparities in health expenditure.

To address this question, the study develops a set of structural indicators adapted from demography (Courgeau, 1988) and applies them to bilateral import trade flows between 103 countries from 2000 to 2019, using UN Comtrade and World Bank data. These indicators capture the intensity and asymmetry of trade relations and are complemented by conventional network centrality measures. The quantitative analysis combines these indicators with multivariate methods and panel regressions to assess their explanatory power for cross-national health spending.

Overall, the findings suggest that structural positions in the trade network contribute, to some extent, to explaining disparities in health expenditure, even after accounting for geopolitical factors. By adapting demographic indicators to international trade flows, this study illustrates their potential for capturing structural asymmetries and opens promising avenues for future investigations into the relational dynamics of international trade.

Keywords : International trade; Health expenditure; Structural asymmetries; Network indicators; Graph theory; Methodological nationalism.

UNIVERSITÉ CATHOLIQUE DE LOUVAIN
Faculté des sciences économiques, sociales, politiques et de communication
École des sciences politiques et sociales (PSAD)
Place Montesquieu, 1 bte L2.08.05, 1348 Louvain-la-Neuve, Belgique | **www.uclouvain.be/psad**